DETERMINATION OF AN EMBEDDING FIELD THEORY BASED MINIMAL NEURAL NETWORK ANATOMY CAPABLE OF GENERATING EQUIVALENCE RELATIONS FOR THE FUNCTION OF COMPARATION AND ASSOCIATED PROXY FUNCTIONS FOR OTHER NOETIC PROCESSES

A Dissertation

Presented in Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

with a

Major in Neuroscience

in the

College of Graduate Studies

University of Idaho

by

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December 2013

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Abstract

Developmental psychology has shown many psycho-functional aspects in growth of early sensorimotor intelligence. The Martian is intended to exhibit these abilities. The Martian is based on the epistemological foundations of phenomenon of mind whose mathematical theory is called “mental physics”. Based on mental physics, the psycho-functional abilities at the sensorimotor stage begin with the ability to represent appearances as intuitions. Mathematical sensibility is the mathematical ability to represent intuitions. Comparation is the first in the three-step process of the “acts of understanding” of mathematical sensibility. The current project is the comparation project. This project aims at: 1) discovering a minimal neural network anatomy that can generate equivalence relations, and 2) also to determine proxy functions for other noetic processes.

Based on embedding field theory, the minimal neural network was discovered with its corresponding property sets. The network exhibits behaviors that are emergent properties. We do not introduce any a priori objective criterion for defining what the network treats as a feature for pattern matching. Predictions were also made by the network. If two pattern shown to have demonstrated no-relationship is placed on a larger retinal-map size, they may demonstrate relationship. This is similar to the visual phenomenon of fonts ‘a’ and ‘e’ appearing similar from a distance. The reported experiments are the first-ever demonstration that ART (adaptive resonance theory) is capable of self-defining feature sets.

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Chapter 1. Introduction

The current project is a culmination of past researches by Richard B. Wells on the study of function of mind [Wells, 2011f] (Fig.1.1). The researches come under the umbrella term 'Martian Program" whose goal is to discover functional system architecture minimally required to model the development of sensorimotor intelligence in first months of an infant's (human) life. Thus the Martian is an abstract proxy neural network system.

The first Martian Program spanned from 2006 to 2009. From the functions the Martian could and could not exhibit it was concluded that an anatomical-functional model was inadequate and a "mind-model" was required. Wells concluded that a better functional knowledge of the neural-code was required [Wells, 2011a; Wells, 2011b; Wells, 2011c; Wells, 2011e].

Developmental psychology has shown many psycho-functional aspects in growth of early sensorimotor intelligence [Piaget, 1952b]. The Martian is intended to exhibit these abilities. This came in concert with culmination of Wells' research on the epistemological foundations of phenomenon of mind which began from mid-1990 [Wells, 2006]. Based on these foundations a mathematical theory of mind function was developed called "mental physics" [Wells, 2009].

Based on mental physics, the psycho-functional abilities at sensorimotor stage begins with the ability to represent appearances as intuitions. Since Martian-I lacked this ability, Martian-II was introduced in 2011 [Wells, 2011f]. The second Martian program incorporates mental physics and hence a mathematical ability to represent intuitions called mathematical sensibility.

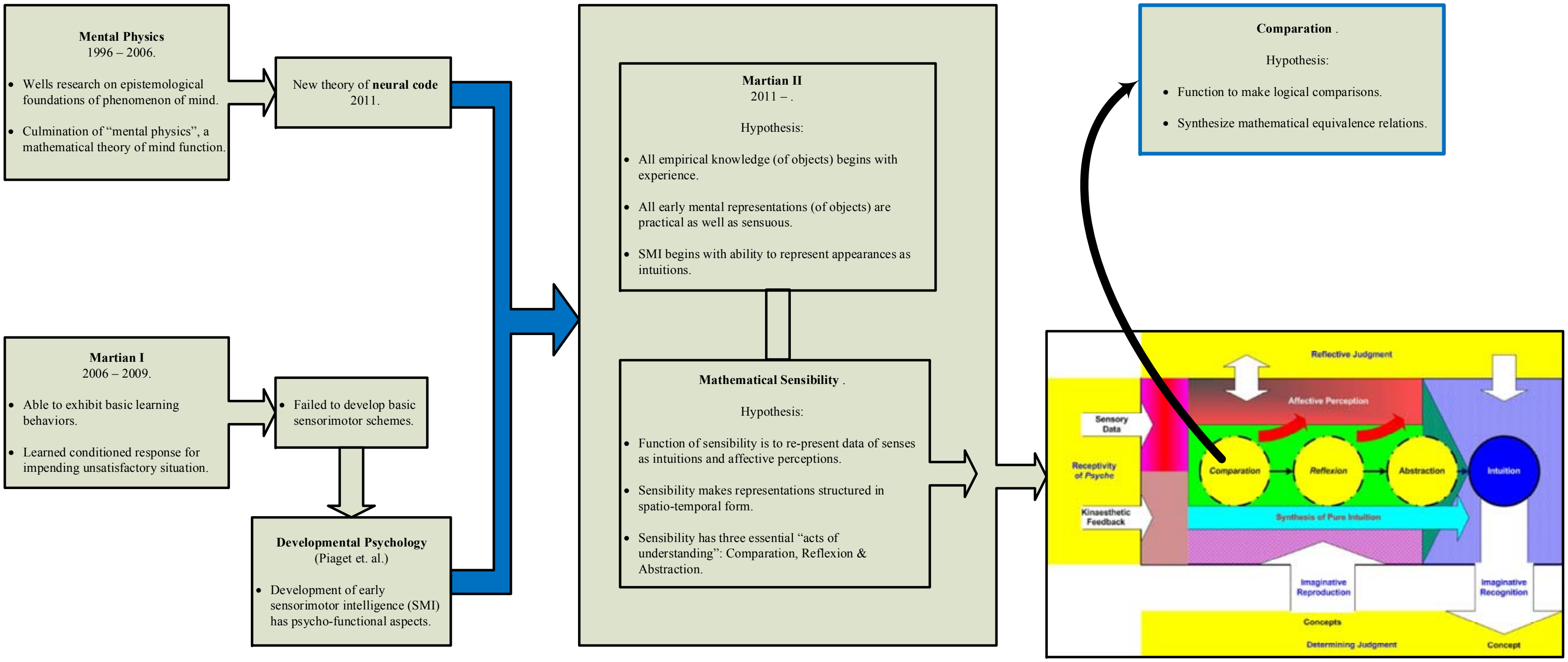

Figure 1.1. Roadmap connecting past research on the Martian and mental physics to current Martian-II program. Comparation as seen in the box illustrating synthesis of sensibility is one of the three "acts of understanding", the Verstandes Actus.

Problem Statement

Mathematical sensibility makes representations (parástases) structured in spatio-temporal form by re-presentations of data of senses to form of intuitions and affective perceptions. This is done from three basic "acts of understanding": **Comparation**, **Reflexion** and **Abstraction** (Fig.1.1). It should be noted that sensibility does not judge. This task is performed by reflective judgment.

The current project is the comparation project. The role of comparation in **sensibility** is to make logical comparisons. Thus its function is to synthesize mathematical equivalence relations. The aims of the project are therefore:

- Discover minimal neural network anatomy to generate equivalence relations.
- Determine proxy functions for interaction between sensibility and reflective judgment.
- Determine proxy functions for generating equivalence relations.
- Demonstrate functional comparation in an embedding field neural network.

Further discussions on the problem of logical comparison and approaches taken for this project is discusses in the succeeding chapters.

A brief overview of general history of our human journey in understanding 'how the brain works?' is given below. Nobody has tackled the problem of logical comparison in the study of mind based on mental physics developed by Wells. However, there have been past and contemporary studies on problems related with discriminating equivalences. These are discussed after the general history overview. Since an exhaustive description is beyond the scope and for the sake of clarity the general discussion is divided in terms of anatomical-physiology and philosophical ideas and arguments. Beginning with the former a brief history is illustrated in figure 1.2.

Brain Function

Alexandrian period saw a major change in idea about brain function from the past concept of brain as repository of soul [Corner, 1919]. The three major figures were Herophilus (~300 B.C), Erasistratus (~260 B.C) and Galen (129 – 199 A.D). Herophilus was first to consider ventricles (cells of the brain) as location for mental processes, favoring 4th ventricle as the precise site [Clarke & O'Malley, pp.713-714, 1968]. This view of ventricular localization shifts from popularity to losing favor back-and-forth until the 19th century. Thus it was probably the longest surviving biological thought [Clarke & Dewhurst, pp.85, 1972]. Erasistratus considered brain convolutions (gyri) being proportional to intelligence and gave the analogy 'coils of small intestine' for their appearance [Clarke & O'Malley, pp.631, 1968].

Galen, the great anatomist of antiquity who gave the detailed description of the ventricles also identified and traced motor nerves to cerebellum and sensory nerves to the cerebrum [Clarke & O'Malley, pp.460-461, 1968]. He considered intellectual functions to have three constituents; imagination, reason and memory. He preferred to locate them to brain substance and not the ventricles but avoided their precise location [Clarke & Dewhurst, pp.10, 1972]. Galen's model is illustrated in figure 1.3.

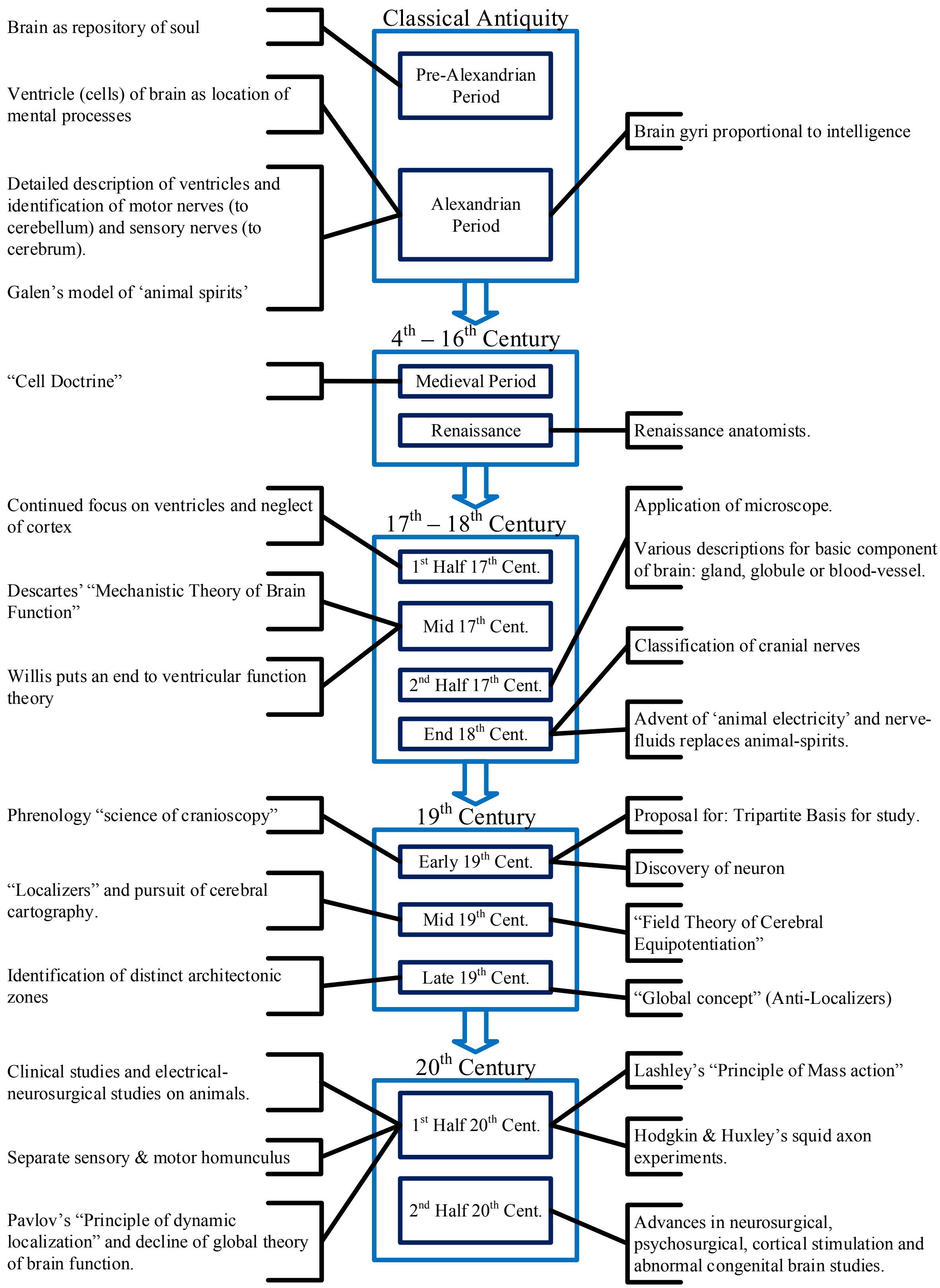

Figure 1.2. Illustration on brief history of attempts to identify and localize brain function.

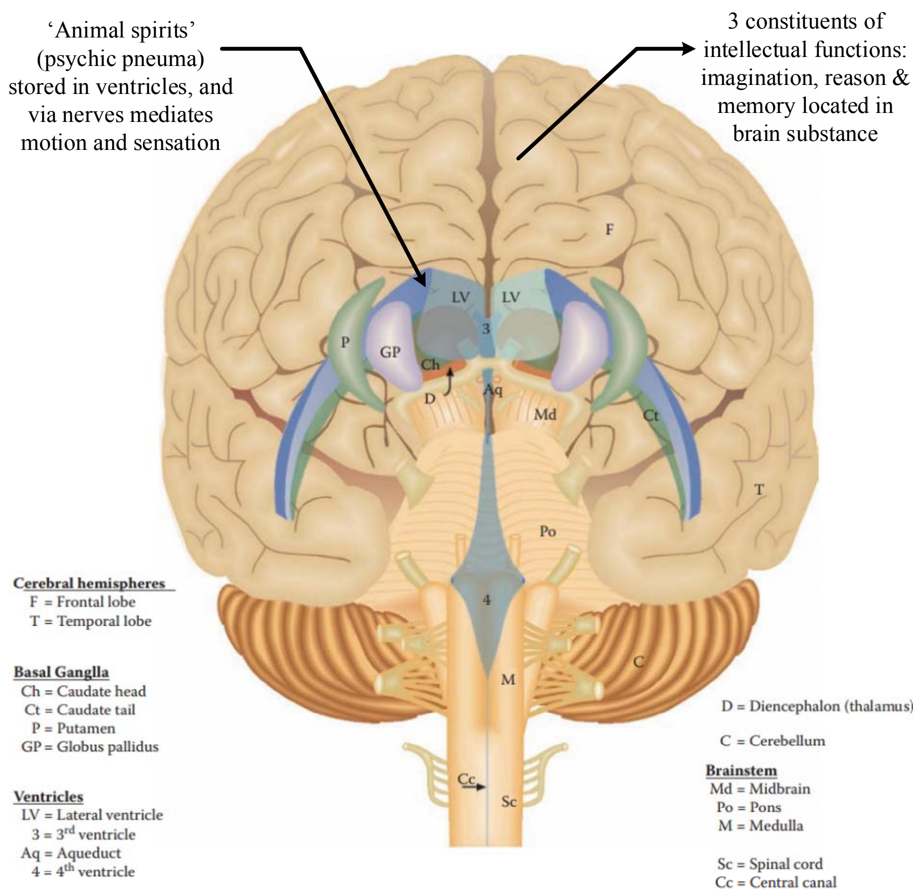

Figure 1.3. Galen's model. According to Galen, the heart produces and distributes 'vital spirits' which through internal carotid arteries and then rete-mirabile (or marvelous net, thought to be fine network of vessels at base of brain first introduced by Herophilus but not proven until 16th – 17th century that it is not a feature of human, monkey or rodent brains) enter the brain. In the brain, by process of refinement 'vital spirit' gets transformed to 'animal (animus) spirits' (psychic pneuma) which is then stored in the ventricle. It should be noted that Galen often contradicted himself. For instance, Galen also postulated that 'animal spirits' were produced in ventricles [Clarke & Dewhurst, pp.5, 1972].

The early church fathers (390 A.D, Nemesis Bishop of Emesia and 354 – 430 A.D, St. Augustine) accepted Herophilus's view of ventricles as the seat of mental processes and refined the theory into the 'cell doctrine' of brain function [Clarke & Dewhurst, pp.10, 1972] (Fig.1.4). With passing centuries the 'cell doctrine' was accepted with variations, such as the addition of dynamic element in 10th century or Avicenna's more complicated rearrangement in a five-cell scheme in the 14th century [Clarke & Dewhurst, pp.30, 1972].

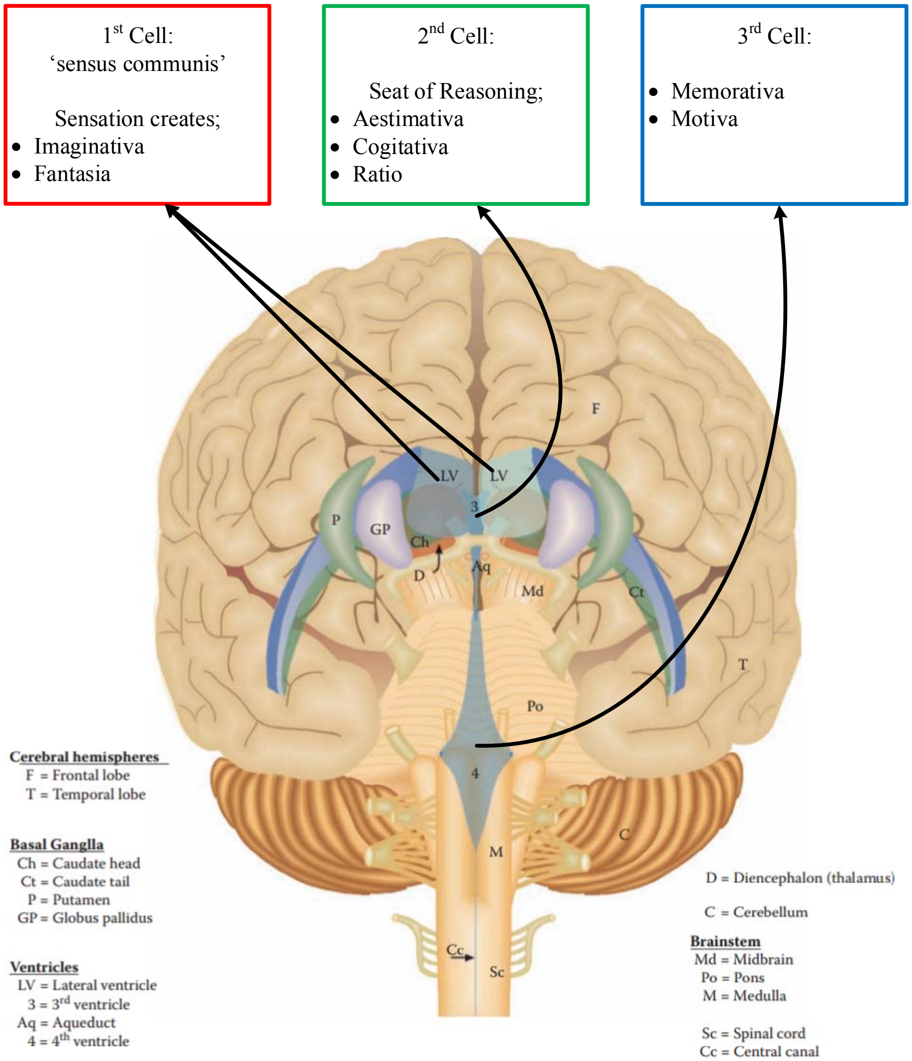

Figure 1.4. Simplest form of the medieval cell doctrine. First cell (lateral ventricles) is the seat of 'sensus communis' ('common sense'), second cell (3rd ventricle) is the seat of reasoning and third cell (4th ventricle) is the seat of memory and action. The first cell receives sensation and creates in the posterior part, imaginativa (imagination) and fantasia (image formation). Second cell is where aestimativa (judgment), cogitative (thought) and ratio (reason) takes place. Finally, third cell is the place of memorativa (memory) and motiva (motion) [Clarke & Dewhurst, pp.10, 1972].

The dynamic element added in the 10th century considered a sequence of events comparable to digestion starting from 1st cell and ending in the 3rd cell.

The renaissance anatomists (Leonardo da Vinci, Jacopo Berengario da Carpi, Andreas Vesalius, Charles Estienne, etc…) re-established original true anatomy of the Alexandrian period and the crude medieval sketches were no longer accepted. Increased understanding of form and function of ventricular system lead to doubts on the ‘cell doctrine’. On the other hand, they re-introduced the concept of ‘animal spirits’ [Clarke & Dewhurst, pp.51, 1972].

In early 17th century there was continued focus in ventricular system over cerebrum though there was decreased support for the ‘cell doctrine’ [Clarke & Dewhurst, pp.68, 1972]. By mid-17th century the cerebrum was seen as the site for some special functions. Rene Descartes’s ‘mechanistic theory’ of brain function focused on ventricular system but pineal body was considered for functional significance as the seat of soul and governing center [Descarte, 1664]. Franciscus de le Boe (Sylvius) and Thomas Willis independently proposed that the cerebral cortex has some special function. The former theorized that ‘animal (psychic) spirits’ are secreted from cerebral and cerebellar cortices [Sylvius, 1963]. Willis is however credited for putting an end to the ventricular function theory [Dewhurst, 1980] and for theorizing three localized mental functions.

The Danish anatomist Niolaus Steano however attacked Descarte [De Ninville, 1669] and also criticized Willis for continued adherence to tradition [Dewhurst, 1968]. Samuel Thomas Soemmerring, noted for clarity and accuracy of his illustration, was responsible for present classification of cranial nerves [Vandenhoeck, 1778] but regressed to medieval theory of ventricular function, of which Goethe and Kant were critical and challenged any attempt to localize soul [Clarke & Dewhurst, pp.85, 1972]. Steano called for a program of research which made good sense [De Ninville, 1669] but there was little or no investigation on cerebral cortex by end of 18th century and hence no notable change in brain function concepts [Clarke & Dewhurst, pp.81, 1972]. However, the application of microscope stimulated research resulting in advent of ‘animal electricity’ (nerve-fluid replaces animal spirits) portending revolutionary change in nerve tissue and brain function studies [Brazier, 1958].

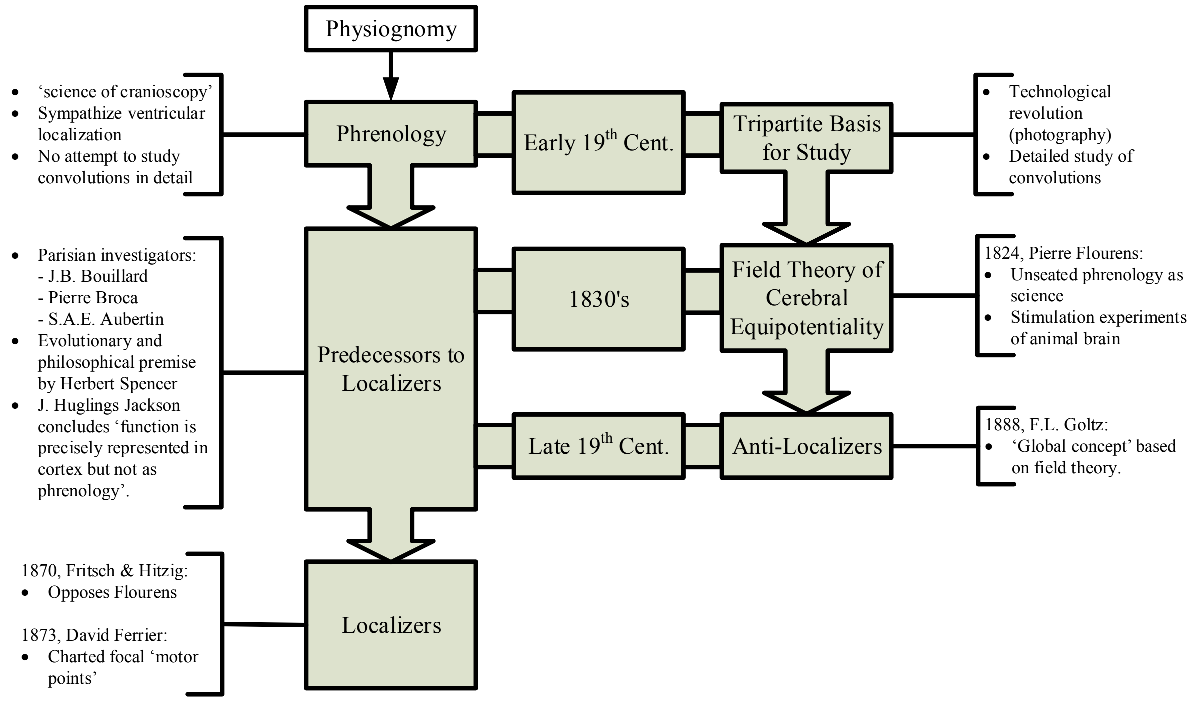

Figure 1.5. Development of investigative approaches in studying the role of cerebral cortex during the 19th century. Physiognomy is "the detailed study of cranial shape and size as a supposed indication of character and mental abilities" [Soanes & Stevenson, 2005]. During the development and increased popularity of phrenology, French and German anatomists led the tripartite study taking advantage of the contemporary technological revolution and the photographer later replaced the artist as the middle man between the anatomist and the reader [Clarke & Dewhurst, pp.106, 1972]. Flourens, using stimulation experiments, unseats phrenology and advances the "field theory of cerebral equipotentiation", which preceded the 'global concept' of Goltz.

The anatomist studied the notion of localizing specific brain function which led to the pioneers, Fritsch & Hitzig, providing experimental support. They did this by eliciting contralateral limb movement following galvanic cortical stimulation of dog brain. They also demonstrated disturbance of limb motor function following removal of the delineated cortical areas. By late 19th century the localizers were not unopposed as the anti-localizers supported 'global concept'.

The 19th century saw developments in the idea of the role of cerebral cortex in brain function that would become the roots of modern era of concepts (Fig.1.5). In early 19th century, physiognomy was transformed by Franz Joseph Gall into phrenology, the science of cranioscopy, but based on unscientifically and naively selected and interpreted evidence [Schoell, 1810]. By correlating mapped areas on cranium (physiognomy) to organ (mental faculties) numbers directly placed on gyri, phrenologists brought together two themes; localization of brain function and morphological arrangement of gyri. Later, the organ boundaries were precisely marked on the brain [Theoré, 1836], thus linking phenology to 20th century cytoarchitectonics [Clarke & Dewhurst, pp.94, 1972].

Contemporaneously, French and German anatomists subscribed to the tripartite (macroscopical, embryological and comparative anatomy) basis of brain research. The French established anatomical interpretation of disease (roots of modern medicine) concurrently developing basic medical sciences and were later joined by the surpassing Germans [Clarke & Dewhurst, pp.101, 1972]. The most renowned French anatomist was Louis Pierre Gratiolet [Broca, 1865; Grandeau, 1865]. Using comparative and evolutionary approaches, he distinguished primary from secondary gyri and defined the limits of 'frontal', 'temporal', 'parietal' and 'occipital' lobes, terms introduced by Friedrich Arnold [Höhr, 1838].

Lack of consistency and overenthusiasm among phrenologists pushed phrenology to extremes and by the 1830's it began to lose favor. Pierre Flourens unseated the notion of functional localization in cortex and hence is credited for unseating phrenology as a science [Olmsted, 1953]. Edwin G. Boring summarizes the contribution of phrenologists as

> "the theory of Gall and Spurzheim is, however, an instance of a theory which, while essentially wrong, was just enough right to further scientific thought … away from the concept of the unsubstantial Cartesian soul to the concept of the more material nerve function … was wrong only in detail and in respect of the enthusiasm of its supporters" [Boring, 1957].

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Flourens using stimulation experiments of animal brains showed that the cerebrum was inexcitable with intellectual and perceptual functions diffusely represented throughout the hemisphere although functions were located in various parts of the brain [Flourens, 1824]. This is the 'field theory of cerebral equipotentiation' [Tizard, 1959].

On the other hand, Gratiolet Parisian anatomists (Pierre Broca amongst them) focused on the problem of localizing language function as a test-case assuming that establishing existence of one function implies others would be identified in time [Soury, 1899; Moutier, 1908]. A contemporary anatomist in London, J. Hughlings Jackson [Broadbent, 1903], based on clinical – pathological data and the evolutionary and philosophical premises of Herbert Spencer [Clarke & Dewhurst, pp.497 – 498, 1968], concluded that brain function is precisely represented in cortex but not as phrenology suggested [Clarke & Dewhurst, pp.113, 1972]. This transition from phrenology to scientific investigation of specific brain function, but still considering cerebral cortex as the seat of function, was aptly summarized by Turner as,

> "the precise morphological investigations of the last few years into cerebral convolutions have led to the revival in Paris of discussions, in which the doctrine of Gall and his disciples – that the brain is not one but consists of many organs – has been supported by new arguments and the opinion has been expressed that the primary convolutions, at least, are both morphologically and physiologically distinct organs" [Turner, 1866].

During this same period, histologists increased our knowledge of the neuron [Clarke & Dewhurst, pp.67, 1968]. Building upon his predecessors, Theodore Meynert contributed to our knowledge of cortical layers of cells and fibres [Clarke & Dewhurst, pp.423 – 437, 1968]. This was followed by histologist Ramón y Cajal identifying the individual cortical constituents [Cajal, 1909].

The experimental support for the notion of local representation of function in cerebral cortex was provided by the investigators Gustav Theodor Fritsch and Eduard Hitzig [Fritsch & Hitzig, 1870]. They opposed Flourens and demonstrated excitability of cortex and located motor function. Their findings and interpretations published in 1870 began an era of progress and continues to revolutionize ideas of brain function [Clarke & Dewhurst, pp.113, 1972].

Amongst the British school of localizers, David Ferrier, pursuing Fritsch and Hitzig's view, tested and confirmed Hughlings Jackson's notion based on concepts of cortical localization for etiology of unilateral epilepsy [Ferrier, 1873]. He did this by performing animal experiments in West Riding Lunatic Asylum and charted local 'motor points', later transposing monkey brain findings to the German anatomist Alexander Ecker's human brain outline [Ranke, 1887]. However, there was little or no experimental evidence of human cortical function at that time though Ferrier's animal experiments are still valid [Bartholow, 1874].

Ferrier, along with the localization pioneers Fritsch and Hitzig, triggered a new field of neurophysiology with clinical undertones. This was followed by the new field of brain surgery [Scarff, 1940], thus inspiring physiologists to study the brain and neurosurgeons in mapping the human brain. The localizers were however not un-opposed. The other school of thought, 'global concept' led by F.L. Goltz, was based on the 'field of equipotentiation' [von Bonin, pp.118 – 158, 1960]. According to the 'anti-localizers' precise localization of cortical functions was impossible because of the massive inter-neural connections and hence they opposed the popular pursuit of cerebral cartography [Clarke & Dewhurst, pp.115, 1972]. The arguments between the two schools of thoughts became public in the encounter between

Ferrier and Goltz at the International Medical Congress held in London 1881 [Wilkins, pp.119 – 129, 1965].

Amongst the anatomist supporting localization, Meynert was the first to relate regional cortical structural differences to functions [Meynert, 1890]. By late 19th – early 20th century architectonics, the mircroscopical study of appearance of cells and fibers was used to identify morphologically distinct areas and argued that the direct correlation with function can be found [Fulton, 1949]. The two pioneers were Walter Campbell and Korbinian Brodmann, both concerned with advancement of knowledge of function and pathological manifestations [Haymaker & Schiller, 1970]. Compared to his German contemporaries Campbell (Australian) was more conservative in identifying distinct architectonic zones and viewed that histology must follow physiologists and clinicians to provide more accurate demarcations of areas corresponding to cortical function [Campbell, 1905]. Brodmann, more concerned with comparative studies, identified 52 areas grouped into 11 histological regions [Broadman, 1909] and helped bring order into the confused state of knowledge [Clarke & Dewhurst, pp.121, 1972]. Oskar and Cécile Vogt with their cyto-architectonic studies of primates and man with electrical stimulation studies dominated the field of cortical localization in early 20th century [Haymaker, 1951]. Otfrid Foerster, a neurosurgeon with interest in localization and excision of epileptogenic foci, advanced the understanding of human cortical physiology and helped dissipate Vogt's confusing results [Zülch, 1969].

Non-localizers criticized architectonics. K.S. Lashley and G. Clark were the most vociferous amongst them [Lashley & Clark, 1946]. Using rat maze studies [Lashley, 1929] Lashley supported the 'theory of equipotentiation' and considered the principle of mass action as applied to intelligence. But with accumulating clinical studies he modified his view to accommodate regional subdivisions of verbal and non-verbal learning abilities [Lashley, 1938]. The concepts of ‘functional pleuripotentialism’ and ‘graded localization of functions’ are considered the basis for Pavlov’s principle of ‘dynamic localization’ [Luria, pp.27, 1966]. I.N. Filiminov, from his study of dolphin olfactory structures developed ‘functional pleuripotentialism’ which views that no part of the cortex is solely responsible for single nervous function but under certain conditions each part of brain may perform other functions [Filiminov, 1961]. H. Nakahama identified four somatotopical regions, each concerned with sensory and motor functions [Nakahama, 1961], thus providing supportive evidence for theory of multiple cortical function.

Thought acceptance of the ‘global concept’ began to decline [McFie, 1972], some psychologist [Vernon, 1950; Bruner, 1964] still supported Lashley’s view and claimed that environmental factors mostly determine intelligence, rejecting any possibility of correlation with specific brain areas. Others such as Chapman and Wolff tried to reconcile the two theories with their not antagonistic but complementary theory. However, Wilder Penfield, initially working with Foerster, continued his work at Montreal with his colleagues making one of the most important contributions to knowledge of cortical localization of functions [Clarke & Dewhurst, pp.127, 1972]. Using electrical stimulation studies of conscious patients Penfield et al. summarized the results of illustrating order and comparative extent of cortical representation of elements in sensory and motor sequence in sensory and motor homunculus [Penfield, 1937; Penfield, 1957]. In attempts to understand brain function contemporary clinical and experimental psychologists continue to investigate for cortical localization but with techniques having better temporal and spatial resolutions [Gazzaniga et al., 2006].

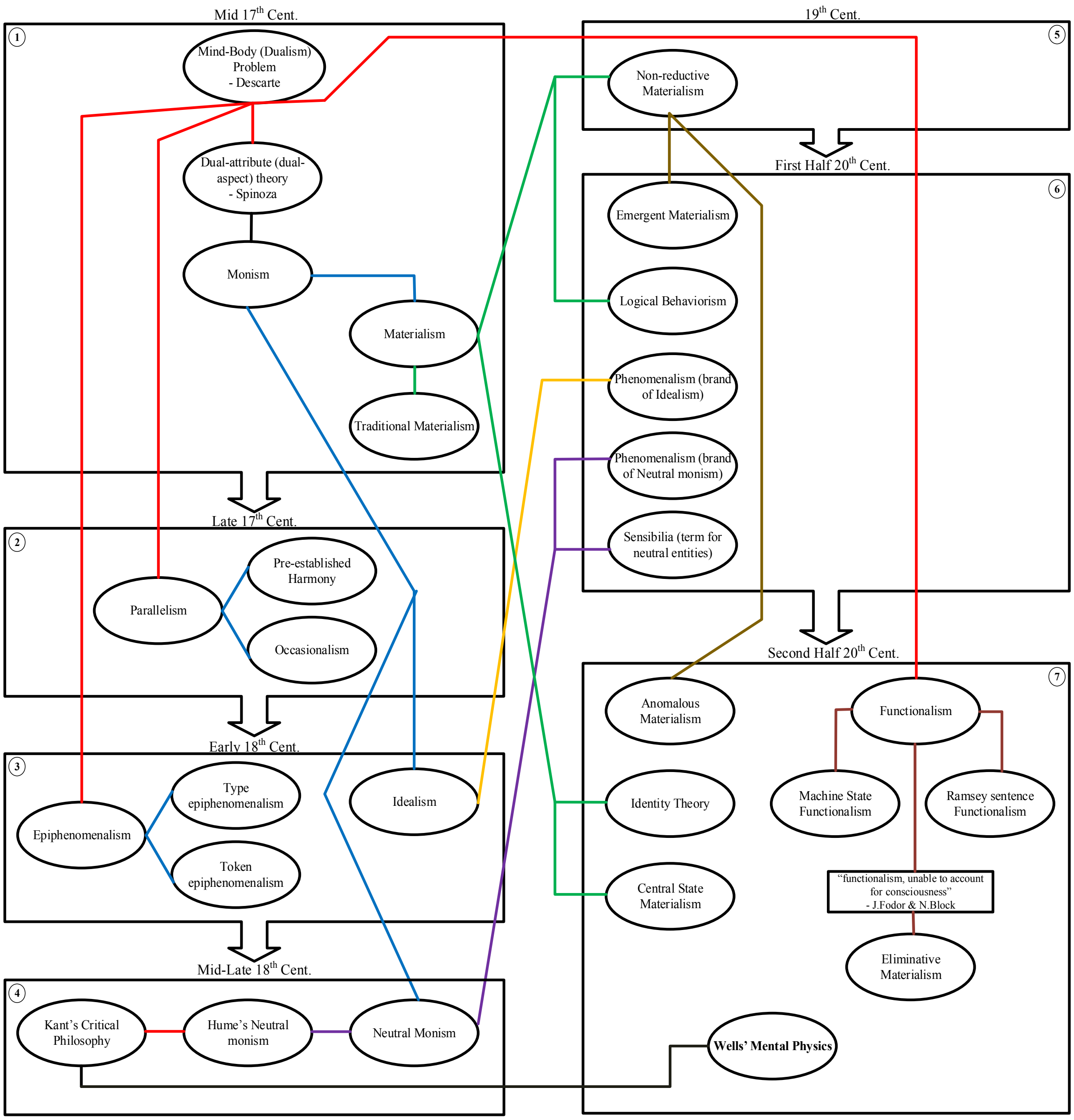

Figure 1.6. Summarized illustration of concepts of philosophy of mind. Blocks (labelled 1 – 7) represent respective period starting from mid-17th to 20th century. Blocks on the left span from mid-17th to 18th century. Ovals represent concepts with lines joining them. Black lines represent evolved or transformation in concept. Red lines represent argument against the preceding concept. Other colored lines represent brands of their respective preceding concept.

Philosophy of Mind and Psychology

The preceding paragraphs indicates inter-linkages between ideas generated from 'laboratory or investigative' works (anatomy, biology, psychology, etcetera) with philosophy. However to avoid confusion an overview of philosophical ideas concerning 'how brains work?' is discussed separately, as illustrated in figure 1.6.

René Descartes is considered father of the modern mind-body problem though the doctrine of distinct soul from body was discussed throughout history [Audi, 1995]. *Cartesian dualism* views minds as substances that are not extended in space and hence are distinct from any physical substance. The mid-17th century Descartes's dualistic view resulted in generation of other philosophical ideas through the centuries, mostly to argue against dualism (Fig.1.6).

Baruch Spinoza, rejecting Descartes's bifurcation of reality into mental and physical substances, held a '*dual-attribute*' of '*dual-aspect*' theory [Audi, 1995]. This view refers to God as the single substance with distinct modes, mental and physical. However, some philosophers opted for the view that 'all reality is really of one kind', also called *monism* [Audi, 1995]. Thomas Hobbes, a contemporary of Descartes, considered 'everything is material or physical'. This is *traditional materialism*, a brand of monism [Audi, 1995].

Contemporaries of Spinoza, particularly Nicolas Malebranche and Gottfried Wilhelm Leibniz, also arguing against dualism considered *parallelism*, 'mental and physical realms run in parallel' (Fig.1.6, block2) [Audi, 1995]. Thus due to God's creation the types of mental phenomenon co-occur with certain types of physical phenomenon but never involve causal interaction. Leibniz's brand or *pre-established harmony* viewed that co-occurrence is only possible in world actualized by God. Similarly Malebranche's brand or *occasionalism* viewed that non-divine phenomena never cause anything and only God's activities cause things to happen.

To solve the mind-body problem while accepting the dualistic view Julien Offray de La Mettrie considered a one-way psychophysical action with physical state causing mental state but not the other way. Thus what we perceive must cause us to undergo sensual experience. This is *epiphenomenalism* [Audi, 1995]. 19^{th} and 20^{th} century materialism raised the issue of whether any state as causes ever fall under mental types. This resulted in two theses; *type epiphenomenalism*, 'no state can cause anything in virtue of falling under a mental type' and *token epiphenomenalism*, 'no mental state can cause anything' [Audi, 1995].

Apart from Hobbes's traditional materialism another brand of monism is *idealism*. George Berkeley's idealism viewed that 'everything (mental and physical phenomenon) is mental, perceptions in God's mind' [Audi, 1995]. Georg Wilhelm Fiedrich Hegel's brand modified this to 'everything is part of the World Spirit' [Audi, 1995]. *Neutral monism*, also a brand of monism considers 'all reality is ultimately of one kind neither mental nor physical'. According to David Hume, 'mental and physical substances are really just bundles of neutral entities' [Audi, 1995]. However in the 20^{th} century Bertrand Russells's version or *sensibilia* viewed 'mind and physical objects as logical constructs out of sensibilia' [Audi, 1995].

Philosophers acknowledged two major problems with monism: characterization of fundamental entities and explaining how they make up non-fundamental entities [Audi, 1995]. With the rebirth of atomic theory and quantum mechanics proponents of materialism believed in its success where idealism and neutral monism failed. In the late 19^{th} century *non-reductive materialism* considered that the 'every substance either is or is wholly made up of physical particles'. Thus the well-functioning brain is the material seat of mental capacities and token mental states are token neurophysiological states. Charles Dunbar Broad's brand or *emergent materialism* viewed 'mental capacities, properties, etcetera emerge from, and thus do not reduce to physical capacities, properties, etcetera' [Audi, 1995; Gustavsson, 2010]. In the second half of 20th century Donald Davidson's brand or *anomalous monism* is a combination of the thesis that 'there are no strict psychological or psychophysical cause' and his 'irreducibility thesis' [Audi, 1995; Malpas, 2013]. According to irreducibility thesis 'every event token is physical but intentional mental predicates and concepts do not reduce to physical predicates or concepts'.

To solve the dualist point that 'one can understand ordinary psychological vocabulary like belief, desire, pain, etcetera and yet know nothing at all about physical states and event in brain' the materialistic doctrine was *logical behaviorism* [Audi, 1995]. They viewed that 'mental states are not internal states with causal effects but are phenomenon that is shorthand for actual or potential overt bodily behavior'. This was much discussed from around 1930's to early 60's with their proponents like Gilbert Ryle and Rudolf Carnap ridiculing Cartesianism's view as 'ghost in the machine (body)' [Ryle, 1949].

Herbert Feigl, a materialist, claimed that mental states are brain states and terms differ in meaning but scientific investigations reveals same referents (morning-star & evening-star differ in meaning but both refer to Venus) [Feigl, 1967]. J.J.C. Smart and U.T. Place, defending this view, introduced the identify theory which considers that 'sensations are identical with brain processes, knowable only by empirical findings' [Audi, 1995]. Another contemporary materialist, David Armstrong supported *central state materialism* which took 'mental states as contingently identical with states of brain apt to produce certain range of behavior' [Audi, 1995; Jackson, 2006]. Thus, compared to logical behaviorists, central state materialists hold mental states as actual internal states with causal effects without implying translation of the mental to behavior, but unlike Cartesianism hold psychophysical interactions are just physical causal interaction [Audi, 1995].

A.J. Ayer supported *phenomenalism*, a view that 'all empirical statements are synonymous with statements solely about phenomenal appearance' [Macdonald, 2010]. Thus if the phenomenal appearance is claimed to be neither mental nor physical it is a brand of idealism and brand of neutral monism if claimed mental [Audi, 1995].

Another argument against dualism is *functionalism* which considers 'specific mental types are types that play a certain causal role'. In the 1960's Hilary Putnam proposed a brand now called *machine state functionalism*. This is a view that 'mental states are types of Turing machine table states' [Putnam, 1995]. Contemporaneously David Lewis proposed *Ramsey sentence functionalism*, a view that 'conjunction of commonsense psychological platitudes to formulate Ramsey sentence defines all mental predicates in platitudes in physical and topic-neutral terms' [Audi, 1995; Weatherson, 2010]. Jerry Fodor and Ned Block raised the problem of functionalism not being able to account for consciousness [Audi, 1995; Block & Fodor, 1972]. Patricia Churchland responded with *eliminative materialism*, a view that 'denies any mental phenomenon, i.e., eliminativist (there is no such thing)' [Audi, 1995; Warburton, 2010]. The philosophy espoused in this present research is mental physics, developed by Wells based on Kantian epistemological metaphysics [Wells, 2009]. This will be separately described later.

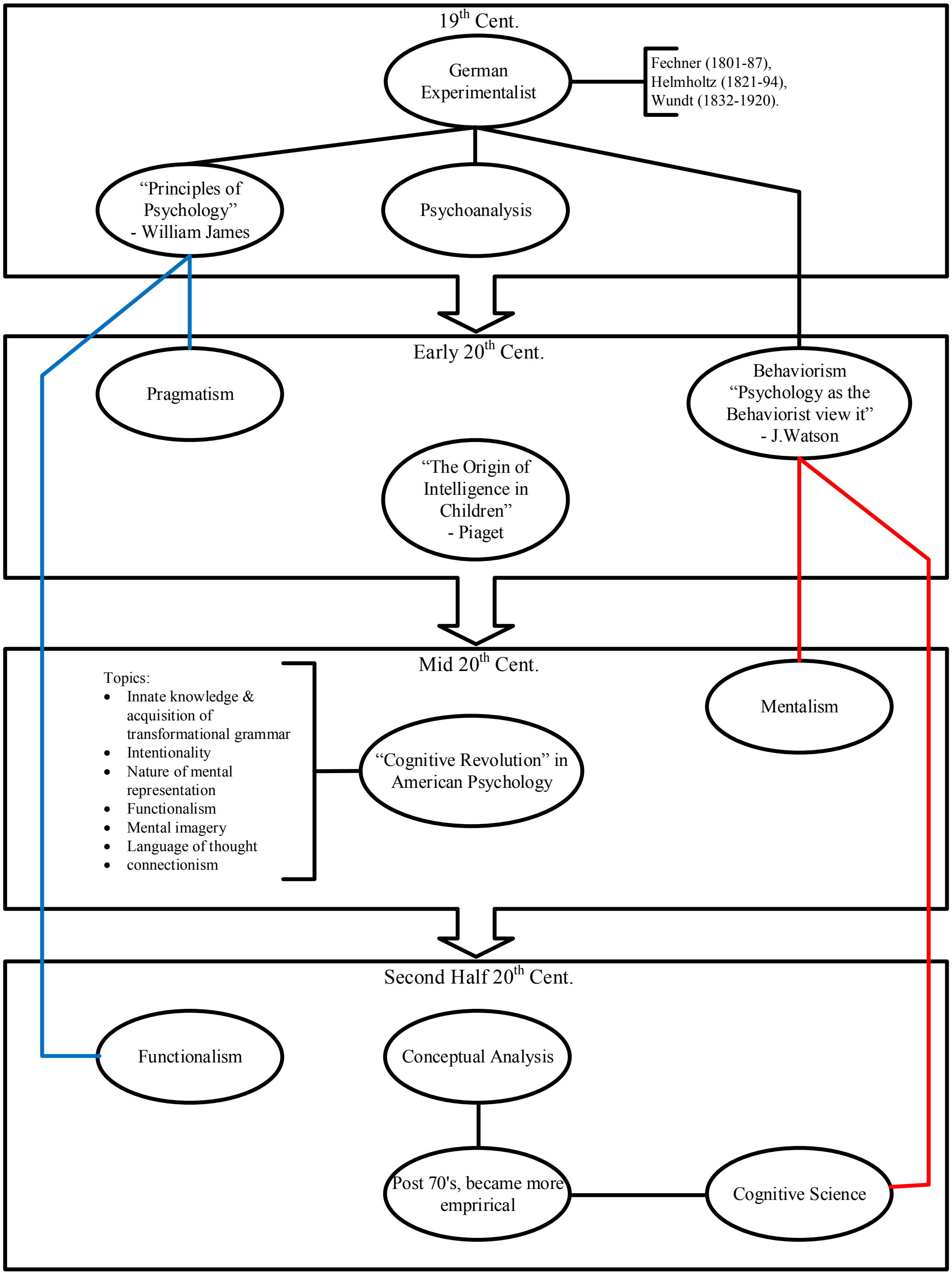

Figure 1.7. Summarized illustration of concepts of philosophy of psychology. Blocks represent respective period starting from 19th to 20th century. Ovals represent concepts with lines joining them. Black lines represent evolved or transformation in concept. Red lines represent argument against the preceding concept while blue lines represent brands of respective preceding concept.

Psychology as the Rebers describe it is philosophers' and scientists' creation "to fulfil the need to understand the minds and behaviors of various organisms, from the most primitive to the most complex" [Reber & Reber, 2001]. Following German experimentalists in the 19th century, psychology began to separate from philosophy (Fig.1.7) [Audi, 1995]. Sigmund Freud, an Austrian neurologist now recognized as the father of psychoanalysis, proposed arguments that continue to contribute to the human understanding of 'how brains work?' [Kandel, 1999]. William James, identified as the father of American psychology, was familiar with the works of the German experimentalist and wrote the classic books 'The Principles of Psychology' (2 volumes) in 1890 [James, 1890]. James's work does not have a structured theory but the adjectival form to his empirical and philosophical underpinnings are *pragmatism* and *functionalism* [Reber & Reber, 2001]. Pragmatism views that 'meanings and truths of propositions are taken as equivalent to practical outcomes' [Reber & Reber, 2001].

James Watson in his 1913 paper 'Psychology as the Behaviorist Views It' supported autonomy of psychology from philosophy and criticized psychologist and experimentalist for relying on introspective methods and making consciousness the discipline's subject matter [Watson, 1913]. Behaviorism is the approach to psychology as a 'purely objective experimental branch of natural science with the theoretical goal to predict and control behavior discarding all references to consciousness.' However the anti-behaviorist argued that if the attempt to explain behavior is legitimate, can the above goal be met without appealing to mentalism ('any theory couched in terms of mental events and processes')? Ironically behaviorists like B.F. Skinner responded with no empirical evidence but gave philosophical arguments to ban mentalistic causes [Audi, 1995].

Jean Piaget published series of classic books and is best known for describing the four development stages from studying psychological development in children [see citations]. He called his theory of cognitive development genetic epistemology. Between around 1945 and 1975 'conceptual analysis' (process of breaking down concepts into simple parts displaying its logical structure) dominates American and English philosophy of psychology peaking with the works of logical positivism [Audi, 1995; Blackburn, 2005]. They took the position that 'philosophy is essentially an a priori discipline' but rarely cited empirical studies. After 1950 the 'Cognitive Revolution' in American psychology (an intellectual movement) highlighted set of topics beyond just mind-body problem and behaviorism and cognitive psychology replaced the latter [Leahey, 1992; Mandler, 2002].

By 1970's behaviorism began to decline and conceptual analysis became more empirical. Coincidentally 'cognitive science' emerged as a new discipline or more accurately 'a cluster of disciplines like cognitive psychology, epistemology, linguistics, computer sciences, artificial intelligence, mathematics and neuropsychology that study the human mind'.

In summary the above overview of philosophical arguments indicate that there is no single argument unanimously supported amongst philosophers. This has led to an aversive reactions from people in disciplines that have separated from philosophy. Using the problem of ambiguity amongst psychologists on the semantic root of "instinct" as an example Wells points out,

> "Unfortunately, almost all the early twentieth century psychologists were eager disciples of positivism and embraced with enthusiasm its *ex cathedra* dogma of *ignórance* that: (1) science could learn nothing from philosophy; and (2) physics was "the queen of all the sciences". Crippled by their ontology-centered prejudices and baselessly subjective pseudo-metaphysics, they managed to turn

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> the idea of "instinct" into such a mishmash of vague and Platonic notions that the subsequent usages of the term actually became counterproductive. Then then, like Aesop's fox, declared the whole idea to be sour grapes and, like medieval inquisitors prosecuting heresy, burned the idea at the stake and scattered its ashes on unhallowed grounds. Psychology has never recovered from the trauma of this historic episode and preserves the transcripts of those ecclesiastical court proceedings in the prosecution of "instinct" in school doctrines today." [Wells, 2011b].

Past and current works on determining equivalence or equivalence like problems

Psychological Works

Following behavioral findings and interpretation from experiments performed by linguists, some behaviorist in the late 20th century studied equivalence. Some of the behaviorists viewed that equivalence relation testing for conditional relation between stimuli such as auditory and visual stimuli provides a behavioral basis for studying language comprehension and production [Bush, 1993]. They defined equivalence class as classes containing finite number of stimuli (N) bearing no overt perceptual similarity but becoming related by baseline training N – 1 conditional discriminations among N stimuli [Sidman, & Tailby 1982; Fields & Verhave, 1987; Sidman, 1994; Fields & Reeve, 2001]. They claimed that, after baseline training, tests evoked emergence of untrained relations, which is an equivalence relation when a particular stimulus evokes selection of a different stimuli which are functionally interchangeable [Fields & Verhave, 1987; Sidman, 1994]. Figure 1.8a illustrates this.

In other words, manipulation of reinforcements can establish arbitrary relation between a given response and stimuli [Lazar, 1977]. They defined such stimuli to be functionally equivalent [Goldiamond, 1962]. Some behaviorist prescribed to "mediation theory" which is an approach to the study of learning which assumes that some event(s) intervenes between response and stimulus. Explication of this intervening process is required to explain behaviors [Reber & Reber, 2001]. They claimed that "mediation-transfer" experiments showed that stimuli can become functionally equivalent by means other than training [Jenkins, 1963].

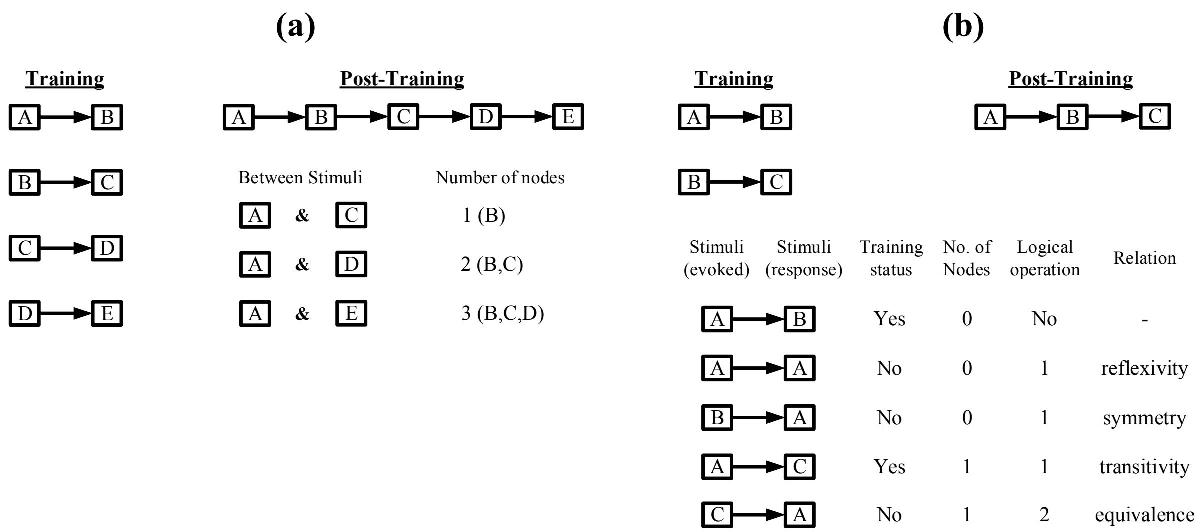


Figure 1.8. Illustration of evoking equivalence and other relations after training. In accordance to their definitions, the structure of equivalence class is defined by four atemporal variables; class size, number of nodes, training directionality and nodal density [Fields & Verhave, 1987]. The variables either independently or in conjunction with each other influence the level of relatedness.

(a) Training for a class size of 6 such that each pair is trained by evoking a response (eg. B) for a given stimulus (eg. A). After training, a stimulus (say, A) can evoke response that was not trained (say, C). The figure also shows how the number of nodes between stimulus and response are counted. Beside the number the elements inside the bracket are the respective nodes.

(b) Training for class size, 3. The table shows some of the possibilities after the training. A→B is already trained and hence no logical operation is considered to be performed. For A→A & B→A the evoked stimuli must connect to A. Hence one logical operation is performed for reflexivity & symmetry. One logical operation is also performed for transitivity because A must connect to B but after that connection of B to C is already trained. Finally, C→A is equivalence relation with two logical operations.

If simple as defined with regard to lesser logical operations then, transitivity is a simpler relation than equivalence relation. Some view that, because of this, transitivity relation will be preferred to more complex equivalence relation [Doran & Fields, 2012].

There are at least two schools of thought. One view is that members of an equivalence class are equally related to each other [Doran & Fields, 2012]. There are numerous claims of support for this view [Barnes et. al., 1995; Barnes Keenan, 1993; Fields et. al., 1993; Rehfeldt & Hayes; 1998; Saunders et. al., 1988; Sidman & Tailby, 1982; Sidman et. al., 1989].

The challenging view is that different pairs of stimuli can have different levels of relatedness under some conditions [Doran & Fields, 2012]. Fields and Doran claim to support this by demonstrating participants who show exclusive preference for transitive relation over equivalence relation. They concluded that members of equivalence classes are differentially related to each other based on relation type and strength of relation is greater for simple relation [Doran & Fields, 2012] (Fig.1.8b).

Therefore, regardless of conflicting views among behaviorists, their definition of equivalence class assumes that a process or processes can be trained to yield equivalence relations. However they do not consider why or how the relations are equivalent in terms of features of the object nor do they consider the situation or context. This is because they assume an equivalence relation already exists and hence are ontology centered. Thus they are unable to explain the source for the claimed equivalences.

Jean Piaget also worked on problems related to equivalence relations as a part of logical thinking in children. In a series of experiments in 59 children from ages 5 years to adolescents he demonstrated three-stages of generating equivalence classes [Piaget et. al., ch.2, 1977] (Fig.1.9). His study was therefore on the three development stages: pre-operational, concrete operations and formal operations stage.

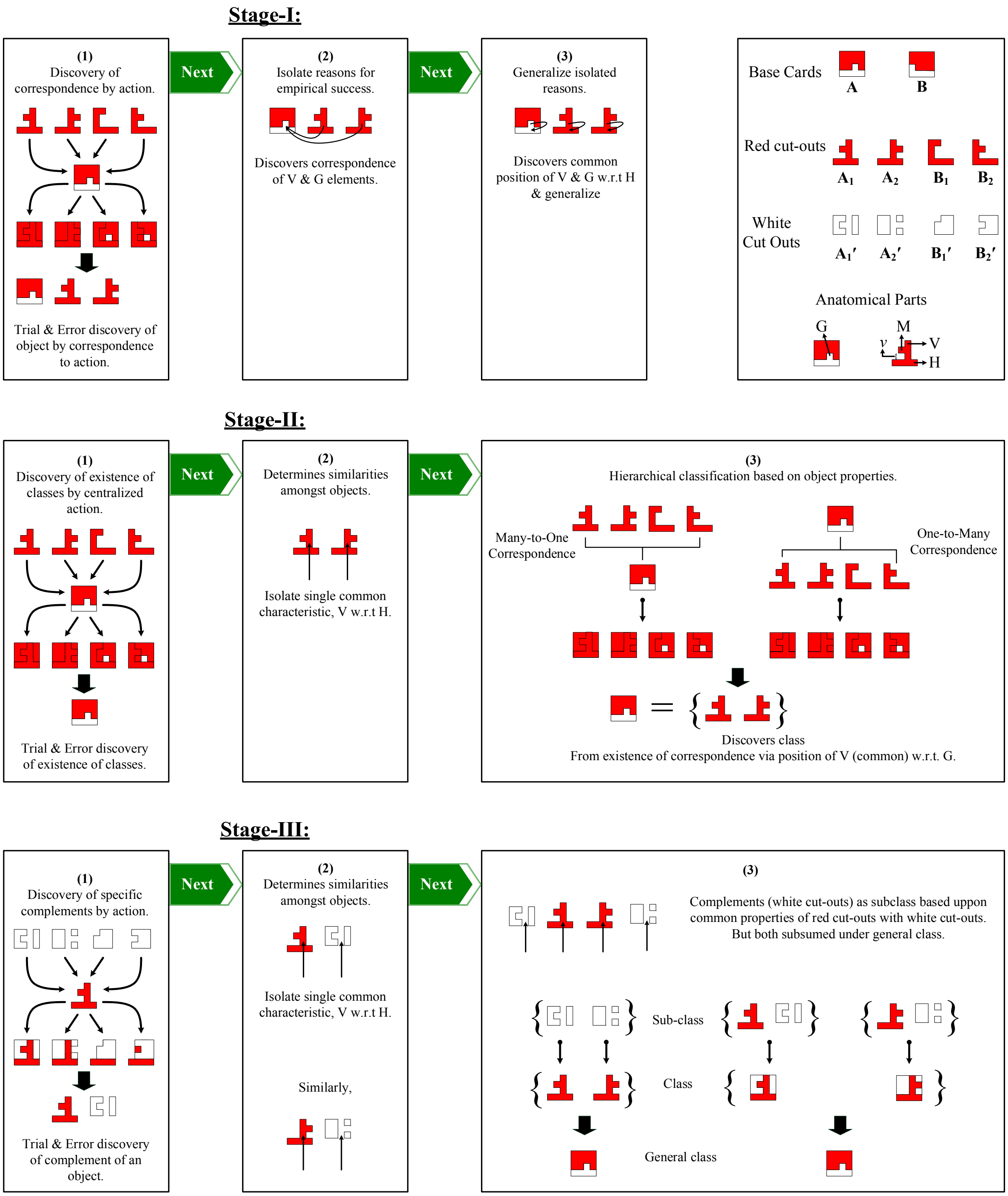


Figure 1.9. Piaget's 3-stages of constructing equivalence classes as observed in children at concrete and formal operational stages. Each stage has three sub-stages. The top far-right box shows the base cards and the cut-outs used in the description of each stages.

Stage-I is the stage of exploration and exclusive 'suitability' [Piaget et. al., ch.2, 1977] (Fig.1.9 Top). He uses the suitability for functional dependence linking the object with action. For instance, a child places a triangle in place of a square as roof of house. This stage may be subdivided into 3 sub-stages which is a passage from a given action to detailed surjective correspondence. First a functional correspondence (i.e., application) is determined by trial and error realized without any anticipatory inspection. This is followed by isolation of some features (reasons) of the object for its empirical success. There is still no anticipation or generalization of the results for subsequent attempts. Finally common features of the object are discovered and immediately generalized.

Stage-II is the stage of successive forms of equivalence classes where similarities between objects are found based upon properties of the objects (Fig.1.9 Middle). There are again 3 sub-stages passing from a functional (action) scheme to operational groupings. First existence of equivalence classes are determined by trial and error. Thus, in contrast to objective correspondence, suitability is determined relative to action. This is followed by search and isolation of a single common characteristic among objects based on appearance of objective correspondence, thus taking into account differentiated characteristics and hence determining similarities. This frees equivalence class from general scheme of action in favor of established direct relation between objects. Finally, hierarchical classification is made by reversible movements of many-to-one and one-to-many. This is done by referring to characteristic positions of the object.

Stage-III is the stage of class union operation with object complements (Fig.1.9 Bottom). Piaget argues that the problem of passing from single classification to operational grouping of classification arises because equivalence classes by simple unions do not divide themselves. To impose this new operations must intervene [Piaget et. al., ch.2, 1977]. First, complements are identified by trial and error without understanding the general relation of complementarity. This is followed by isolation of feature (or absence of feature) of the complement with regards to the object. Finally, complements with common properties corresponding to the objects form subclasses for the hierarchical construction.

Some psychologist have also researched on equivalence classes based on Piaget's INRC group of action (identity, negation, reciprocation, correlation) of formal operation stage [Inhelder & Piaget, 1958; Common, 1993]. Using the scenario of doctor-patient relationship Commons researched equivalence classes on adults with the hypothesis that classes can be arranged according to order of hierarchical complexity [Common, 1993].

Therefore, though Piaget's explanation is more rigorous than the behaviorists it still assumes that some scheme of actions exists which forms the basis for grouping operations. It also fails to explain how the common features of the objects are isolated or discovered.

This project does not implement any of the above views on equivalence. Our approach to this problem is based on Kantian metaphysics and hence is epistemological. We claim that apart from Kantian's critical acroams, the process of comparison can be explained by mental physics (application of Kant's metaphysics to phenomenon of mind study) which does not make presupposition about the source of knowledge of comparison.

Mathematical Theories

19th century psychophysicists studied intensity of sensations as mathematical laws to predict stimulus magnitude versus sensory discrimination. The pioneers were Weber, Fechner, Helmolz and von Frey [Kendel, 2000]. Weber in 1834 demonstrated that sensitivity depends on absolute strength of stimuli. He is best known for Weber's law, which states that the 'just noticeable difference' between the stimuli is proportional to the strength of the reference stimuli. Fechner in 1860 extended this law using logarithmic function. According to this law, intensity of sensation is proportional to the logarithmic function of the reference stimuli. In 1953 Stanley Stevens modified Fechner's version by using a power function in place of the logarithmic function (Fig.1.10).

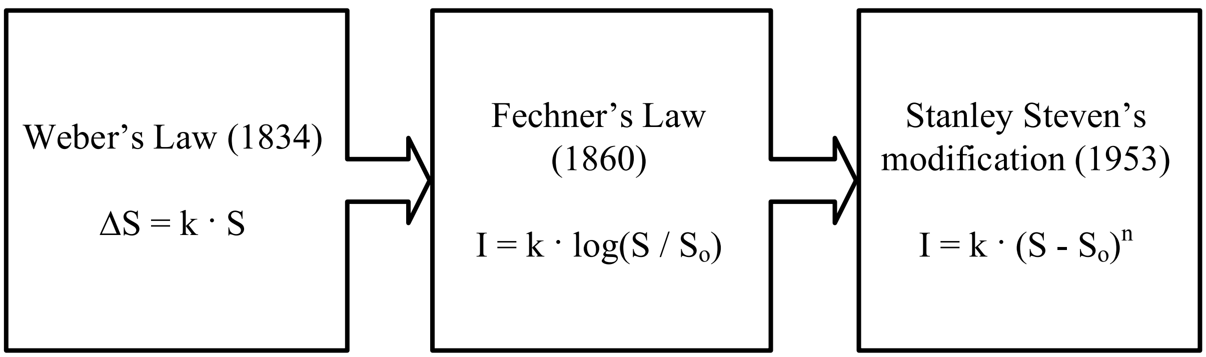


Figure 1.10. Intensity of sensation as mathematical laws. In general, S is the strength of the reference stimulus being compared against, k is a constant and I is the intensity of sensation.

ΔS in Weber's law is the minimum difference between S and another stimulus. This is often called the 'just noticeable difference' or difference limen.

S_o in Fechner's law is the threshold amplitude of the stimulus.

In the power function form of Fechner's law, if n=1 the intensity of sensation is linear. Sensory experience of hand pressure is linear [Kandel, 2000].

In the early 20th century, Nicolas Rashevsky, Herbert D. Landahl and Alston S. Householder pioneered mathematical biophysics [Rashevsky, 1938; Householder & Landahl, 1945]. Their work ranged from study of cellular diffusion and metabolism to excitation-conduction in peripheral nerves and organization in central nervous system (CNS).

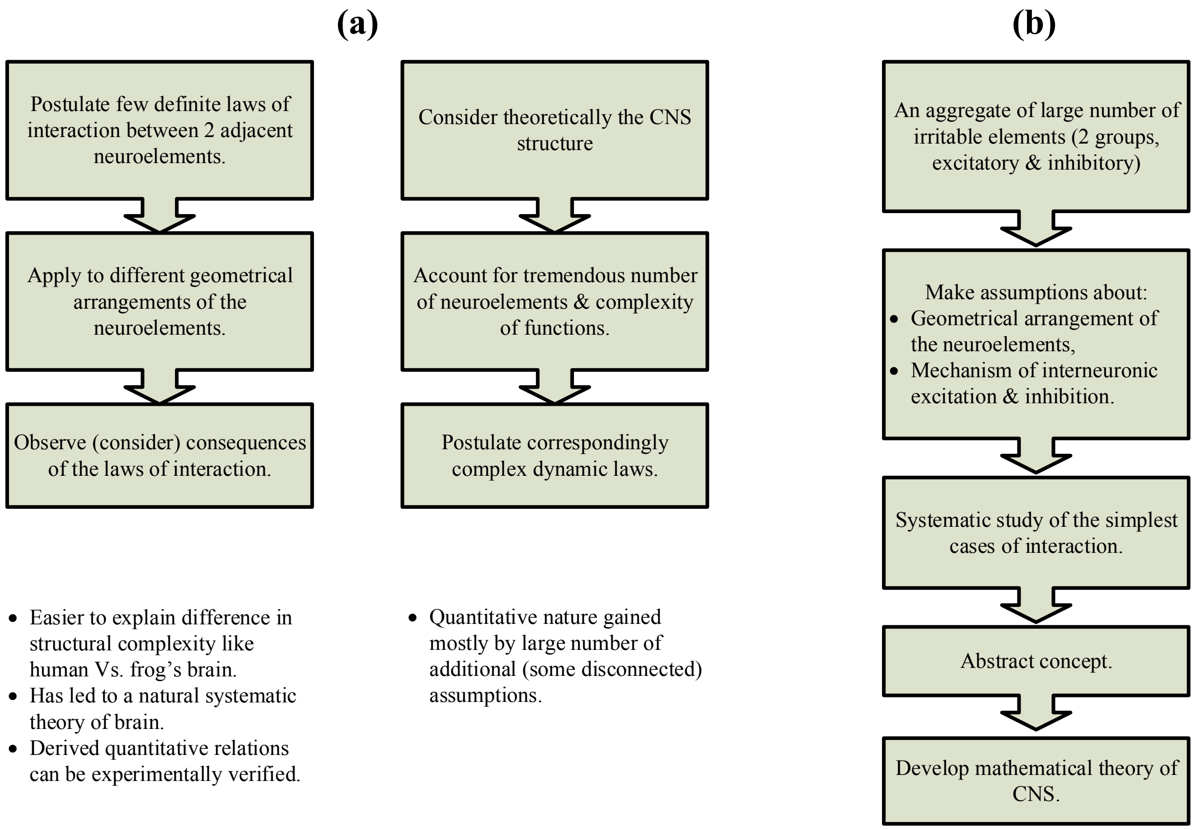


Figure 1.11. Rashevsky's approach to a systematic mathematical study of central nervous system (CNS) functions. (a) Shows the two possible approaches with commentaries about them given in bullet point underneath them respectively. (b) Elaboration of the left method shown in (a).

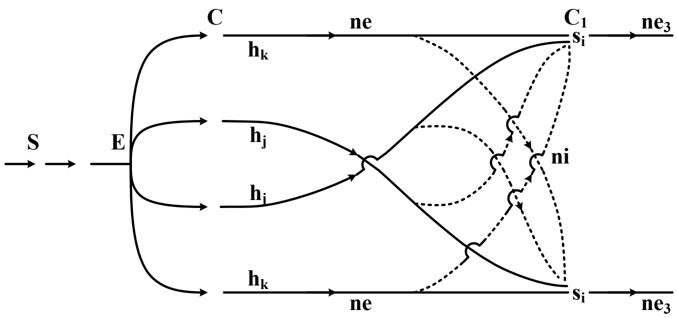
In his book Rashevsky states that a systematic abstract mathematical study of functions of the CNS can be done from two approaches [Rashevsky, pp.355 – 356, 1938]. The fundamental idea of the first method is to postulate few definite laws of interaction between two adjacent neuroelements and then consider their consequences when applied to various geometrical arrangements (Fig.1.11a, left). The second method is to consider theoretical structure of the enormously complex CNS and postulate corresponding complex dynamical laws of interaction between individual elements (Fig.1.11a, right). Rashevsky prefers the first of the two approaches because additional assumptions are needed to gain any quantitative nature from the second method while the first method reduces complexity of CNS functions to complexity of its structure yet keeping fundamental dynamic process as simple as possible.

On analyzing the abstract concepts, in the first edition of the book Rashevsky's main interest was on proving that complicated phenomenon can be systematically designed by simple systems of postulates. Householder and Landahl elaborated that though the postulated equation may not seemingly agree with experimental evidences on interaction of two neurons Rashevsky's prescribed approach (Fig.1.11b) makes good agreement with actual observations. Thus, postulated equations are more than mere mathematical assumptions and in second edition of his book Rashevsky was not much concerned with direct relation of the fundamental postulates to actual observations [Rashevsky, 1938].

Based on the fundamental postulate by Rashevsky some geometrical arrangements (neural network) can discriminate two stimuli (Fig.1.12a). With such arrangements, an intensity S yields an excitation of a definite group of connections s_i (synapse) while a different S′ excites a different group of s_i'. In Rashevsky's version (Fig.1.12a) he showed the above property by mathematical arguments and concluded that 'each intensity may be considered as a different stimulus pattern' [Rashevsky, ch.33, 1938]. A similar property but with different arrangement was discussed by Householder [Householder, 1939] (Fig.1.12b). Using Weber's ratio as a measure of just-determinable difference of total intensity it was shown that the theory compared well with experimental findings of intensity-discrimination at varying intensity levels of visual, auditory and tactile sensations [Householder & Landahl, ch.9, 1945].

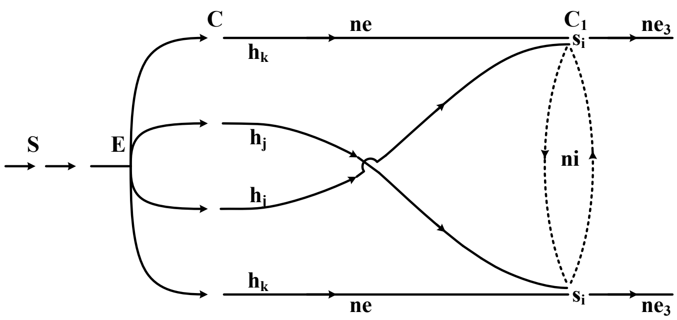
Absolute discrimination between two stimuli.

(a)



- A sensory (or chain of) pathway receives sensory stimulus of intensity S.
- The sensory pathway divides into several branches having intensity E which is same as the original pathway.
- Each branch connects to neuroelement, ne with threshold, h.
- The branches arrive at a particular region, C_1 such that:
  has same neuroelement but of higher order, ne_3,
  all ne_3 have the same threshold, h.
- Group s_i of connections in C_1 receives:
  excitation from each ne with same h_k,
  Inhibition from ni with h_j ($\neq h_k$, excited by ne).

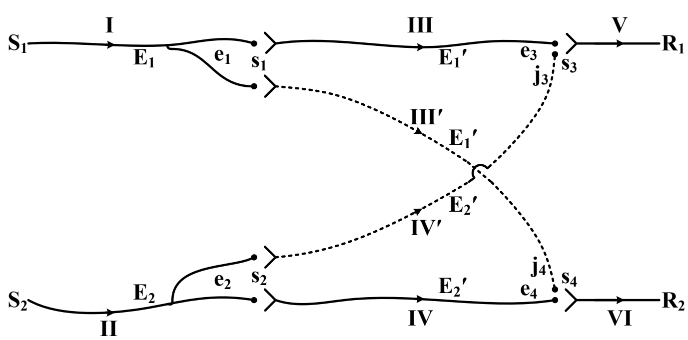
(b)



- This arrangement tackles the same problem as above.
- Arrangement uses most of the above postulates and assumptions.
- Inhibition unlike above is from only one branch.
- This illustrates that different arrangements can produce similar functions.

(c)

When absolute discrimination is difficult (2 stimuli intensities very close to each other) but differences exist

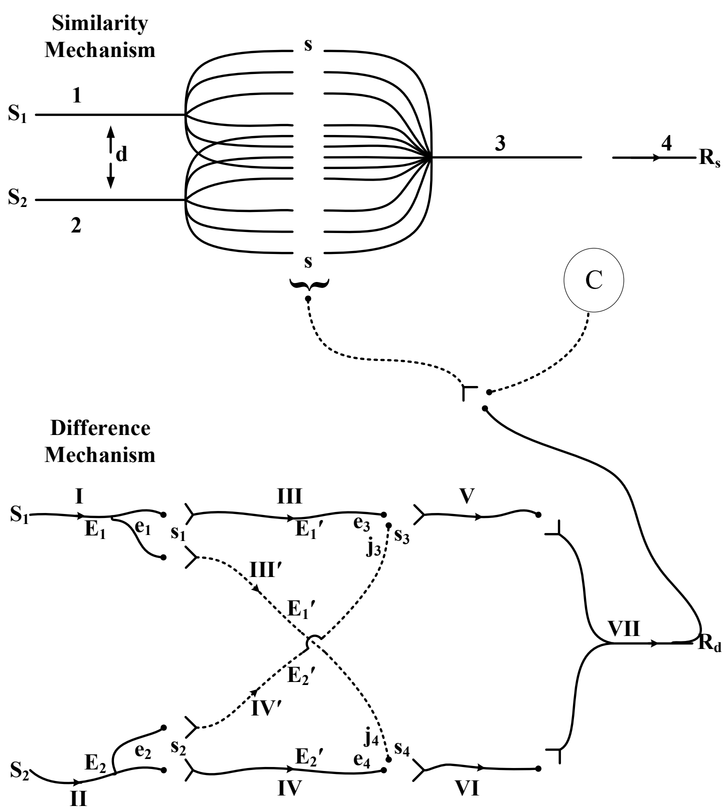


- A stimulus intensity S_1 is received by pathway I resulting in corresponding intensity E_1.
- The pathway is then connected to pathways, excitatory III & inhibitory III′ via synaptic connection s_1 having threshold h.
- The synapse s_1 has an amount e_1 (monotonically increasing function of S_1).
- When $e_1 > h$, III & III′ pathways with intensity E_1' ends at synapses s_3 (with e_3) and s_4 (with j_3) respectively having threshold h′.
- When $(e_3 - j_4) > h'$, pathway V produces response R_1.

Figure 1.12. Geometrical arrangements proposed by Rashevsky, Householder & Landahl for discriminating stimuli. (a) & (b) discriminates by receiving stimuli one at a time. (c) discriminates by receiving two stimuli simultaneously. This was introduced for problems when the difference between the stimuli is small such that (a) and (b) failed.

The above arrangement discriminated stimuli when they were presented independently. But the question then arises when two different stimuli intensities are very close to each other such that absolute discrimination become difficult. For such problems Landahl introduced a geometrical arrangement (Fig1.12c) such that it receives two stimuli simultaneously [Landahl, 1938; 1939; 1940a]. Though the postulates are very different one may notice the similarity with Grossberg's dipole network [Grossberg, 1972a; 1972b].

Stimuli S_1 & S_2 sets into action two mechanisms working together.



- The similarity mechanism conditions stimulus S_1 to produce reaction R_s.

  Concurrently,

  The difference mechanism produces difference reaction R_d if stimuli S_1 & S_2 are different.
- The inhibitory pathway VII′ receiving R_d is connected to synapse, s.
- If unconditioned stimulus S_2 also poduces Rs, meaning 'S_1 can be substituted by S_2'

  But,

  If R_d is strong, S_2 will not produce R_s.

  Therefore, S_1 & S_2 are not similar.
- If $S_1 \neq S_2$ and network considers S_1 & S_2 are similar but there will always be a difference.
- This small difference is disregarded by field (or connection) center C which inhibits pathway V.

Figure 1.13. Geometrical arrangement introduced by Landahl for discriminating stimuli which evokes two mechanisms: similarity and difference. In the similarity mechanism d is parameter that corresponds to spatial distance between the sensory stimuli. The amount of s is a function of d such that the closer the stimuli are so are the number of connection between 1, 2 & 3 pathways. Center-C was not explicated and hence can be thought of as a proxy function determining the amount of acceptable small differences for similar stimuli.

Expanding on this Landahl tackled the problem of discriminating two stimuli which are temporally separated [Landahl, 1940b]. He merges ideas from the above two basic arrangements resulting in a more complicated form (see Fig.1 in [Landahl, 1940b]). The resulting arrangement has cross-coupling inhibitory pathway seen in figure 1.12c but has a single input pathway receiving simultaneously the temporally separated stimuli. By mathematical analysis Landahl concluded that spatial separation of the two stimuli is an important factor.

All the above arrangement dealt with the problem of discriminating stimuli intensities assuming they are the same sensory modality. Landahl then considered the problem of stimuli of different modalities, for instance, touch sensation from different parts of the skin. Thus for the case when two stimuli may have different intensities with same or different modalities he came up with a network system based on the hypothesis that the two stimuli set into action two mechanisms; a similarity mechanism and a difference mechanism (Fig.1.13).

The similarity reaction (R_s) from a similarity mechanism is a function of spatial distance between the stimuli. In other words, the density of connections between the branches of 1 and 2 with 3 pathway, and hence the excitation in pathway-3, is a function of the distance between 1 and 2. However, this reaction is inhibited if the difference mechanism yield a difference reaction (R_d).

Landahl further points out that no two different stimuli can be exactly identical. In other words, they may be similar but R_d occurs due to the small difference from their inequality, thus requiring a center-C which judges the amount of small difference to be neglected. Based on this, center-C inhibits the inhibitory connection from the difference to similarity mechanism.

In conclusion, the works of Rashevsky, Householder and Landahl, though modelled at a neuro-physiological level, provide great insight for possible geometrical arrangements while building neural networks modelled at the psychological level.

The neural network developed for this project is based on Stephen Grossberg's adaptive resonance theory (ART). To our knowledge the developed neural network is the first to demonstrate self-determination of features without being forced upon it.

Feature detection has been a principal task of neural networks since the beginning of the field in the late 1950's work of Rosenblatt and, independently, Widrow. Throughout the 1960's "features" were predefined by the designer of the neural network and supervised training was used to force the network to "learn" the feature. This approach is quite obviously one that, epistemologically, presumes it is legitimate to build into the network objective knowledge (since "features" are object features) a priori. Furthermore, it has long been realized by neuroscientists that supervised learning is a wholly inaccurate and inadequate model for human learning and intelligence. A baby is simply not capable of performing supervised learning.

The need to develop neural network learning systems with unsupervised learning capability was recognized at the time of the 1960's and beginning of the 1970's by Grossberg. Grossberg's Avalanche Network [Grossberg, 1969a] was the first neural network that successfully demonstrated the capacity for unsupervised learning of spatio-temporal pattern sequences. However, this network was not capable of self-determining what features should trigger its learning and had to rely upon the designer to supply it with an externally-generated triggering signal. Grossberg came to call this "ritualistic learning".

For the next 15 years, owing to a drying up of the neural network research funding after the publication of Minsky and Papert's influential book criticizing the perceptron, there were only three neural network theorists of any note carrying out research: Grossberg in the U.S., Kohonen in Finland, and Malsburg in Germany. Of these three, only Grossberg's work maintained a focus on biological and psychological plausibility for the models used. Grossberg recognized the shortcomings noted above in the Avalanche Network and was working in parallel to find solutions for them. By 1974 he was able to present a grand overview that addressed many of the key issues involved in unsupervised learning, including what turned out to be a very prescient observation that affectivity capacity in the brain was, psychologically, the most promising likely source for triggering the learning function in an Avalanche. He also came up with an empirical hypothesis that motor unit functions, properly ordered with the network, appeared to have important involvements in unsupervised pattern learning. Grossberg summarized his results in what became a landmark paper in neural network theory [Grossberg, 1974]. However, in all this work what was to constitute a "feature" in comparison and classification was still left to the network designer to define. This is again, nothing else than the injection of objective knowledge a priori into the structure of the network. Epistemologically, this is unacceptable. However, the design paradigms Grossberg developed during this period became the de factor design methodology for neural network theorists used to this day. Shortly afterward, Grossberg discovered the ART principle and attention shifted away from the still-unsolved problem of how to get a neural network to self-define what is to constitute a "feature".

There were legionary issues in the problem of what became known as feature detectors still to be solved. By 1975 Grossberg had made important advances for solving many of these issues, which he laid out in another important paper [Grossberg, 1975]. However – and this is very important – a "feature detector" was by definition a network that actually identified objects or parts of objects based upon already-predefined "features". It did not identify what a "feature" per se was. What was to be regarded as a "feature" was still left to the ad hoc decision of the network designer.

By the mid-1980's neural network funding had been revived, largely due to papers published by the "parallel distributed processing (PDP) school" led by Rumelhart and McClelland. Although the "new" neural network theory that emerged generated much enthusiasm, in point of fact these works did nothing else but rediscover, in incomplete forms, things already discovered by Grossberg – a fact Grossberg himself noted forcefully in another paper [Grossberg, 1987].

By 1985, Grossberg himself had turned away from exploring fundamental issues – especially the issue of how a network could be capable of self-recognizing what to use for a "feature" – to more applications-oriented applied network theory based on ART. Grossberg himself tells us that his focus had shifted in one of his books [Grossberg, p.143, 1988]. Thus, for the last quarter of a century no research effort has been devoted to returning to the "what is a feature?" problem until the work presented in this dissertation.

Below is an illustrated example that is representative of the sort of very complicated neural network systems that have been standard approaches for the many ad hoc attempts to deal with ill-posed problem issues that the inability of conventional neural networks to self-determine "what 'features' are" lead to. The alternative to these sorts of very complex networks is, at the time of this research, still the venerable but neurologically and psychologically unacceptable recourse to supervised learning [Grossberg, 2005].

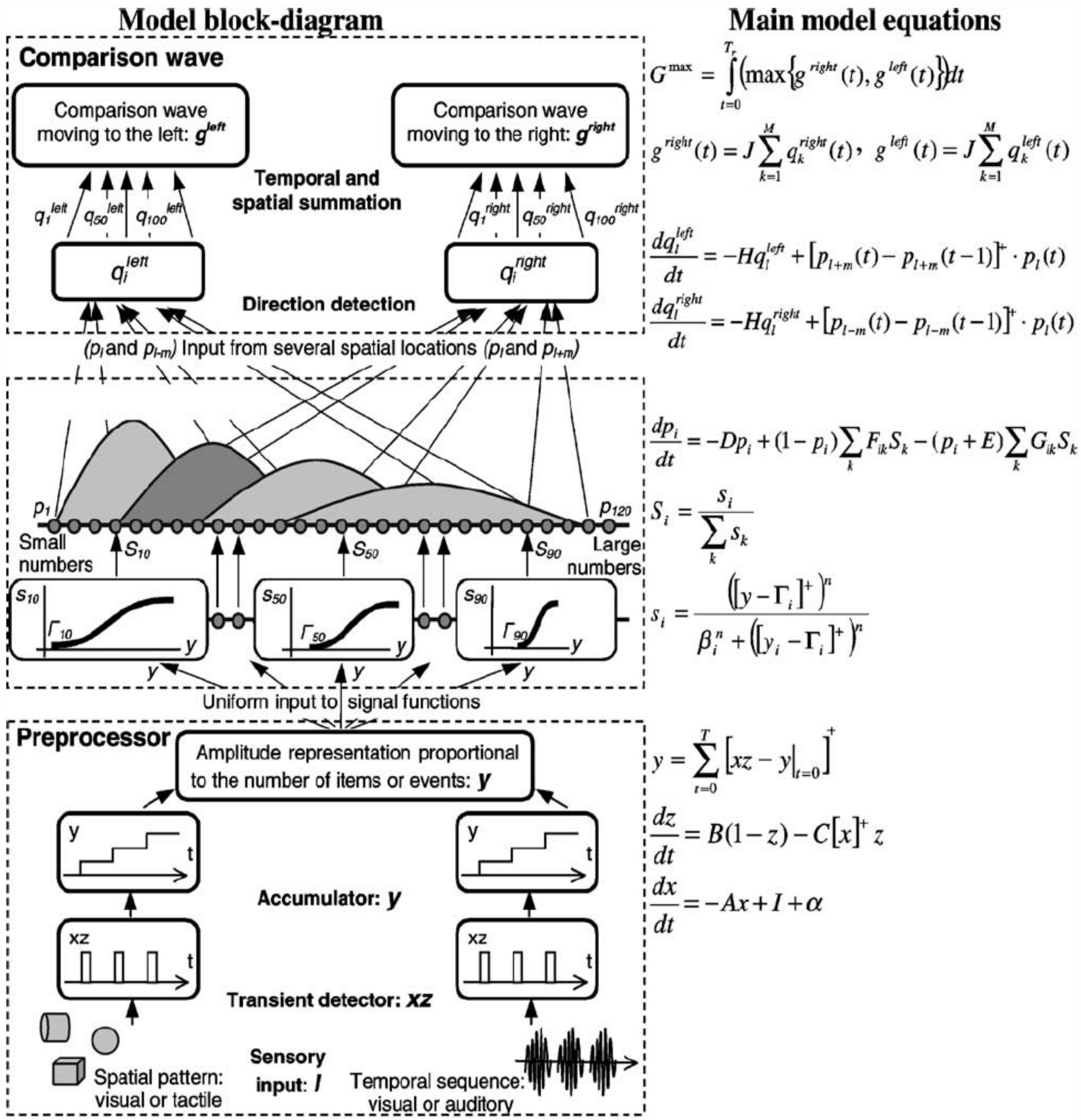


Figure 1.14. Functional diagram of the SpaN model. Preprocessor: For each sensory input (pattern or sequence), a value of the integrator y is computed at each moment in time and then uniformly fed in to the spatial number map. Spatial number map: Each activity p_i of the map receives the normalized output S_i that is derived from the same integrator input y: The signal functions s_i that give the rise to S_i have increasing thresholds and slopes at each successive map cell i. Examples for cells 10, 50, and 100 are shown on the diagram. Each 'bump' on the spatial number map schematically represents the activation pattern p_i for sensory inputs with different number of items at the moment when the whole pattern is already processed. Comparison wave: Activation of both left and right direction-sensitive cells (q_i^{left} or q_i^{right}) receives the input from two cells of the spatial number map (p_l and $p_{l\pm m}$). Both right and left magnitudes (g^{left} or g^{right}) at each moment are computed as summed activations of corresponding direction-sensitive cells (q_i^{left} or q_i^{right}). [Grossberg, 2003]

Grossberg and Repin in their 2003 paper [Grossberg, 2003] introduces a neural network for the problem of numerical representation (in brain) and their comparison. They called their network Spatial Number Network (SpaN). It is functionally made up of: preprocessor, spatial number map and comparison wave (Fig.1.14).

At preprocessor stage pattern inputs presented spatially or temporally are given a numerical input (dc) value for each respective pattern. An input induces an activity level. The activities are accumulated proportional to the number of presented patterns.

The accumulator value passes on to the spatial number map which is made up of k-nodes. The accumulator is transformed to normalized input for the spatial number map. This is done such that, map nodes on the left hand side gets activated faster than those on right for a given accumulator value.

The spatial number map output is then transformed to direction-sensitive (left & right) activities. They are respectively added to form comparison waves, moving to left and moving to right. For two pattern inputs, if amplitude of left-wave is greater, then the second input is smaller. On the other hand, if amplitude of right-wave is greater, then the second input is larger.

Though the SpaN demonstrates capability of comparing patterns, it is different from our neural network for comparation. First, patterns are assigned numerical values in SpaN. In other words, features are determined beforehand. Second, the on-center, off-surround property of nodes in the spatial number map is incorporated by using normal-distribution equations for excitatory (F) and inhibitory (G) Gaussian kernels.

This ends the background discussion. The next chapter demonstrates the subtleties in the task of comparison, in other words, things we take for granted in our everyday performance of comparison.

Chapter 2. Comparison

What does it mean to compare?

We compare things every day but do not usually concern ourselves with the meaning of comparison. But when confronting the question one gets confronted with some deep metaphysical ideas. For instance “is 1 and 1 equivalent to 3?” (Fig. 2.1). The answer, as one notices, would depend on the observer. If the observer is making the judgment based upon addition then they are clearly not equivalent. However, they become equivalent if his/her basis is “family of numbers”.

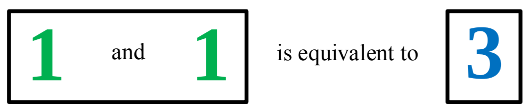


Figure 2.1. The numbers 1 and 1 are equivalent to 3 in the context of family of numbers. However in the context of addition as operation, 1 and 1 is not equivalent to 3 but to 2 (sum).

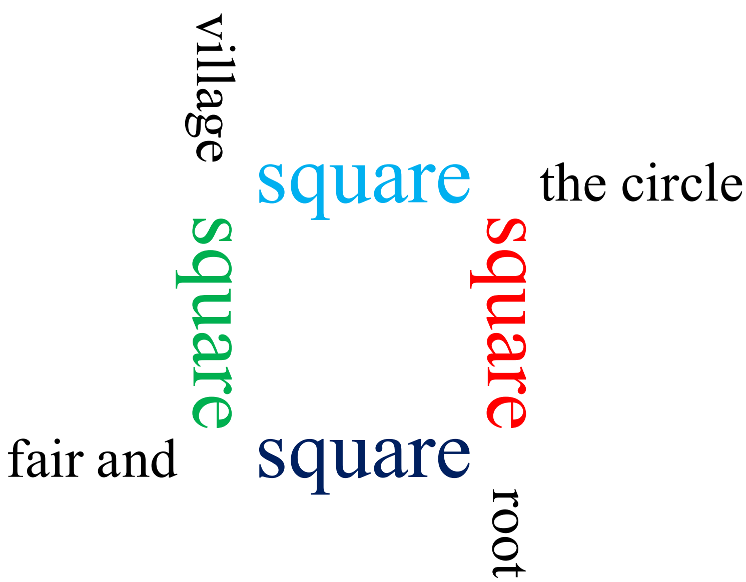


Figure 2.2. The parts of speech of an individual word is determined by the context, i.e., syntax of a given phrase or sentence. In above example (clockwise from top), square is a verb, adjective, adverb and a noun respectively. [Miller, 1991]

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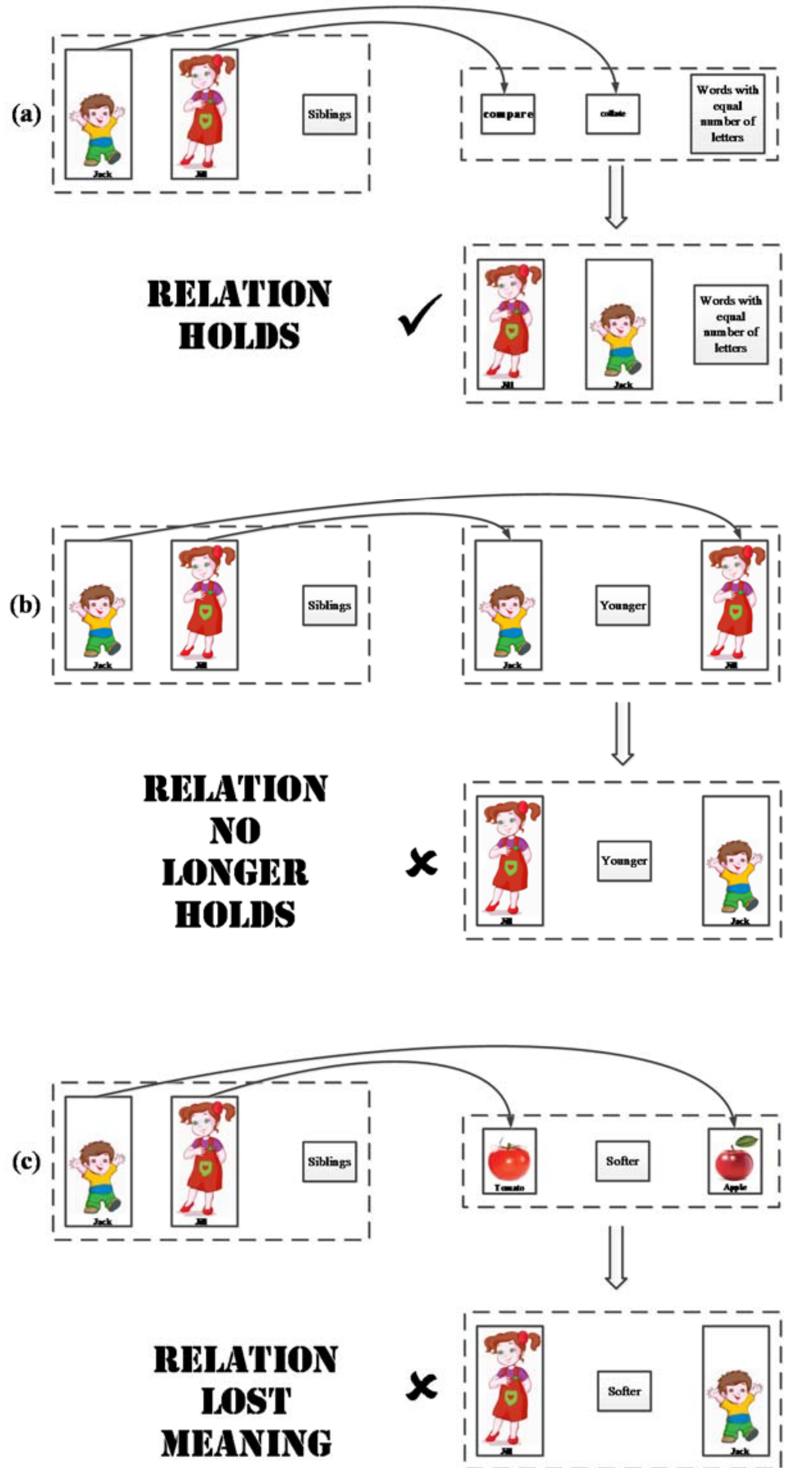

Figure 2.3. Examples demonstrating the three possible outcomes following replacing things from a particular comparison to those in a different comparison. The comparisons or relations between the objects are indicated by respective boxes on the right for some and middle in others. The thing arrows indicate transposition and the large arrows the result after.

Thus comparison of objects depends upon the given situation (context). Figure 2.2 illustrates this where determining the part of speech of the word square depends on the sentence it is associated with.

Observing the above two examples one can then assume that if things in a particular comparison replaces things in a different comparison, then three possible situations are possible [Schreider, 1975]:

- The relation will again hold (Fig. 2.3a).
- The relation will no longer hold (Fig. 2.3b).
- The relation will lose its mean (Fig. 2.3c).

Definition of "compare" and "comparison"

Since subtlety involved in the task of comparison is indicated, before we proceed into a deep discussion let us return to the generic usage of comparison. Figures 2.4, 2.5 and 2.6 shows the various dictionary definitions and usages of the word compare.

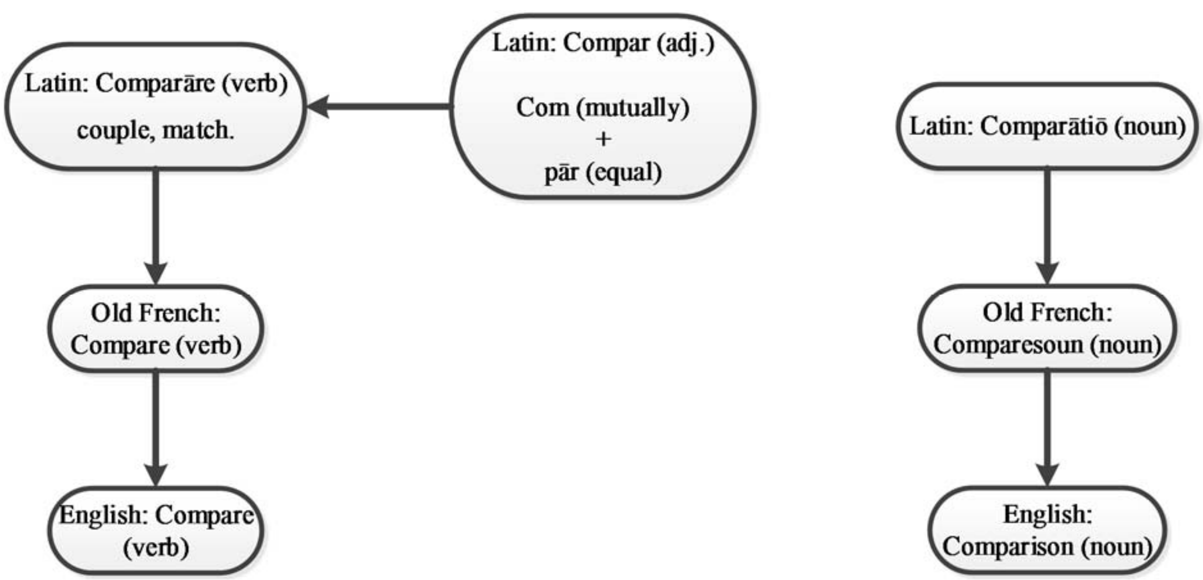

Figure 2.4. Etymology of the words, compare (verb) and comparison (noun) [Ayto, 2005].

Compare (verb)

- estimate, measure or note the similarities or dissimilarities between …(things).
- Grammar: form the comparative and superlative degrees of an adjective or an adverb.

Compare (noun)

(in phrases like beyond compare or without compare)

- Literary: of a quality or nature surpassing all others of the same kind.

Comparison (noun)

- a consideration or estimate of the similarities or dissimilarities between two things or people
- Grammar: the formation of the comparative and superlative forms of adjectives and adverbs.

<u>NOTE:</u>

In describing resemblance by analogy of two different things ⟶ compare to

In estimating the similarity or dissimilarity between things ⟶ compare with

In practice, 'compare to' and 'compare with' distinction is not clear cut and is used interchangeably.

Figure 2.5 Definition and usages of the words compare and comparison [Soanes, 2005].

Compare (verb)

- Contrast
- Juxtapose
- Collate
- Differentiate
- Weight up

Compared to

- Liken
- Equate
- Analogize
- Class with
- Bracket with
- Set side by side with

Compared with

- Be as good as
- Be comparable to
- Bare comparison with
- Be the equal of
- Match up to
- Be on a par with
- Be in same league as
- Come close to
- Hold a candle to
- Be not unlike
- Match
- Resemble
- Emulate
- Rival
- Approach

Figure 2.6. Synonyms of the word compare (verb) [Waite et al, 2005].

For our case the word corresponding to ordinary usage is given by the first definitions of the compare (verb) and comparison (noun) in figure 2.5. Synonyms for this defined 'compare' are listed in figure 2.6. Thus, for this usage, compare is to couple, match or estimate the similarities and dissimilarities of things. But the question still remains for the deeper meaning of "what does it mean to compare?" In other words, "how is the comparison between things made?"

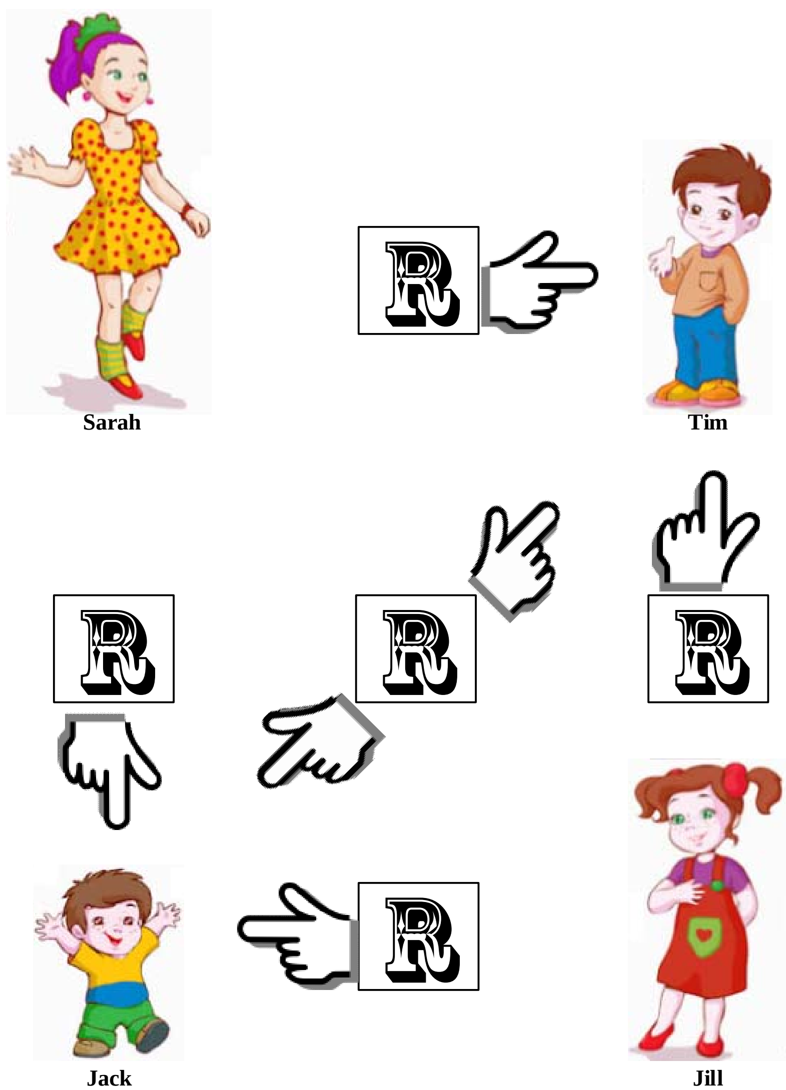

Figure 2.7. An example illustrating the relation (R) "is brother of" indicating only the valid connections for the assumed case that Sarah, Tim, Jill and Jack are children of same parents. Notice that the pointer on either side of R implies that R indicates the objects between which the above relation holds.

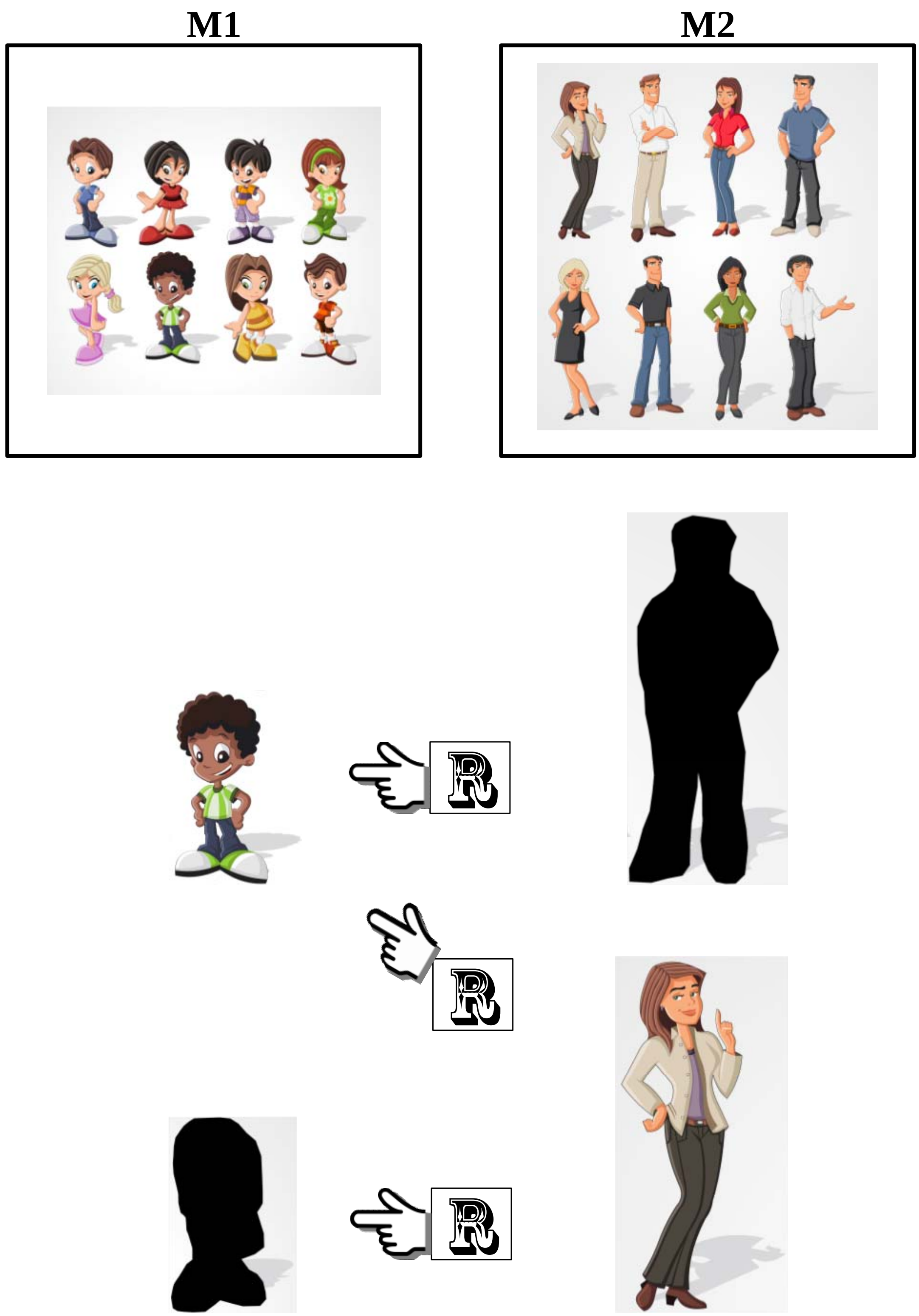

Figure 2.8. An example illustrating the relation (R) "is pupil of" indicating only the valid connections for the assumed case that M1 and M2 are sets of pupils and teachers of the same school. Thus illustrating relations for objects of different sets. The pointer implies that R indicates the objects between which the above relation holds. Silhouettes indicates any.

Giving a "relation"

For a deeper discussion of comparison we will introduce another word here, relation, and consider "how is a relation given?" Understanding the latter will lead us to understanding the former. But before we attempt understanding how a relation is given one's curiosity raises the question of meaning of relation. The verb relate comes from the Latin "relat-" for 'brought back' (from verb referre) and, as the *Oxford English Dictionary* indicates is 'to make or show a connection between' [Soanes, 2005]. Thus the noun relation is 'the way in which two or more people or things are connected' [Soanes, 2005].

Sticking with the everyday meaning of the word relation, giving a relation implies indicating between which objects *the relation* holds. For example let us assume Sarah, Tim, Jill and Jack are children of same parents. Then figure 2.7 shows the valid connections for *the relation* "is brother of". Notice that the children are objects of the same set.

Relations also work for objects of different sets. For example let us assume that a particular school has set of pupils, M1 and set of teachers, M2 (Fig. 2.8). Then, for the relation "is pupil of" a particular pupil is related to a particular teacher or any teacher. Also, that teacher has other pupils. This and the earlier example relates two objects hence binary-relations. Though much of the discussion will be binary-relations one must remember that a relation can have multiple number of objects (Fig. 2.9).

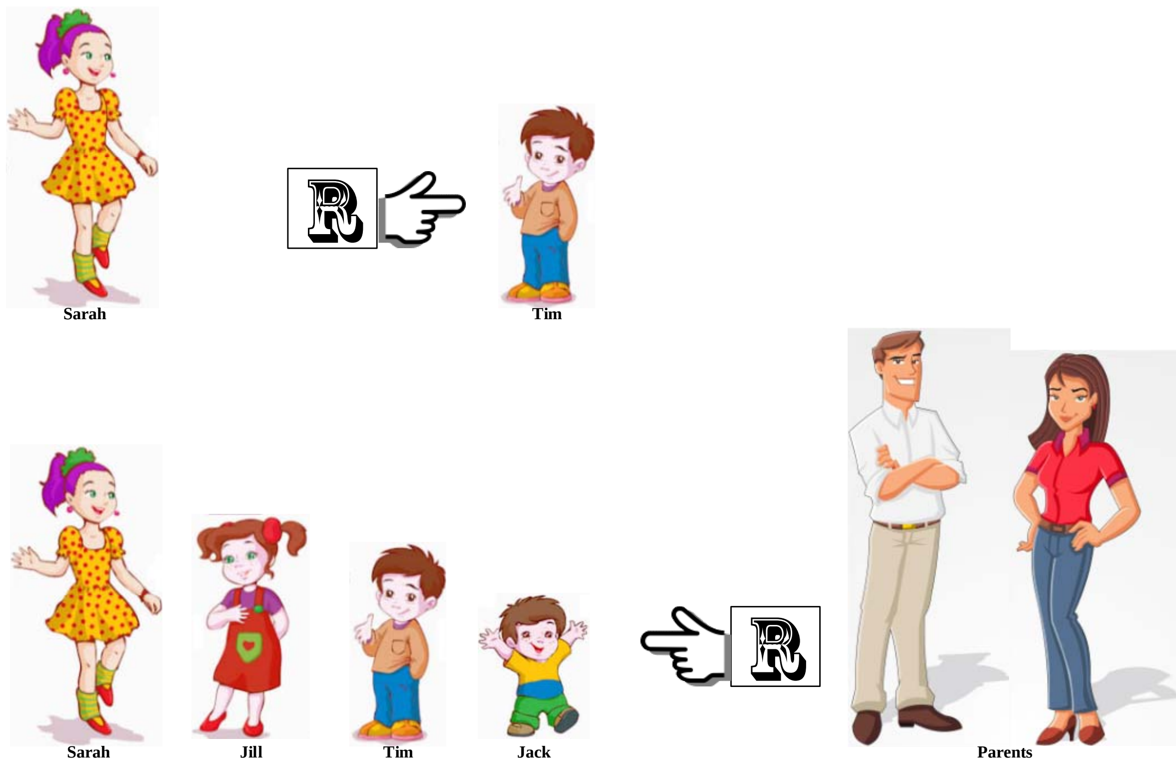

Figure 2.9. Illustration of binary-relation and quaternary-relation. The top example is for relation (R) "is brother of" as seen in Fig. 2.7. The pointer of R indicating that Tim "is brother of" Sarah. Thus relating two object, Tim & Sarah and hence binary-relation.

The bottom example however is for the relation (R) "form children of". The pointer indicating that Sarah, Jill, Tim and Jack "form children of" same parents, thus relating four objects and hence quaternary-relation. Note that there can be any number of objects for a *given* relation.

Precise definition of "relation"

Following the above qualitative description of what a relation does the next step is to give a formal definition.

Definition 2.1. Given,

M is a set s.t (such that) x, y are any elements belonging to M, $x, y \in$ M;

Ordered pairs $< x, y >$ s.t $< x, y > \neq < y, x >$ unless $x = y$; and

M x M is the set of all ordered pairs $< x, y >$.

Then if a set R is contained in M x M, R $\subset$ M x M, then R is called relation R on the set M.

The informal meaning of above definition is as follows. Let us assume a set of objects (M) and hence set of ordered pairs of the objects (M x M). Then, determined by which pair are connected for a *given relation*, we can choose the subset of M x M, R. In other words if $< x, y > \in$ R then *x* is related by R to *y*, i.e., *x* R *y*. Figure 2.10 illustrates this.

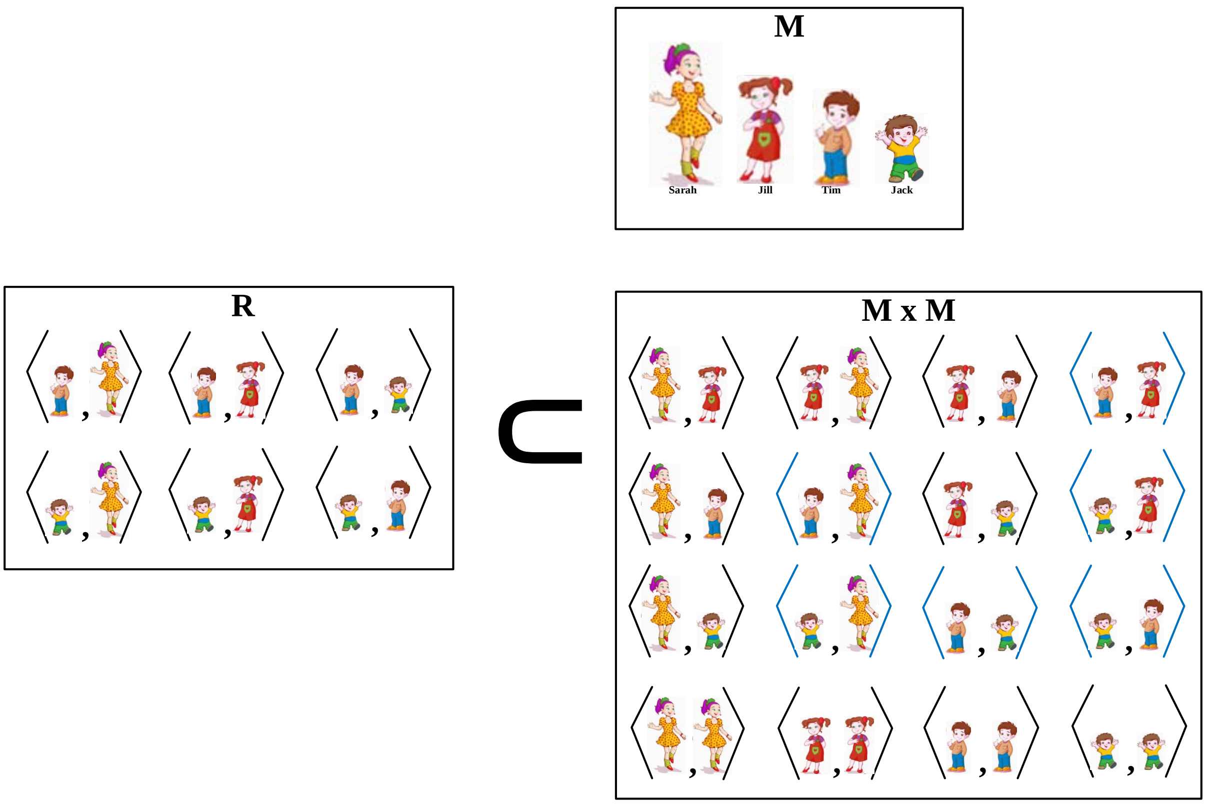

Figure 2.10. An illustrated example of formal definition of relation (Definition 2.1). Let us assume set M to contain the siblings of the same parents and M x M a set of ordered pair of objects. Then for the relation "is brother of" (Fig.2.9) we can construct a set R whose elements are determined from the set M x M (blue brackets) and hence R ⊂ M x M. Note that by definition and for the considered relation $< Tim, Sarah >$ implies Tim "is brother of" Sarah or Tim R Sarah. But $< Tim, Sarah > \neq < Sarah, Tim >$ since the latter does not belong to R ($< Sarah, Tim > \notin$ R), i.e., Sarah "is brother of" Tim does not hold.

The above formal definition of relation is one just form. There are other forms of formally defining representation which all precisely define relation from different perspectives. The curious reader is referred to Schreider's text [Schreider, 1975].

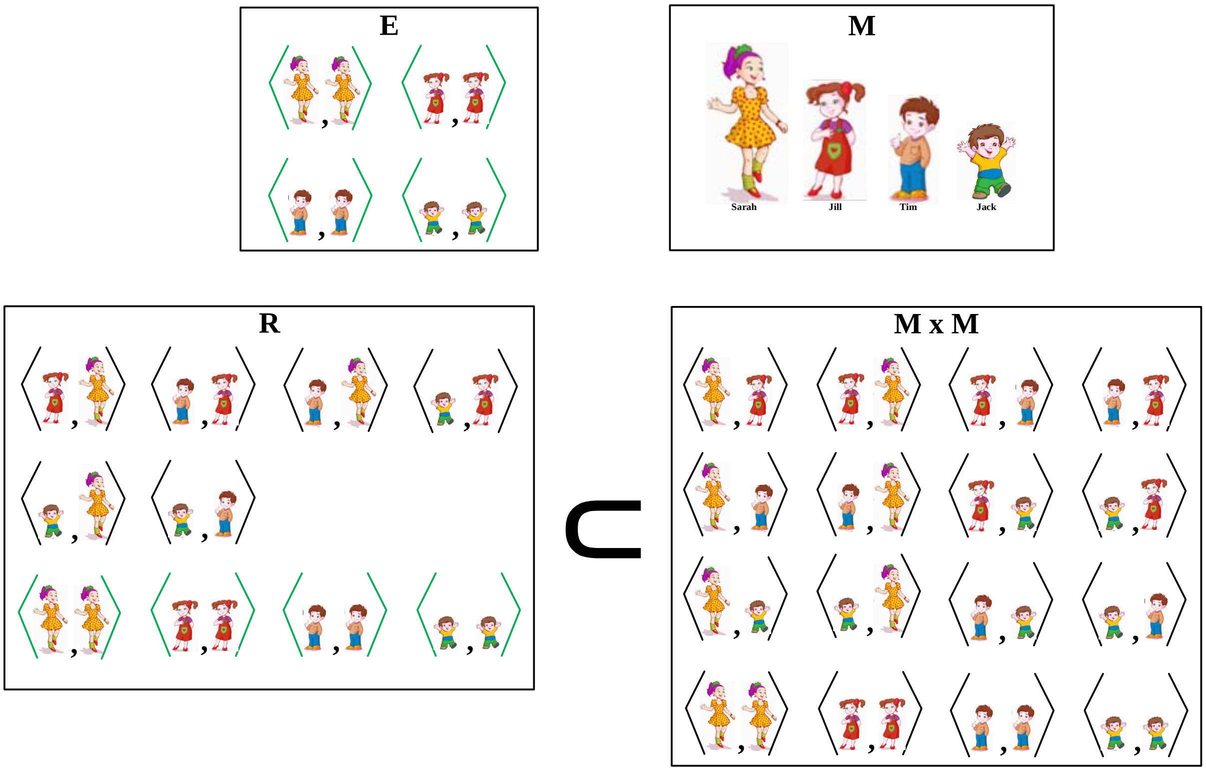

Figure 2.11. An illustrated example of properties of relation (Definition 2.2 & 2.3). Let us consider the same assumptions as Fig. 2.10. For the relation "is not older than" we can determine that Jill "is not older than" Sarah ($< Jill, Sarah >$), Tim "is not older than" Jill ($< Tim, Jill >$) and so on. Hence we can construct the proper subset of M x M, R ⊂ M x M.

Since everybody "is not older than" themselves, all the elements (green bracket) of equality relation (E) is inclusive in the set R, E ⊆ R. Thus, R has the reflexive property.

Some Properties of Relation

This section shall discuss only the properties that would be important for the discussions that would follow. Thus proofs will not be provided here.

Definition 2.2. If x E y is such that x and y are the same element of the set M, then the relation E is called equality relation.

Definition 2.3. If the equality relation E is inclusive in the set R (E ⊆ R), then R is said to have the reflexive property.

Alternatively, a relation R is said to possess reflexivity if it contains ordered pairs $< x, x >$ for every $x \in$ M.

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The relation “has the same birthday as” is an example of equality relation. The equality relation E in matrix form will be such that its principal diagonal entries equal one with zero for other entries. Thus E is also called diagonal relation. The relation “is not older than” has the reflexive property because *x* “is not older than” *x* (x R x) and hence E is included in the relation (Fig.2.11). However for the relation “is brother of” (Fig.2.10), since nobody “is brother of” themselves E ⊈ R and hence is not reflexive. Thus, a relation might not possess reflexivity (Fig.2.12).

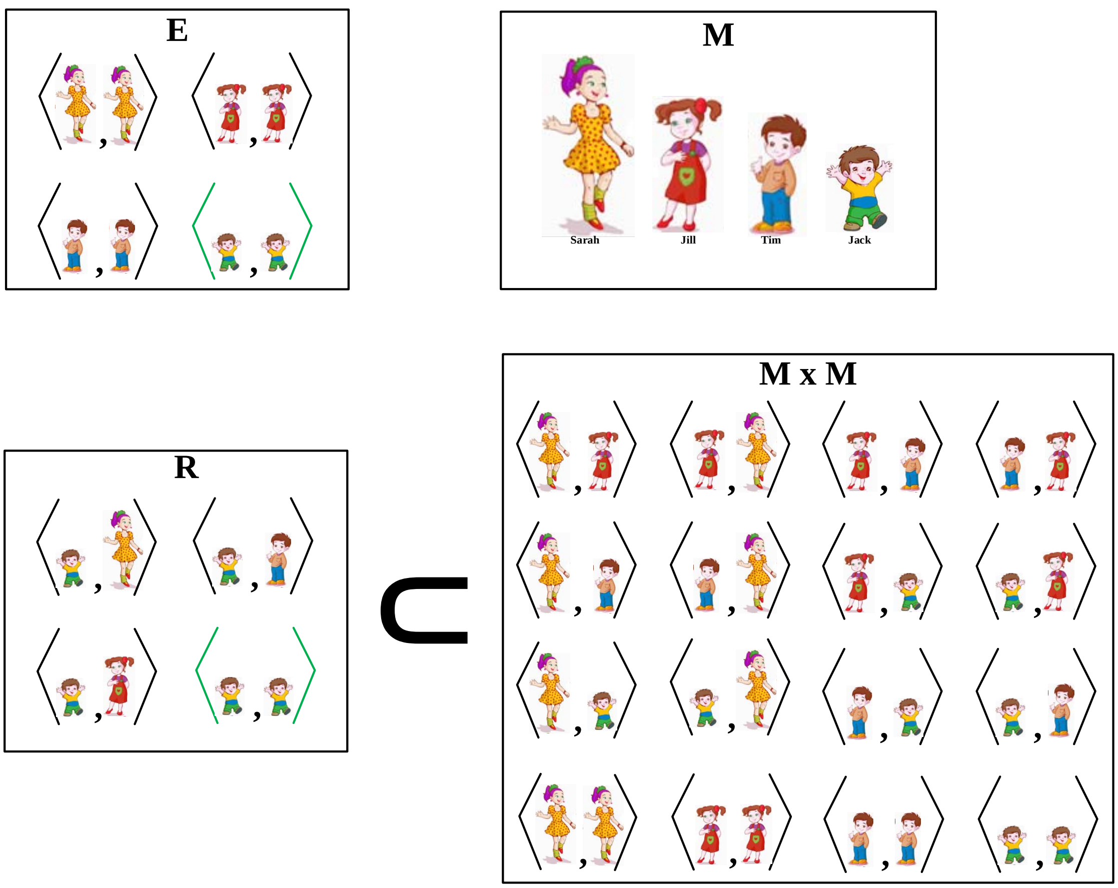


Figure 2.12. An illustrated example of relation not possessing reflexivity. In addition to the earlier assumptions let us also assume that the youngest, Jack is the most popular sibling so much so that others (Sarah, Jill and Tim) are recognized as siblings of the same parent once you identify Jack.

Thus for the relation “is standard for” (siblings of same parent) we can determine that Jack “is the standard for” Sarah, Tim, Jill and himself, hence constructing the proper set, R ⊂ M x M. This relation does not possess reflexivity.

(a)

(b)

(c)

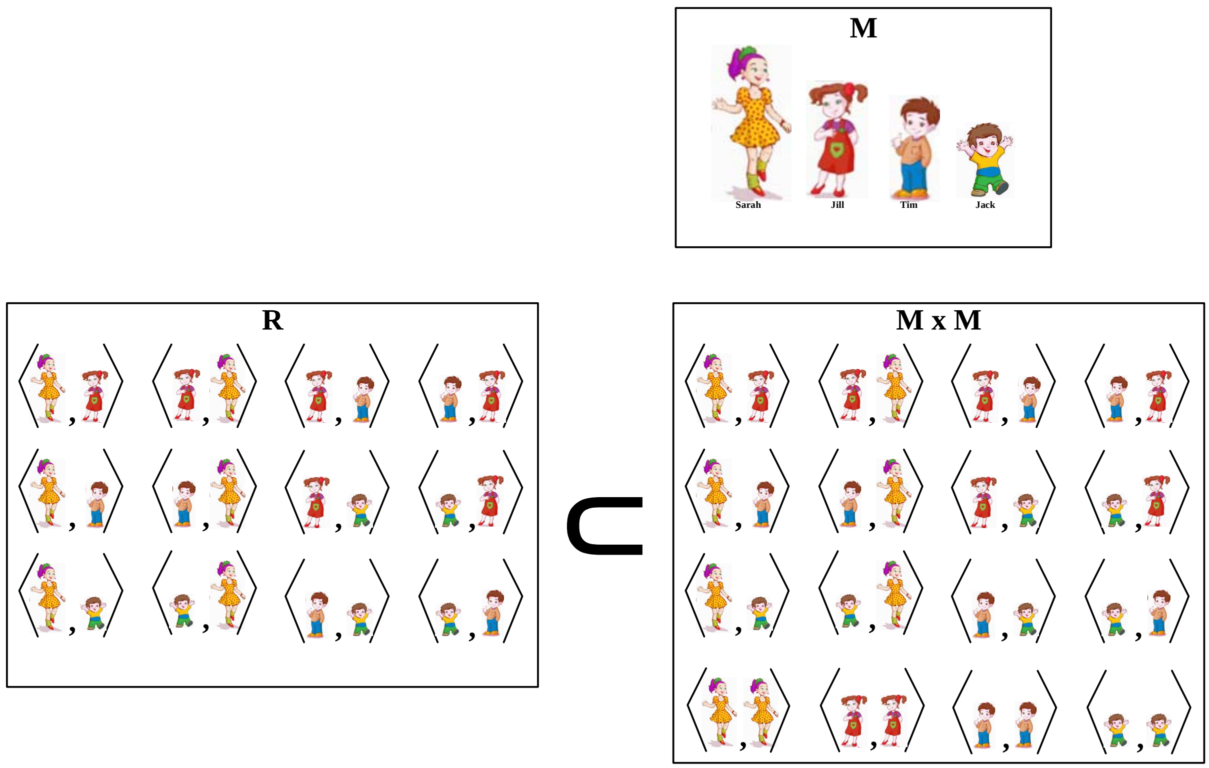


Figure 2.13. Illustrated example for symmetric relation. Let us consider the same assumptions, set of all siblings, M.

(a) Shows the relation "is brother of". Hence, Tim "is brother of" Sarah, $< Tim, Sarah >$.

(b) The relation "is sister of" is the inverse relation R^{-1} of "is brother of". Thus, Sarah "is sister of" Tim, $< Sarah, Tim >$. Pointer indicates the first object of respective ordered pair.

(c) For the relation "is sibling of", we can determine that Sarah "is sibling of" Tim and also Tim "is sibling of" Sarah. Thus, $R = R^{-1}$ and we can construct the proper set, $R \subset M \times M$. This relation will have the symmetric property.

Definition 2.4. Let us assume R is a relation in a set M, x R y. If a relation R^{-1} is defined such that y R^{-1} x, then R^{-1} is called inverse relation.

Definition 2.5. If R ⊆ R^{-1}, then R is called symmetric relation.

Theorem 2.1. A relation R is symmetric if and only if R = R^{-1}.

Alternatively, a relation R is said to possess symmetric property if it contains ordered pairs $< x, y >$ and $< y, x >$.

An example for inverse relation is as follows. If R is the relation “is brother of”, i.e., Tim “is brother of” Sarah, Tim R Sarah (Fig.2.13a). Then R^{-1} will be the relation “is sister of”, Sarah R^{-1} Tim (Fig.2.13b). However, for the relation “is sibling of”, the relations Tim R Sarah and Sarah R Tim holds. Therefore, “is sibling of” has the symmetric property (Fig.2.13c). Notice that if a relation R is symmetric, every element of R is in its inverse.

Definition 2.6. If R ∩ R^{-1} = ∅, then R is called asymmetric relation.

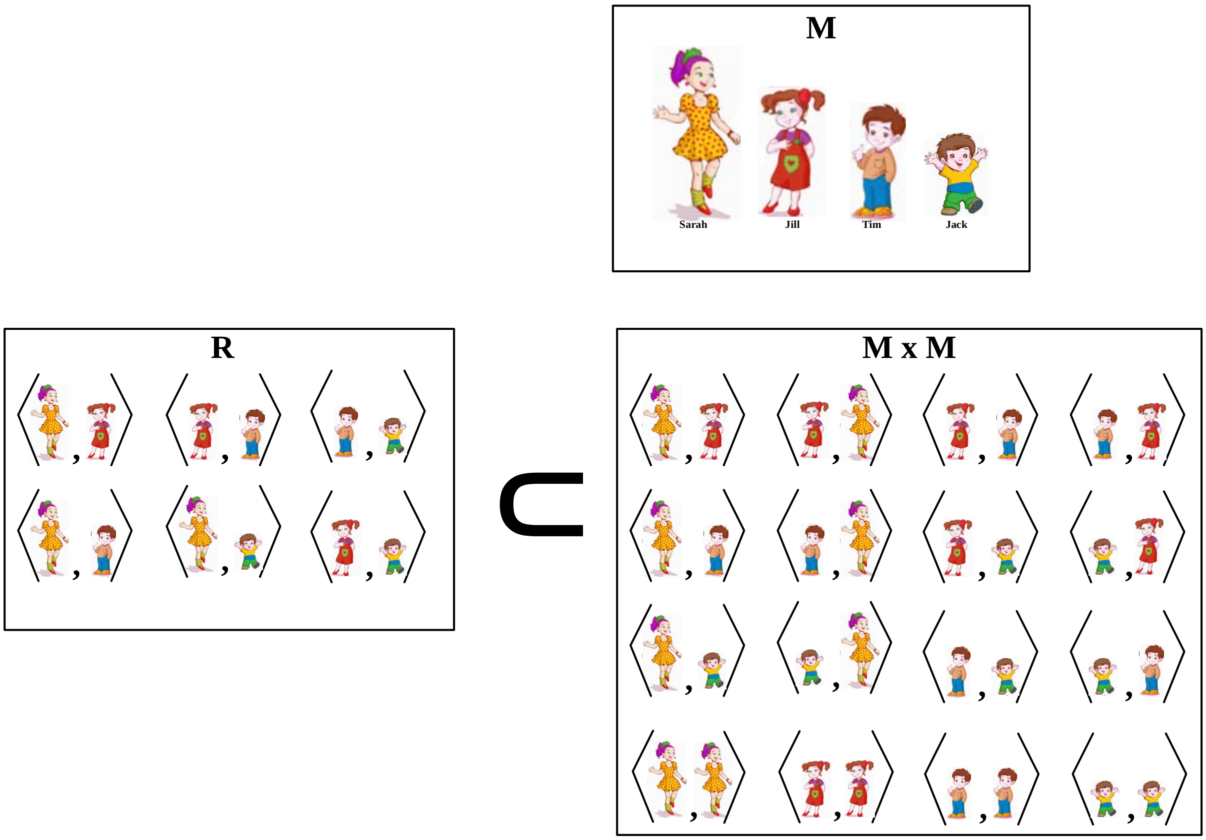
Therefore, the relation “is shorter than” is asymmetric.

Finally, we come to the transitive relation.

Definition 2.7. Given a relation R on a set M, if, for any x, y, z, in M, x R y, y R z implies x R z. Then R is said to be a transitive relation.

Thus for the example “is taller than” (Fig.2.14), Sarah “is taller than” Jill (Sarah R Jill), Jill “is taller than” Tim (Jill R Tim) and Sarah “is taller than” Tim (Sarah R Tim).

(a)



(b)

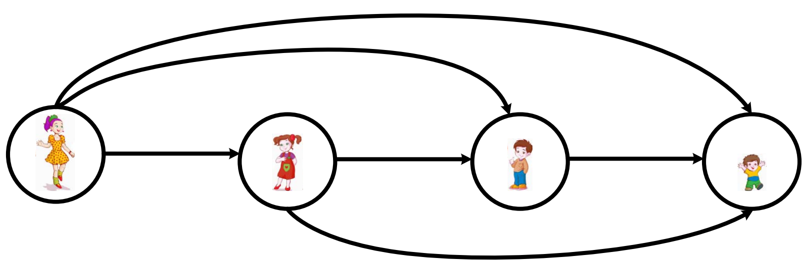


Figure 2.14. Illustration example for transitive property. Let us consider the same assumptions, set of all siblings, M.

(a) For the relation “is taller than”, the proper set R is constructed R ⊂ M x M.

(b) The relation set R (or matrix form) may be represented as graphs. The arrows denoting the ordered pairs $< x, y > \in$ R.

For further discussions on comparison the three important properties are the reflexive, symmetric and transitive properties. Illustrating binary relations as network graphs will be helpful in correlating their representations with neural networks. Therefore, the above three properties of relations are summarized using graphs (Fig.2.15).

The illustrated examples shows that comparisons and hence relation between things were possible only after we could single out ordered pairs of things. This identification is necessary for formalizing an understanding of comparison.

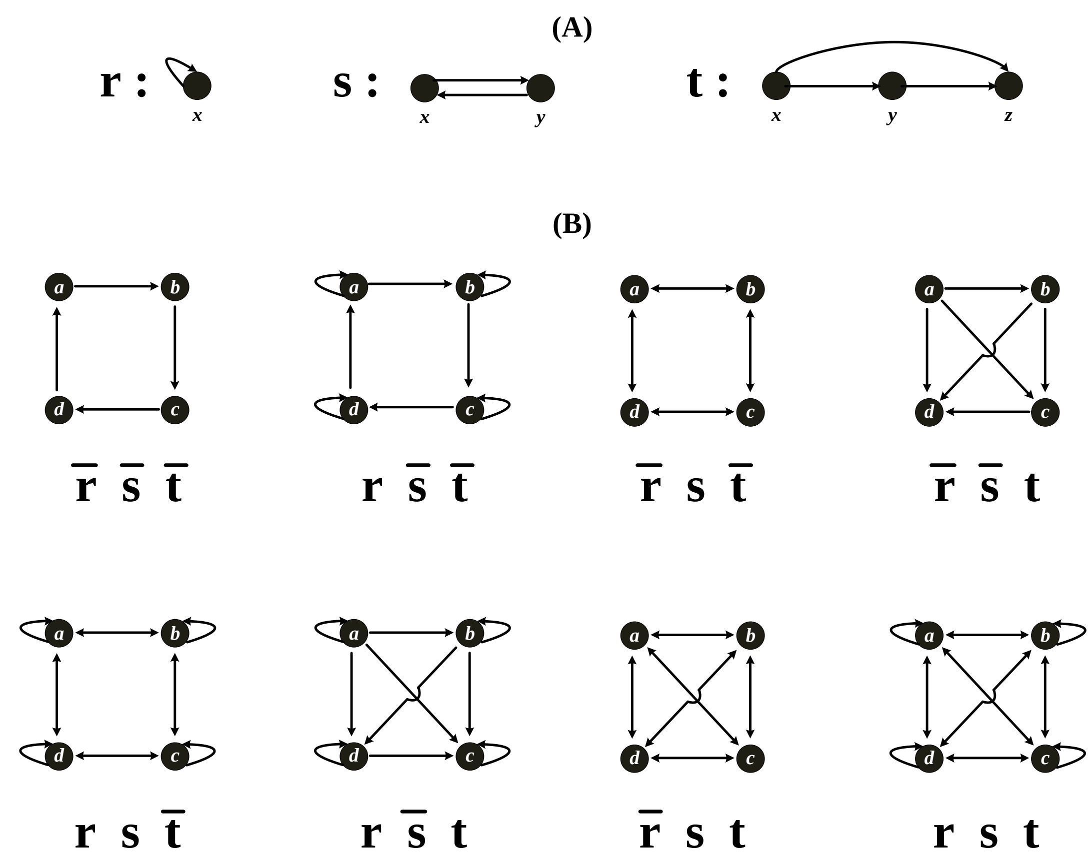


Figure 2.15. Graph illustration of the three relation properties: reflexive (r), symmetric (s) and transitive (t).

(A) Shows the properties individually. Where, **r:** x R x; **s:** x R y & y R x; and **t:** x R y, y R z and x R z.

(B) Shows various combinations of the three properties, from far top left which does not possess any of the three properties ($\bar{\boldsymbol{r}}\ \bar{\boldsymbol{s}}\ \bar{\boldsymbol{t}}$) to bottom right corner possessing all three (***r s t***).

The notion of "identical" (identity)

Just as we considered the ordinary usage of relation let us do the same for the word identical. In everyday usage we say objects are identical without concerning ourselves with the exact meaning of the word. Hence (Fig.2.9), from the point of view of a stranger evaluating in term of physical development and seeing Sarah, Jill, Tim and Jack, they are "all children" and hence identical. However from the point of view of their parents they acquire individuality but again becomes identical when evaluated in terms of development.

We can make three important observations from the above example. They are

1. For a certain set of objects the word "identical" is always understood as a binary-relation. For instance from the point of view of the stranger Sarah "is identical to" Jack;
2. The content of this relation depends on the considered situation or observer passing the judgment with his/her point of view. Thus from the point of view of their parents calling out their names, Sarah "is identical to" Jack no longer holds;
3. The word "identical" is related to the notion of with "interchangeability". From the point of view of the stranger, Jack "is identical to" Sarah also holds true and to him/her Jack and Sarah are interchangeable as "children".

Therefore, it is fair to assume that in a given situation if objects possess same collection of formal features in a particular context then the objects are interchangeable in that context.

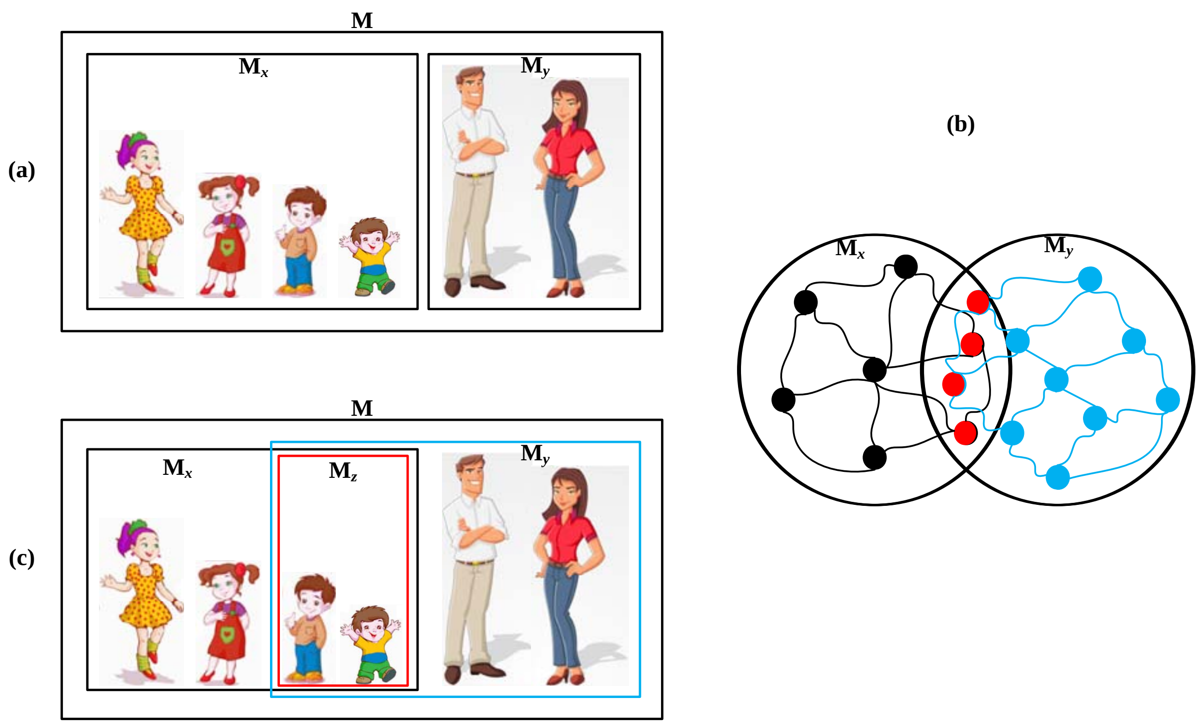


Figure 2.16. Illustration for example set of interchangeability. (a) Considering M as set of family members, if M_x is subset of children and M_y the subset of parents then union of all the subsets is M.

(b) If $M_x \cap M_y \neq \emptyset$ for some M_x, $M_y \subset M$, then there are objects (red) that are common to both M_x & M_y. Since M_x is a particular subset of interchangeable (black lines) objects belonging to M_x, black objects in M_x are interchangeable with red objects. Similarly blue objects in M_y are interchangeable (blue lines) with red objects.

(c) Let us assume M_x is the subset of children, M_y is the subset of parents & sons and M_z, the subset of boys. Then, for the relation “are family member”, the boys are interchangeable in M_x ($M_z \subseteq M_x$) and also in M_y ($M_z \subseteq M_y$).

Interchangeability of elements in $M_z(= M_x \cap M_y)$ is conditioned by the context. Thus for this case the family of all the proposition for the interchangeability or “property set” is, {“there exist a set of siblings of same parents”, “there exist a set of parents & sons”, “set of boys”}.

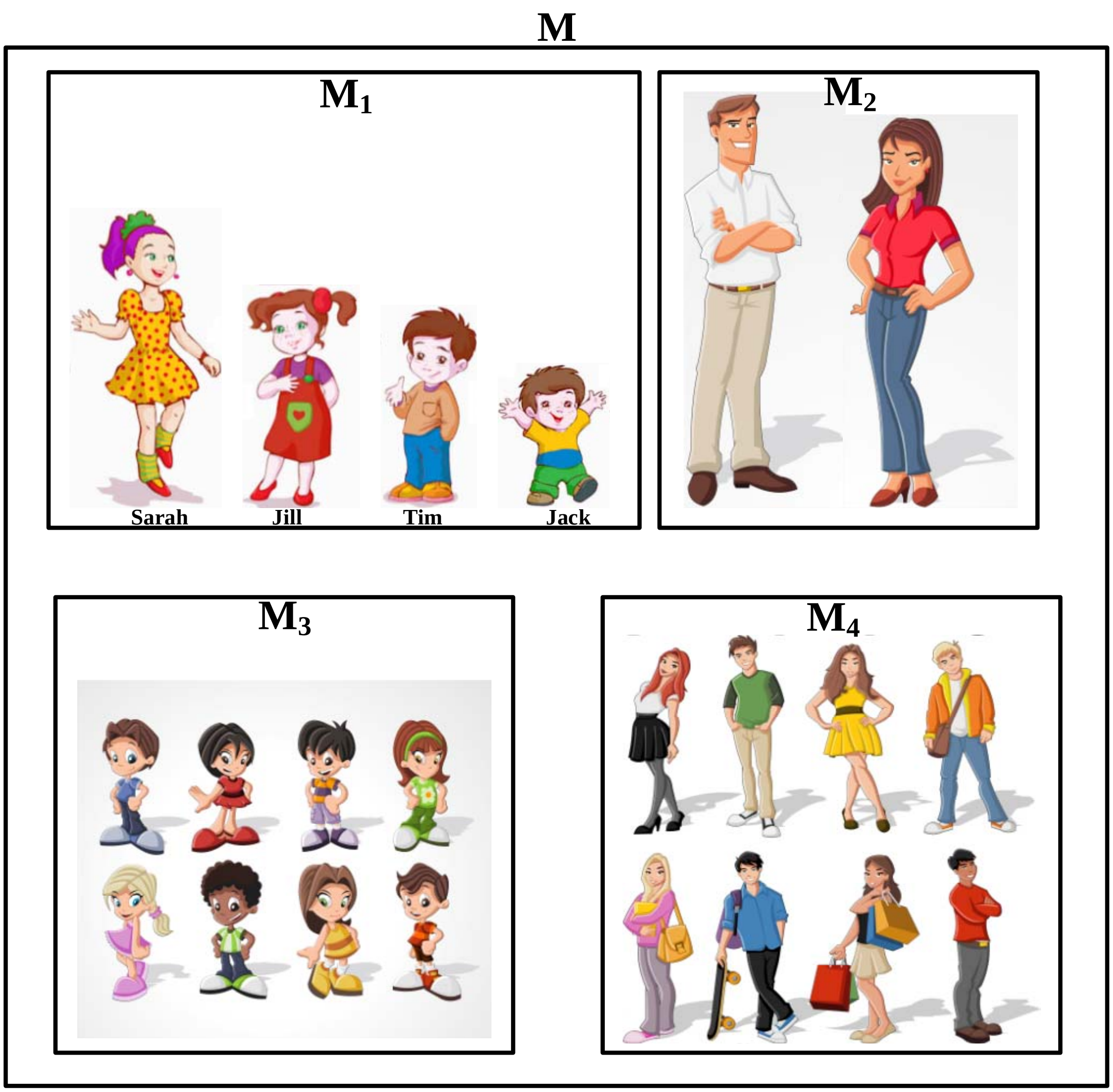


Figure 2.17. Illustration for definitions of equivalence. For the set M of objects (people) let us assume M_1 to be a subset of siblings, M_2 a subset of parents, M_3 a subset of pupils and M_4 a subset of university students. Thus the system of non-empty subsets $\{M_1, M_2, M_3, M_4\}$ of M satisfies the two condition: $M = M_1 \cup M_2 \cup M_3 \cup M_4$ and $M_i \cap M_j = \emptyset$ for $i \neq j$, for these four defined property set specifications. Thus, the system is the partition of M and M_i's are its classes.

For the class M_1 let us consider the relation R, "children with same parents". Then x R y only hold for all people in M_1. This is an equivalence relation. Note that that the relation is reflexive, $< Sarah, Sarah >$, symmetric; $< Sarah, Jill >$ and $< Jill, Sarah >$ and finally transitive, $< Sarah, Jill >$, $< Jill, Tim >$ and $< Sarah, Tim >$.

On the other hand for the relation "are two boys", the relation holds only for some people in M_1 and M_2 and hence no longer specifies an equivalence relation in M_1. It can, however, hold for some subset $M_5 \subset (M_1 \cup M_3)$. If the relation is "are two males" it holds for a subset $M_6 \subset M$ and M_6 is a partitioning of M in which the relation is an equivalence relation.

The notion of “interchangeability”

Let us consider M to be a set of objects such that some of them are interchangeable. Now consider M_x to be a set of all objects x in M that are interchangeable, $x \in M_x$. Thus for all such subsets of M, the union of all M_x is

$M = \bigcup M_x$ (Fig. 2.16a).

Let us now assume $M_x \cap M_y \neq \emptyset$ for some $M_x, M_y \subset M$. Then there must exist some element z (red, Fig.2.16b) belonging simultaneously to both M_x and M_y. Thus, x is interchangeable with z and z is interchangeable with y. This implies set M_z possess some relation-defining property $P \Longrightarrow R'$ such that under R' any $x \in M_x$ is interchangeable with any $x \in M_y$.

Thus, the union $M_x \cup M_y$ comprises a superset M of interchangeable elements within context(s) by which $M_z = M_x \cap M_y$ is interchangeable in both M_x and M_y. The context of the interchangeable property of M is conditioned by the interchangeability context of $M_x \cap M_y$ (Fig.2.16c). This intersection, $M_x \cap M_y$, is said to define a “property set”.

The notion of “equivalence”

Now, clearly a singleton object x is identical to itself. Were that not so the notion of an “object” would have no comprehensible meaning. Consider, therefore, two interchangeable objects x and y. If there is some relation R under which x and y can also be said to be identical then we say x and y are **equivalent** and R is called as equivalence relation. The question then become, “what is required for a relation of equivalence to exist?”

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We can conclude that the concept of "equivalence" is conditioned by the existence of some property set. Contextual equivalence therefore provides a foundation for higher abstract levels of set inclusions and formal equivalences, and thereby provides a mathematical principle for constructing the concept of **Nature** as a unity of objects in one **Nature**. This, by the way is the principal function of **teleological reflective judgment** in mental physics.

Building upon the preceding discussion of sets and subsets containing interchangeable objects of M, we can make the following observations. If x and y are objects then clearly x R x and y R y are required for the relation. If x and y are interchangeable then it must also hold true that x R y implies y R x because otherwise saying x and y are interchangeable would have no comprehensible meaning. Finally, if x, y, and z are interchangeable objects such that x R y and y R z, then it must likewise be true that x R z. But these are merely the reflexive, symmetric and transitive properties of relation. In order to say x, y, and z are appearances of the same object O it is sufficient to say

> Definition 2.8. An equivalence relation R is a relation that has the reflexive, symmetric, and transitive properties.

Figure 2.17 illustrates this definition.

The possibility of logical partitions is based on equivalence.

> Theorem 2.2. If relation R on set M is reflexive, symmetric and transitive, then there exist a partition $\{M_1, M_2, \ldots\}$ of M such that x R y hold if and only if x and y belong to a common class M_i (in the partition).

The above is in fact a theorem in the mathematics of discrete structures. Again refer figure 2.17 for an illustrated example. Also since an equivalence relation possesses the reflexive, symmetric and transitive property, the bottom right corner of figure 2.15b is a graph of equivalence relation.

It was assumed above that in a given situation interchangeable objects possess one and same collection of formal features. This implies that an object in a particular class contains information about other objects within this class. This idea of information is further developed and explicated using “resemblance” and Christopher Zeeman’s “tolerance” by Schreider [Schreider, 1975].

The reader must have noticed that though “equivalence” has been explicated the question of “how do we get ‘a given situation’?” or context is yet to be answered. To understand this will require a philosophical perspective and hence must consider the metaphysics behind “context”. This is discussed in the next chapter.

Chapter 3. Mental Physics

The 18th century German philosopher Immanuel Kant made a "Copernican turn" from an ontologically centered philosophy to epistemologically centered one. Kant's works [see citations] were laid out and expanded in the 2500 paged, The Critical Philosophy and the Phenomenon of Mind [Wells, 2006]. CPPM is the abbreviation for this book.

CPPM is a theory of fundamental principles and laws of mind, beginning with observable phenomena and progressing down to the underlying principles for understanding phenomena. This approach is consistent with Francis Bacon's investigative method,

> "There are and can exist but two ways of investigating and discovering truth. The one hurries on rapidly from the senses and particulars to the most general axioms, and from them, as principles and their supposed indisputable truth, derives and discovers the intermediate axioms. This is the way now in use. The other constructs its axioms from the sense and particulars, by ascending continually and gradually, till it finally arrives at the most general axioms, which is the true but unattempted way". [Bacon, 1620]

Mental physics as coined by Wells is defined as the application of these principles to the study of mind and brain [Wells, 2009]. This work was presented in the Principle of Mental Physics or PMP [Wells, 2009].

It is not the objective of this chapter to go through every detail of mental physics (cf. above) but to provide a few principles or concepts that help understand the problem of comparison mentioned in the earlier chapter. To differentiate technical terminologies from ordinary English words they will be in bold texts with or without other highlights.

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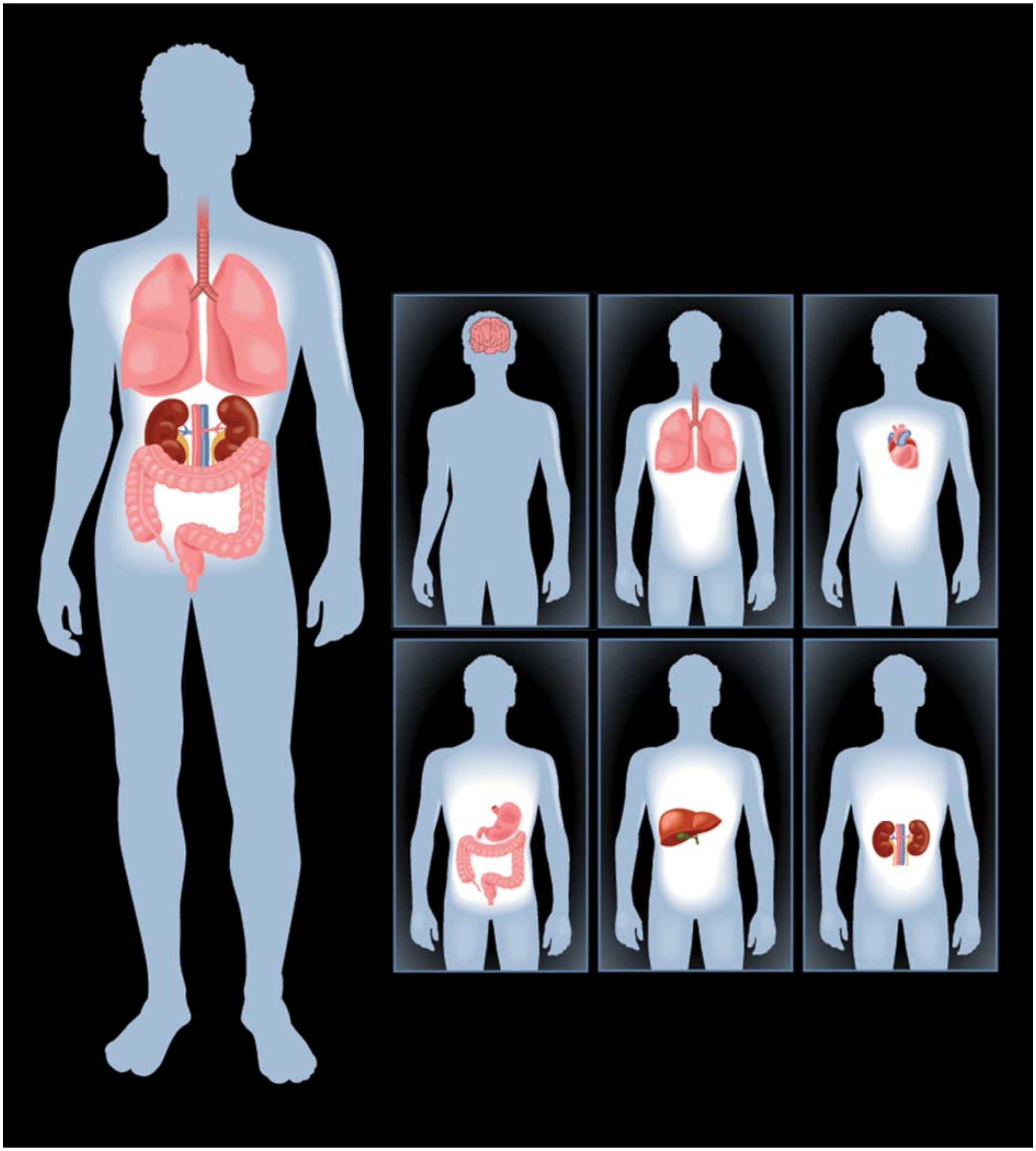


Figure 3.1. **Logical division** of human physiology as systems. Central nervous system, respiratory system, cardiovascular system, gastrointestinal system, hepato-biliary system and renal system.

Logical vs. Real division

Logical division (**LD**) is technically defined as,

> "a disjunctive anasynthesis in which the determinant judgment of the coordinate concepts carries the Modality of possibility" [Wells, 2009 Glossary]

and the **real division** (**RD**) is defined as,

> "a disjunctive anasynthesis in which the determinant judgment of the coordinate concepts carries the Modality of actuality". [Wells, 2009 Glossary]

For practical application of the definition, what do they mean? For analysis and hence understanding a thing or concept, if we divide it such that the parts are possible then the division is LD but if the parts are actual then it is RD. Thus, LD is an epistemological division while RD an ontological division.

In most medical-physiology textbooks the human body is divided as systems: central nervous system, respiratory system, cardiovascular system, etcetera (Fig.3.1). But in actuality (function) they are not independent. For instance, the heart does not function independent of the lungs, hormones, nerves, etc. Thus, this is a LD. On the other hand, a man and his car are actually separate (Fig.3.2). Hence this a RD.

Figure 3.2. Logical versus Real division. (a) The man and his theoretical silhouette is a logical division because the latter is only a representation of the former. However (b) the man and the car is a real division.

Descartes' error and why Mind-Body division is a logical division

René Descartes' most famous statement was,

in French "Je pense donc je suis" [Descarte, 1637],
in Latin "Cogito ergo sum" [Descarte, 1644],

which in English translates as "I think therefore I am". Descarte considered thinking as a separate activity from the body. Thus, he regarded *res cogitans* or 'thinking thing' as ontologically separate from *res extensa* or 'extended substance' (causative mechanical parts). Mental physics considers them not to be ontologically separate. However, Descartes' view has pervaded both popular culture and academia.

The result is to this day brain is taught in terms of "specific brain region for respective function" (Fig.3.3). With the evolution of computing power and motivation to build the 'electronic-brain' people working in the field of artificial-intelligence, most notably Marvin Minsky [Minsky, 1986], have developed the notion of brain as the hardware analogue while mind is the software analogue (popularly termed wetware with the prefix 'wet' referring to the living tissue of the brain).

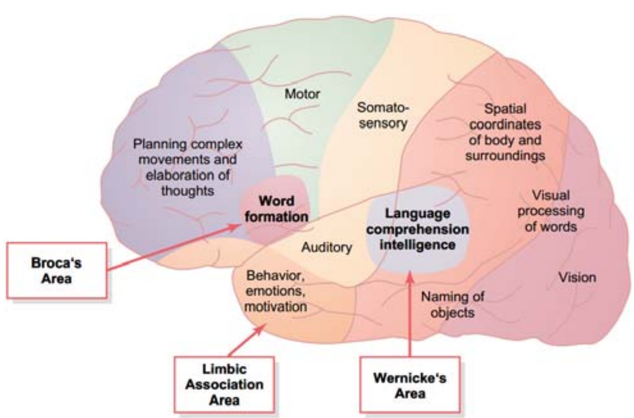


Figure 3.3. Map of specific functional areas in the cerebral cortex as taught in medical physiology textbooks [Guyton, 2006].

Figure 3.4. Mind and body as two sides of the same coin.

Experimental evidences have proven that this separation is not real in the *context* of experience. Therefore, Descartes' res extensa and res cogitans or body-mind division is a LD. In other words, body and mind are like two sides of the same coin (Fig.3.4). This term Descartes' error was coined by Antonio R. Damasio, which he describes as,

> "This is Descartes' error: the abyssal separation between body and mind, between the sizable, dimensioned, mechanically operated, infinitely divisible body stuff, on the one hand, and the sizable undimensioned, un-pushpullable, nondivisible mind stuff; the suggestion that reasoning, and moral judgment, and the suffering that comes from physical pain or emotional upheaval might exist separately from the body. Specifically: the separation of the most refined operations of mind from the structure and operation of a biological organism". [Damasio, 1994]

Organized being (OB)

Let us call the model of the subject whose phenomenon of mind we are interested in studying, **organized being** (**OB**). OB is that in which 'concepts of everything we think about it is united'. The adjective comes from the verb **organization** as shown in figure 3.5, where concepts are combined by synthesis and given structure and function. This avoids Descartes' error. A natural follow up question then is how to regard the existence of OB.

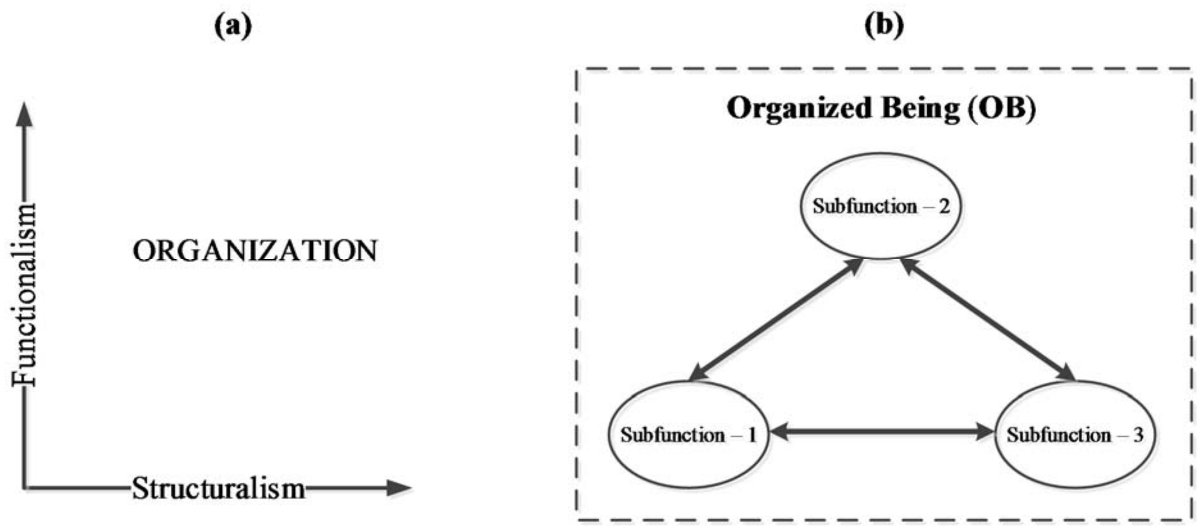


Figure 3.5.(a) Coordinate concepts of organization. (b) Illustration of idea of functional totality in an OB.

The knowledge of existence has two components, one that answers the question "what exists?" and another "how does it exists?" The former is called **Dasein** and latter **Existenz** (Fig.3.6). Thus before saying anything about 'it' we must first judge that 'it' exists in the context of having Dasein. A proposition of Dasein states nothing more than that some transcendental **Object** exists as the logical subject in other propositions that describe its Existenz, i.e., "how it exists". The transcendental Object is said to be the **matter** for Existenz propositions. The latter propositions are collectively said to constitute its **form**.

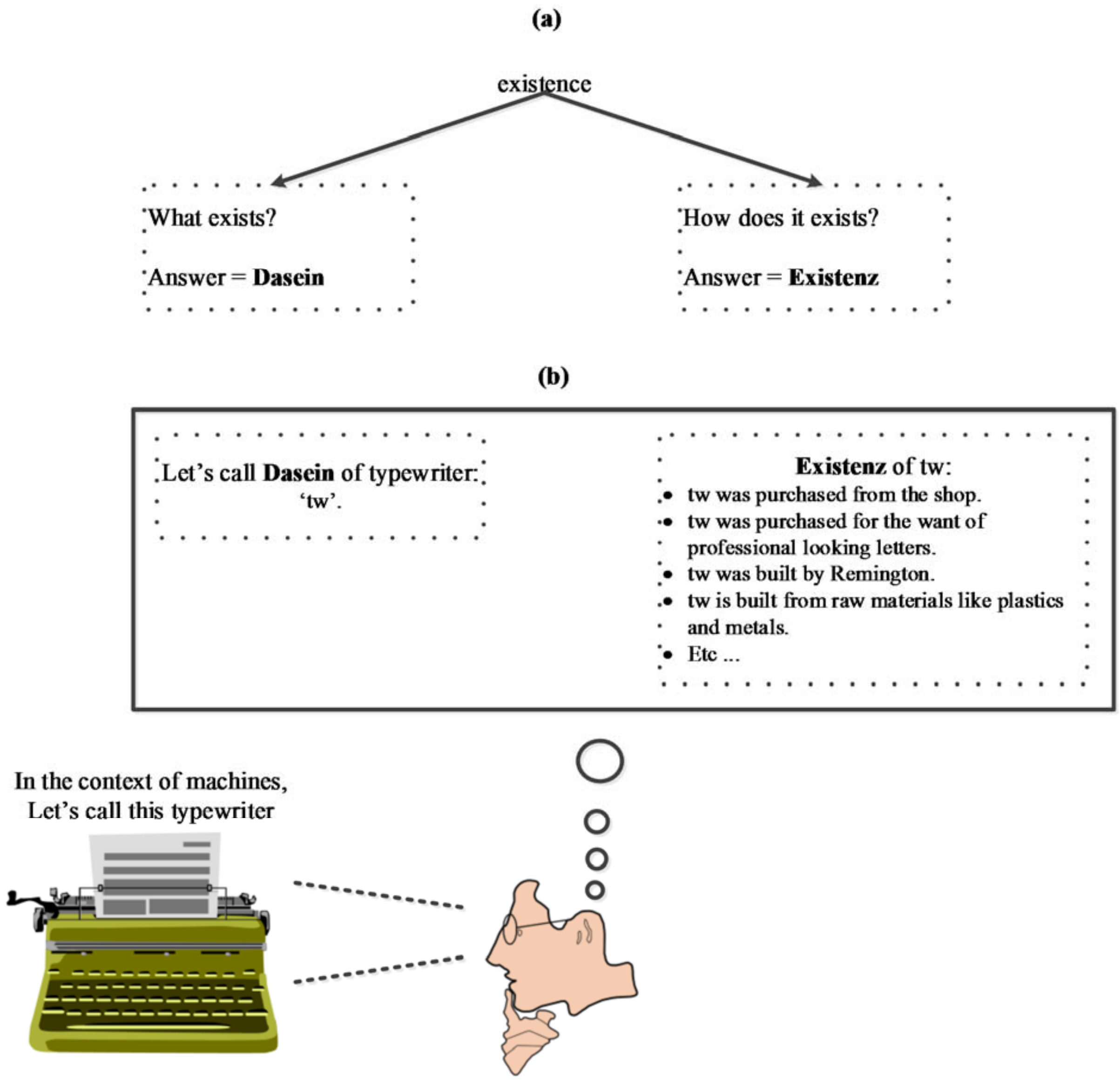
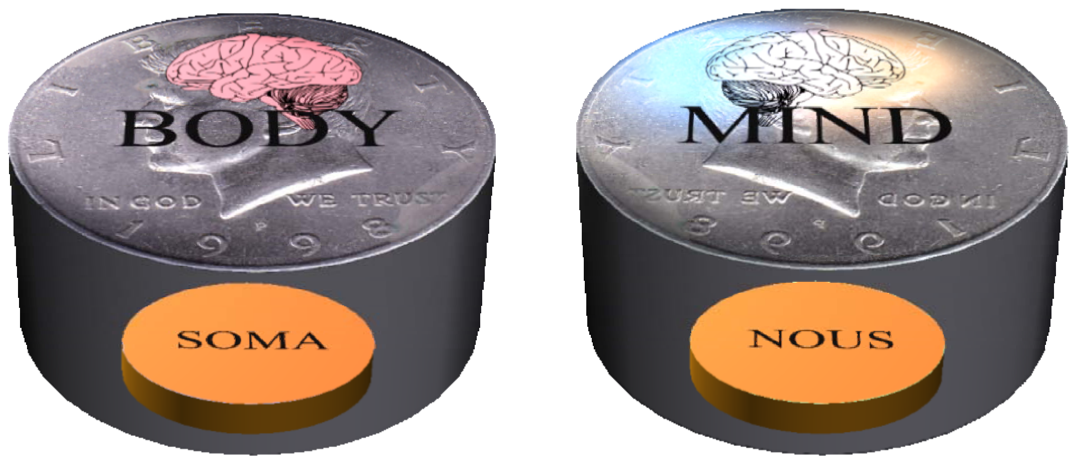


Figure 3.6. Knowledge of existence. (a) Shows the division of knowledge. (b) An example.

Mental physics calls the **notion** of the Dasein of body **soma** and the notion of the Dasein of mind **nous** [Wells, 2009]. Since mind-body are two sides of the same coin, nous and soma have concurrent Existenz (Fig.3.7). The animating principle linking **nous-soma** in a relationship of thorough-going mutual reciprocity is called **psyche** (Fig.3.7) [Wells, 2009]. The OB model is shown in figure 3.8.

(a)



(b)

Figure 3.7. Mind-body and nous-soma. (a) One side of the coin is body. The notion of the Dasein of body is the soma. The other side of the same coin is mind. The notion of the Dasein of mind is nous. (b) Thus, nous-soma are also two-sides of the same coin. The animating principle joining nous-soma is called psyche.

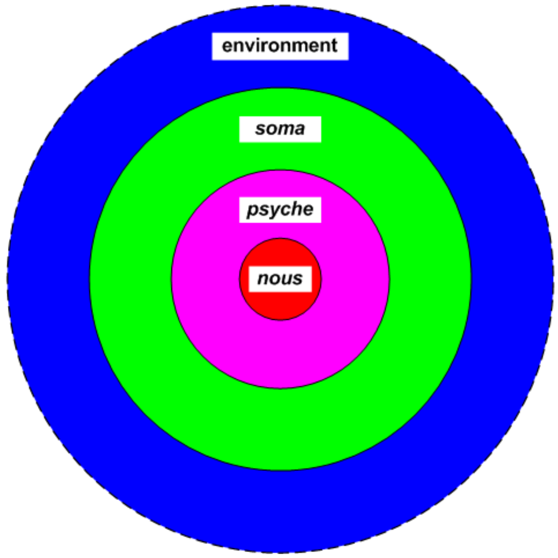


Figure 3.8. Model of the organized being (OB). And all OB's exist within the 'world model' which is an objective representation (parástase or depiction) of all-that-exists called **Nature** [Wells, 2009 Glossary]. Nature if applied to specific things (Nature of OB) is then the objective parástase of all its characteristics and relationships with other things.

Mind-Body relation to Nous-Soma

Since mathematics is a product of human intellect an obvious question is "How is mathematics able to truthfully tell us anything about objects of the natural world?" The answer is best described by the two-world model of David Slepian, one of the pioneers in information theory who in 1975 presented his model as a solution to the bandwidth-paradox [Slepian, 1976].

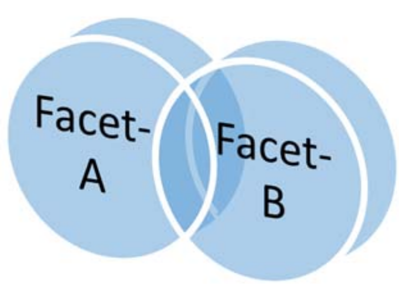


Figure 3.9. Slepian two-world model. Facet-A represent physical world and facet-B represent mathematical world. The intersection between the facets correspond to mathematical quantities (principal quantities) which immediately correspond to observables.

The description of the model is as follows. The physical world, the world of sensible objects and hence the world of experience and experiment is facet-A (Fig.3.9). The mathematical world, the world of mathematical objects is facet-B. When we force quantities in facet-B to correspond to measurements and observations in facet-A, then these mathematical quantities are called principal quantities. The quantities that do not correspond to observations in facet-B are called secondary quantities. Thus, secondary quantities are intelligible mathematical quantities with no direct counterpart in facet-A.

There are two fundamental principles for the two-world model:

- Two different mathematical models can produce the same physical situation. The mathematical measure of difference between the models was defined by Slepian as 'criterion of distinguishability'.
- A necessary and important condition for a mathematical model to be useful in science is that the principal quantities of the model be insensitive to small changes in secondary quantities.

For more in depth knowledge on the model and its application to neuroscience the reader is directed to Wells' publication [Wells, 2011d].

Since an OB experiences his/her mind-body, it is in facet-A of the two-world model. However, nous-soma is a product of human intellect (mathematical) and hence is in facet-B (Fig.3.10). On the question of whether mathematics is in nature or in the human mind, Jean Piaget says

> "Does mathematics exist in nature, including the human mind, or does it exist outside nature … and then you have Platonism? In the latter case, mathematics is the set of possibilities, and the real, including the human mind, is a tiny portion,

infinitely small with respect to the infinity of possibilities. But for me, mathematics exists in nature, and nature encompasses the human mind; the human mind develops mathematics with the body, the nervous system, and all the surrounding organism, which, itself, belongs to physical nature, in such a way that there is harmony between mathematics and the real world through the organism, and not through physical experience bearing on objects". [Bringuier, 1980]

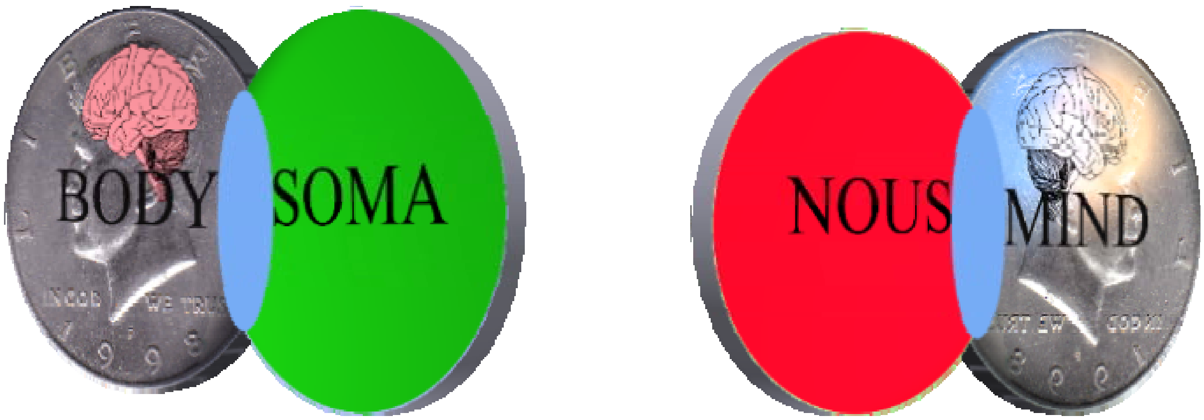


Figure 3.10. Application of Slepian two-world model to body-mind soma-nous division. Soma and nous represent mathematical world, facet-B (Fig.3.9) to respective physical world, facet-A body and mind.

Mathematical description of the OB

As a science mental physics results in the mathematical description of the Organized Being as shown in figure 3.11. Mental physics does this by divide-conquer, described by Francis Bacon as,

"The human understanding is, by its own nature, prone to abstraction, and supposes that which is fluctuating to be fixed. But it is better to dissect than abstract nature; such was the method employed by the school of Democritus which made greater progress in penetrating nature than the rest. It is best to consider matter, its conformation, and the changes of that conformation, its own action, and the law of this action or motion; for forms are a mere fiction of the human mind, unless you will call the laws of action by that name". [Bacon, 1620]

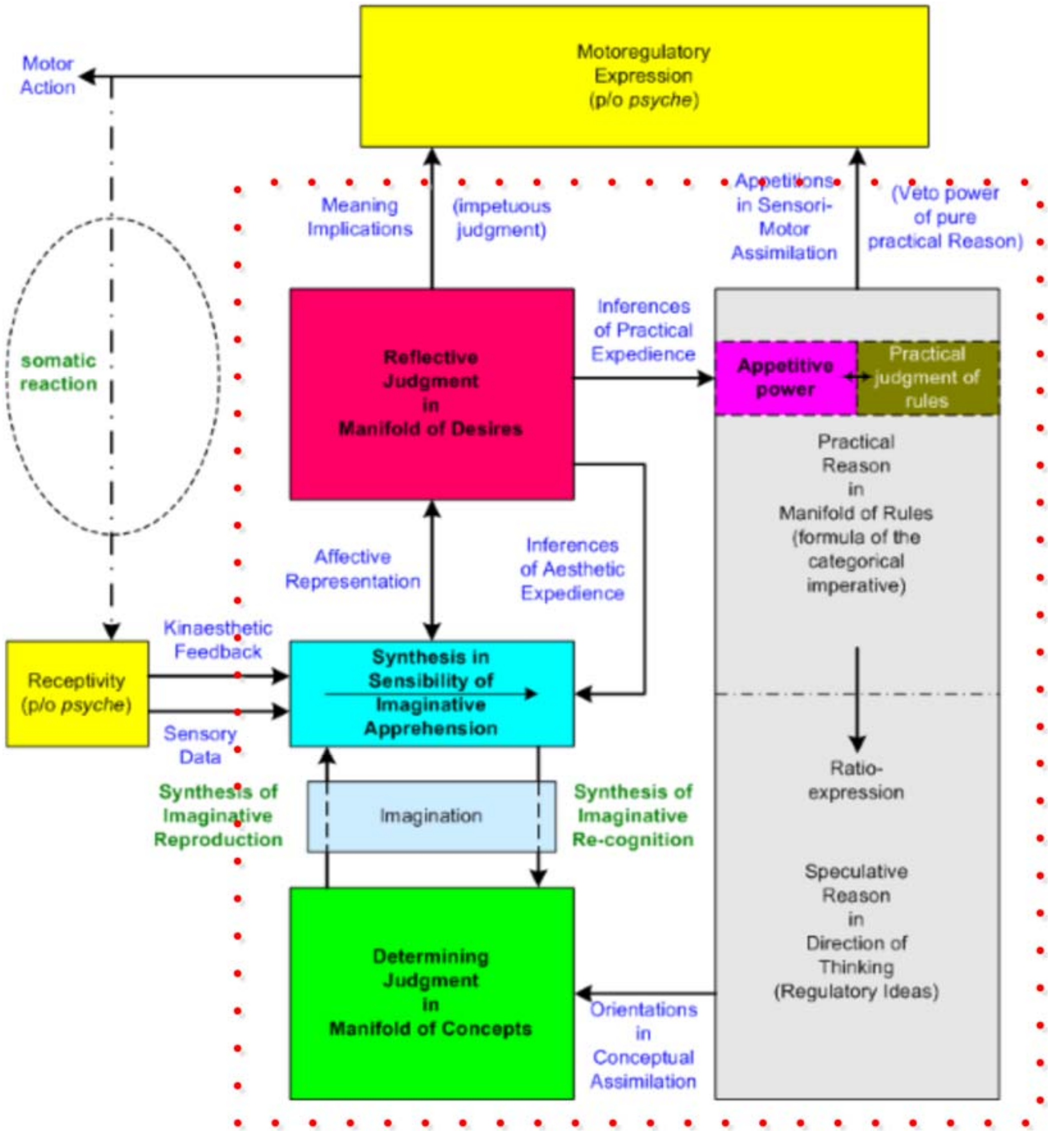


Figure 3.11. Mathematical description of the organized being (OB). The two yellow blocks are part of psyche. The blocks within the red dashed line are part of nous. The noetic or mental parástases always stand in thorough-going reciprocity with somatic parástase, i.e. they coexist in time.

The processes shown in figure 3.11 should be understood as functions with capabilities for production and transformation of parástases. The somatic parástases are called **signals** as they are physical phenomenon exhibiting variations in time that carry information. Mental physics abbreviates somatic-parástase to signal and noetic-parástase to parástase. The soma ↔ nous reciprocity and hence the relation signal ↔ parástase is handled by psyche.

There are two ways of understanding somatic effects:

1. Change in soma regarded as effect of environment on soma, i.e. soma → nous (Fig.3.12a). Mental physics calls the "capacity for soma to stand as the agent" of **representation** the **receptivity** of OB (|**R**o**OB**|). In the co-determined nous, the sensuous depiction of the somatic effect is called sensibility. This is represented within the **synthesis of sensibility** block (light blue within nous part of the model/Fig.3.12a).

2. Change in soma regarded as co-determination of nous act, i.e. soma ← nous (Fig.3.12b). Mental physics defines the "capacity for nous to stand as the agent" of representation the **spontaneity** of OB (|**S**o**OB**|). The parástase is transformed to signal resulting in motor action in soma. This transformation is called **motoregulatory expression**.

The resulting soma ↔ nous reciprocity is a fundamental real law of the OB. The Sensorimotor system of the OB as mental physics defines it is receptivity and motoregulatory expression taken together (Fig.3.12c).

The mathematical description is a generalization of the OB. But for this thesis, the discussion will be limited to a particular sub-function within the synthesis of sensibility block. This approach has been argued for by Francis Bacon as he warns,

> "…for although the greatest generalities in nature must be positive, just as they are found, and in fact not causable, yet the human understanding, incapable of resting, seeks for something more intelligible. … But he would be an unskillful and shallow philosopher who should seek for causes in the greatest generalities, and not be anxious to discover them in subordinate objects". [Bacon, 1620]

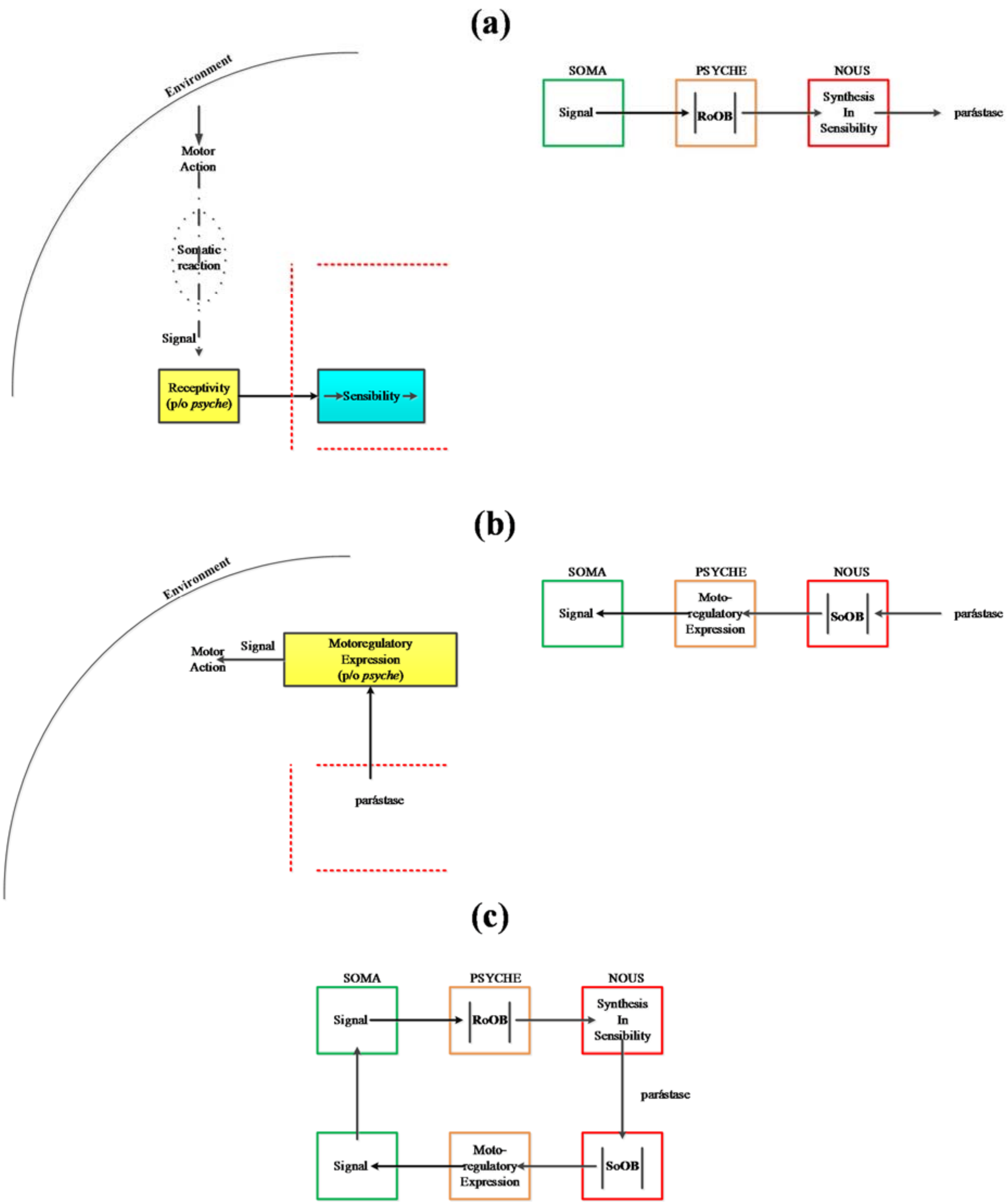


Figure 3.12. Two ways of understanding somatic effect. (a) Soma standing as the agent, soma → nous. Right hand side shows the block diagram view where signal is co-determined in the nous as sensibility. RoOB (receptivity of OB) is the capacity of soma to stand as agent. (b) Nous standing as the agent, soma ← nous. Right hand side shows the block diagram view where parástase is co-determined to signal. SoOB (spontaneity of OB) is the capacity of nous to stand as agent. (c) Sensorimotor system, soma ↔ nous. Block diagram showing receptivity and motoregulatory expression taken together.

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Synthesis in sensibility

Synthesis in sensibility is a process within nous whose task is to transform obscure (unconscious) parástase to conscious parástase (perceptions). The obscure parástase or input to the process may be regarded as source of possible matter in conscious parástase. Thus mental physics calls them **materia ex qua** (matter out of which) or determinable-matter of parástase. The **materia ex qua** may enter via receptivity or somatic effect or from spontaneity or imaginative reproduction.

The resulting perception are of two types, **intuition** and **affective perception**. Mental physics defines intuition as perceptions in sensibility that refer to objects and affective perception as perceptions that refer only to subjective state of OB.

There are four synthetic processes [Wells, 2009]. This thesis will deal mostly with synthesis of **Verstandes-Actus** (acts of understanding). From a logical perspective Vertandes-Actus follow a logical progression in logical steps named **Comparation**, **Reflexion** and **Abstraction** (Fig.3.13). Kant tells us,

> “The Vestandes-Actus, though which concepts are begat as to their form, are:
>
> 1. Comparation, i.e. the comparison of parástases among one another in relationship to unity of consciousness;
> 2. Reflexion, i.e. reconsideration as to how various parástases can be comprehended in one consciousness; and finally
> 3. Abstraction or separation of everything else in which the given parástases differ”. [Kant, pp.94, 1800]

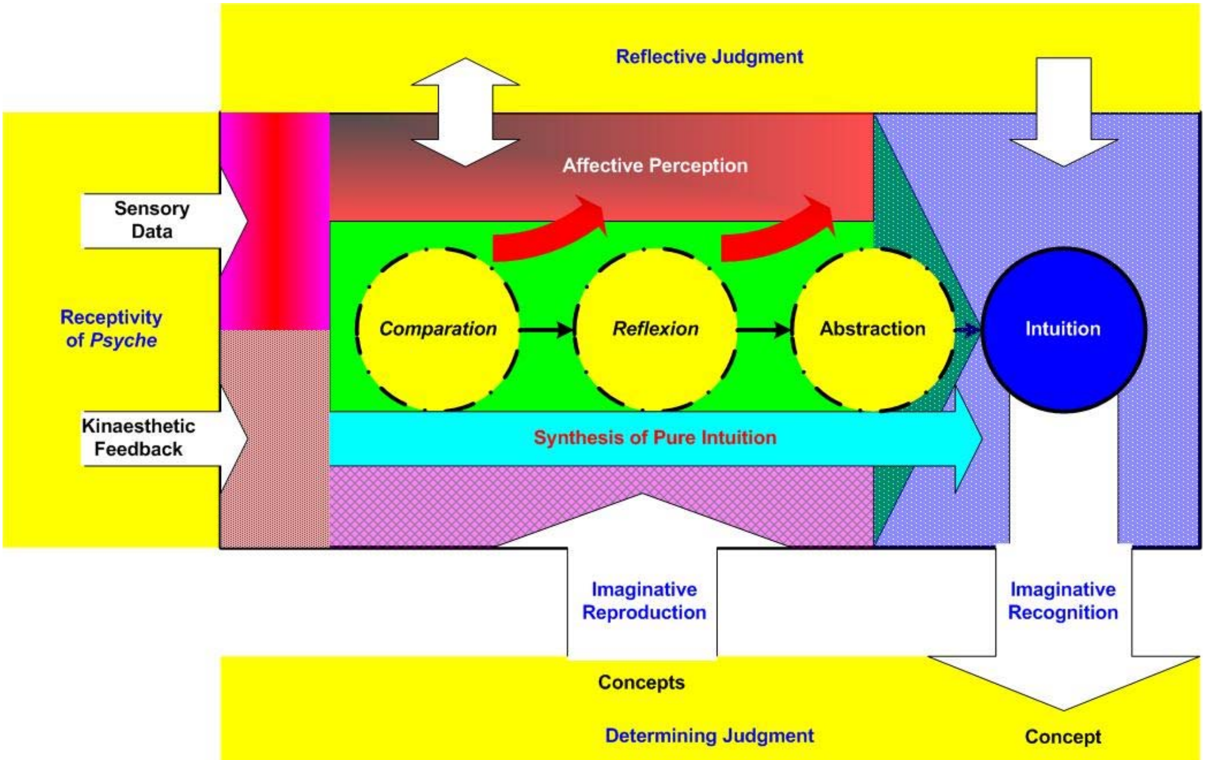

Figure 3.13. Illustration of synthesis of apprehension in sensibility. The materia ex qua from receptivity and spontaneity (imaginative reproduction in nous) enters the process resulting in intuition and affective perception.

Comparation is logical comparison

Comparation is defined as

> "an act of Verstandes Actus of comparison (an act of understanding of comparison) making logical comparisons of comparate parástase in the context of a relationship between them and unity of consciousness. In other words, comparation is the synthesis of equivalence structures" [Wells, 2009 Glossary].

Let us analyze this this definition. Logical comparison implies comparison using formal argument/s. What is it comparing? Parástases, particularly obscure parástases, and hence materia ex qua from soma (receptivity) or imagination (spontaneity) (cf. above).

Note that in comparation, this being an act of logical comparison, the resultant comparison made will also be obscure parástase, and hence a source of possible matter in conscious parástase. Thus the act of comparation does not pertain to immediate perception but rather preliminary preparation of matters-of-perception (sensation & feeling, [Wells, 2009]). Following the act, this obscure parástase becomes conscious parástase after the act of reflexion (subjective comparison). The project will deal only with comparation, i.e., equivalence relationship, and hence reflexion will not be discussed.

Comparation will determine whether comparate parástase are possibly equivalent or not. This is done using the earlier mentioned definition of equivalence relations. That is, a model depicting comparation will perform the task of synthesizing an equivalence relation. Thus, the act of comparation results in a secondary quantity.

An inquisitive reader might ask "how do we know that the comparates and determination (of comparation) are obscure parástase?" Notice that we have been using the term **parástase** to differentiate it with **representation** which is a technical Kantian term (Vorstellung). This is not the same as ordinary usage. It is defined as,

> "a primitive act of mind that tells the OB 'something is in me that refers to something else'. Its matter is called composition and form is called nexus" [Wells, 2009 Glossary].

Parástase is therefore the outcome of representation. To understand a representation and hence parástase one must analyze the structure of representation. We can choose any level of structural analysis (x-LAR, x^{th} level analytic representation) [Palmquist, 1993]. Figure 3.14 shows 1-LAR and 2-LAR structure.

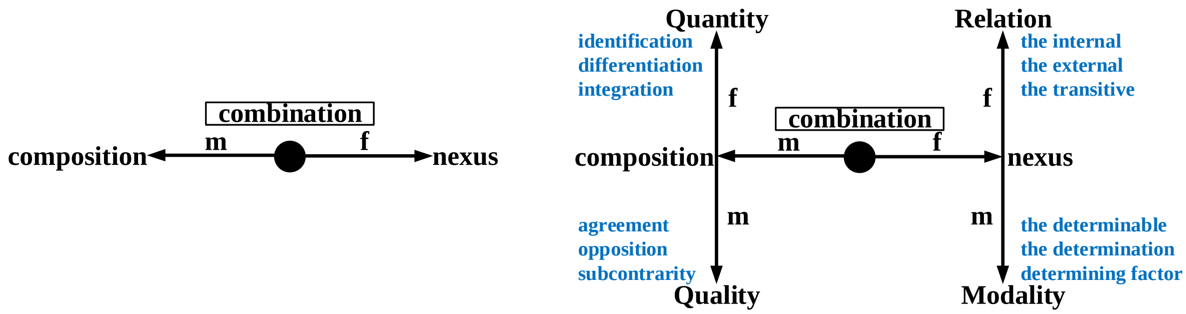

Figure 3.14. Dimensional structure of 1-LAR (1^{st} level of analytic representation) on the left and the general 2-LAR on right. The letters 'm' and 'f' are for **matter** and **form**. Every structure of representation has composition (its matter) and nexus (its form). The composition and associated nexus must therefore combine to get a structure of the representation.

The poles, composition and nexus, can be further expanded in a 2-LAR. The poles of composition are then Quality (its matter) and Quantity (its form). The poles of nexus is Modality (its matter) and Relation (its form).

Since the 2-LAR is commonly used, functions, or **momenta**, for respective poles are given technical terms, e.g., agreement, opposition and subcontrarity for the pole Quality. Note that each pole has three functions because there are three standpoints or perspectives (theoretical, judicial or practical) [Wells, 2012] and because every synthesis requires three terms.

In most cases a 2-LAR structure is sufficient. Thus, its poles are given the technical terms **Quality**, **Quantity**, **Relation** and **Modality** [Wells, 2009]. Representation will not be discussed any further here and the reader is directed to chapter-2 of Wells' text [Wells, 2009].

We analyze the comparates and determination (of comparation) using a 2-LAR. In other words, for these to be a parástase they must satisfy each of the functions with all four poles from a given perspective.

The determination by comparation is a secondary quantity but we want to understand human mind-brain and not just do some mathematical exercise. Thus one must always remember to link this to principal quantity/ies for objective validity. In other words, the model (built) performing equivalence relation (comparation) required connection of implications. But all meanings are at root *practical* which is the perspective of comparation in its connection to motoregulatory expression in psyche (Fig.3.11). As explained below this linking provides *context* for comparation.

Figure 3.15. Linking secondary quantity/ies to principal quantity/ies. ● Represent secondary quantity/ies in facet-B, nous. ● Represent principal quantity/ies in facet-B, nous. ● Represent principal quantity/ies in facet-A, mind-body.

For the case of comparation: ● determination or result of act of comparation, ● instincts & preferences, ● neural & endocrine system physiology.

Principal quantities of comparation

Recall that nous is facet-B of corresponding mind (its facet-A) (Fig.3.10) and comparation is an act in the logical organization of nous (Fig.3.11) and hence is in facet-B. As mentioned above, determination by comparation is a secondary quantity.

For objective validity, this secondary quantity must be linked to principal quantity/ies in facet-B, nous (Fig.3.15) and also must be linked to principal quantity/ies in facet-A, mind. This is same as making the link to facet-A, body because mind and body are two sides of same coin. The question then is “what are the principal quantity/ies of facet-B, nous and facet-A, body.

In facet-A, body of the OB, its sensible aspect, is logically divided into two general classes of structures: stereotyped (rigid, inflexible to change) and non-stereotyped (adaptable) [Wells, 2011g]. Stereotyped structures provide innate capacities necessary for possibility of forming later developed structures [Wells, 2011g]. Jean Piaget call these "constitutive functions" which he defines as,

> "Constitutive functions refers to those links or dependencies which are inherent in schemes of actions at a pre-operational level. These functions represent the point of origin, whether of operations which are properly of the subject or of causal systems at a level where causality consists of operations attributed to the object" [Piaget et al, pp.16, 1977].

The benefit of calling stereotyped structures "constitutive functions" is argued by Piaget as,

> "The use of the term 'constitutive functions' has real benefit not only because it preserves the continuity between functions and operations without reducing the latter to the former but also because it makes possible a functional analysis of physical actions whose irreversibility renders them irreducible to operations. It is the attribute of the latter to objects which ends up by completing the external functional links until the causal explanation which derive from the system qua system are attained" [Piaget et al, pp.13, 1977].

Many neural (brain-stem, spinal cord) and endocrine structures are stereotyped and hence are "constitutive functions". In contrast to expressions through biological maturation, structures formed in post-natal development of experience are then called constituted functions of OB [Wells, 2011g].

For building the fundamental blocks of semantic or contextual relations with soma we must therefore consider constitutive structures [Wells, 2011g]. In other words, neural and endocrine structures stand as principal quantities in facet-A (Fig.3.15).

In facet-B, nous of the OB it must overlay the constitutive structures. That is, its principal quantities must explain the **Nature** of phenomena of the constitutive structures. These are **instincts** and **preferences** (Fig.3.15). The reason why these are the principal quantities is explained from their definitions.

The term instinct used here does not have the same meaning as in everyday usage or common psychology usage. The term refers to what one might call Bergsonian instinct after Henri Bergson [Wells, 2011g; Bergson, 1911]. Understanding the practical significance of instinct gives us the meaning of instinct. This is summarized as

- Instinct is always accompanied by intelligence and never found in pure state because they are different and complementary. Quoting Bergson "what is instinctive in instinct is opposite to what is intelligent in intelligence" [Bergson, 1911].
- Intelligence considered as the original feature, is the faculty of manufacturing tools and faculty of indefinitely varying the manufacture. Thus, intelligence perfected is the faculty of making and using unorganized instruments while instinct perfected is faculty of using and constructing organized instruments [Bergson, 1911].
- Both instinct and intelligence involves knowledge but points towards unconsciousness for instinct and towards consciousness for intelligence.

Therefore, the sucking reflex of a baby in nous is instinct and in body the stereotype neural and endocrine structures, constitutive functions. Under motoregulatory expression the term preference will then be considered the subjective counterpart of instinct.

After identifying the principal quantities the question then is “how do we link them?” In other words, a judgment must be passed. However, comparation is a part of synthesis in sensibility, but synthesis of apprehension in sensibility (Fig.3.13) performs no act of judgment (as per mental physics). This is summarized by Wells as,

> “(practical) Reason knows no objects and feels no feeling; sensibility makes no judgments; the categories of understanding provide not but local laws objectively valid only for sensible experiences” [Wells, pp.289, 2009] (also refer Fig.3.11).

Context for comparation

The process of judging sensible parástases (parástase in synthesis in sensibility, Fig.3.13) and hence the task of organizing the understanding of a system of Nature (Fig.3.8 for definition) is reflective judgment (Fig.3.13). Thus reflective judgment is the mediator for the relationship between comparation and motoregulatory expression in psyche.

The relationship between comparation and motoregulatory expression is transcendental, i.e., is required for the possibility of experience. This provides *context* for comparation. It should also be pointed out that since comparation is logical and its relationship to motoregulatory expression is transcendental, the somatic responses are transcendental. In other words comparation gets its *context* in part from relation to possible motor action (i.e., pre-motor response) and not actual motor activity.

Comparation is logical comparison, therefore it is judged by the form of reflective judgment called teleological reflective judgment (TRJ). Thus somatic and noetic co-organization is done by teleological reflective judgment (Fig.3.16). Hence *context* for comparation is provided in part by TRJ.

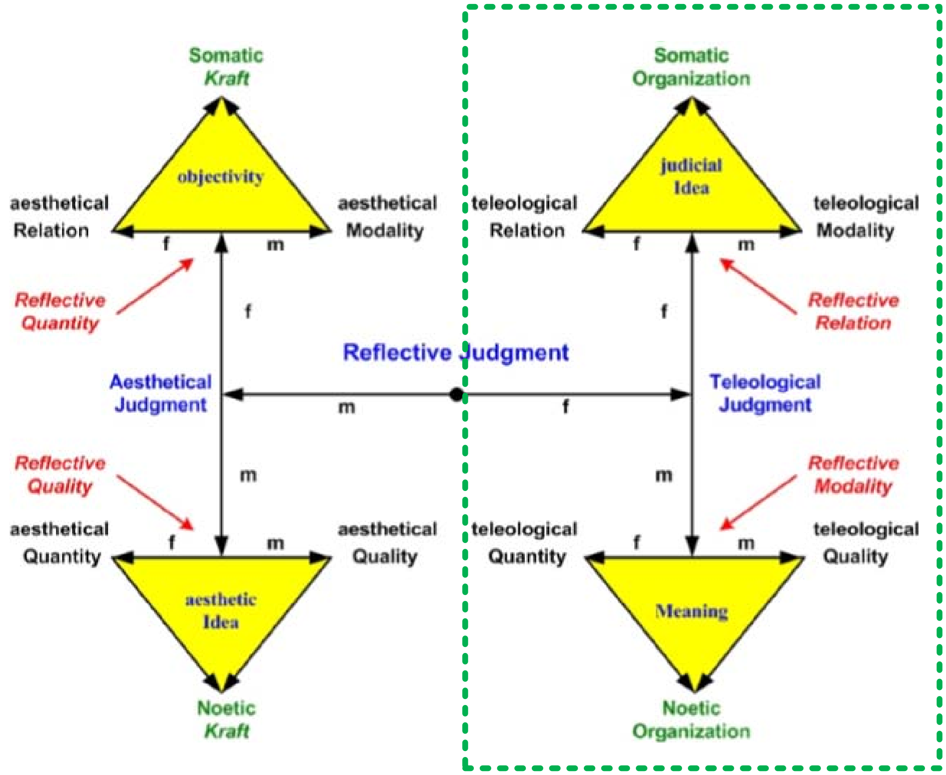

Figure 3.16. Relationship of reflective judgment and structure of division of psyche. Inside the green dash is the teleological reflective judgment that mediates comparation with motoregulatory expression of psyche by co-organizing soma with nous.

Grounds or basis for TRJ to judge comparation.

In the above discussion we have mentioned not only the linkages needed to be made between nous and soma but also the mediator, that is, reflective judgment **(**TRJ**)** which eventually provides part of the *context*. But these are requirements for objective validity of comparation. Therefore, an obvious question is “on what grounds does TRJ judge?” Put another way, “how or when does TRJ judge?”

As mentioned above, the determination by act of comparation is an obscure parástase. Thus, TRJ judges this parástase. But this parástase though obscure must be transcendental or possible for experience if there is going to be any nous-soma co-organization. This property of parástase is called **expedience** [Wells, 2009 Glossary]. What does it mean to be “possible for experience"? This is the appetitive power of OB, that is, connection with *practical* purpose. The OB has one innate pure purpose of *practical* reason. This is called the **categorical imperative** which is a *practical* formula for acts to achieve a state of complete equilibrium.

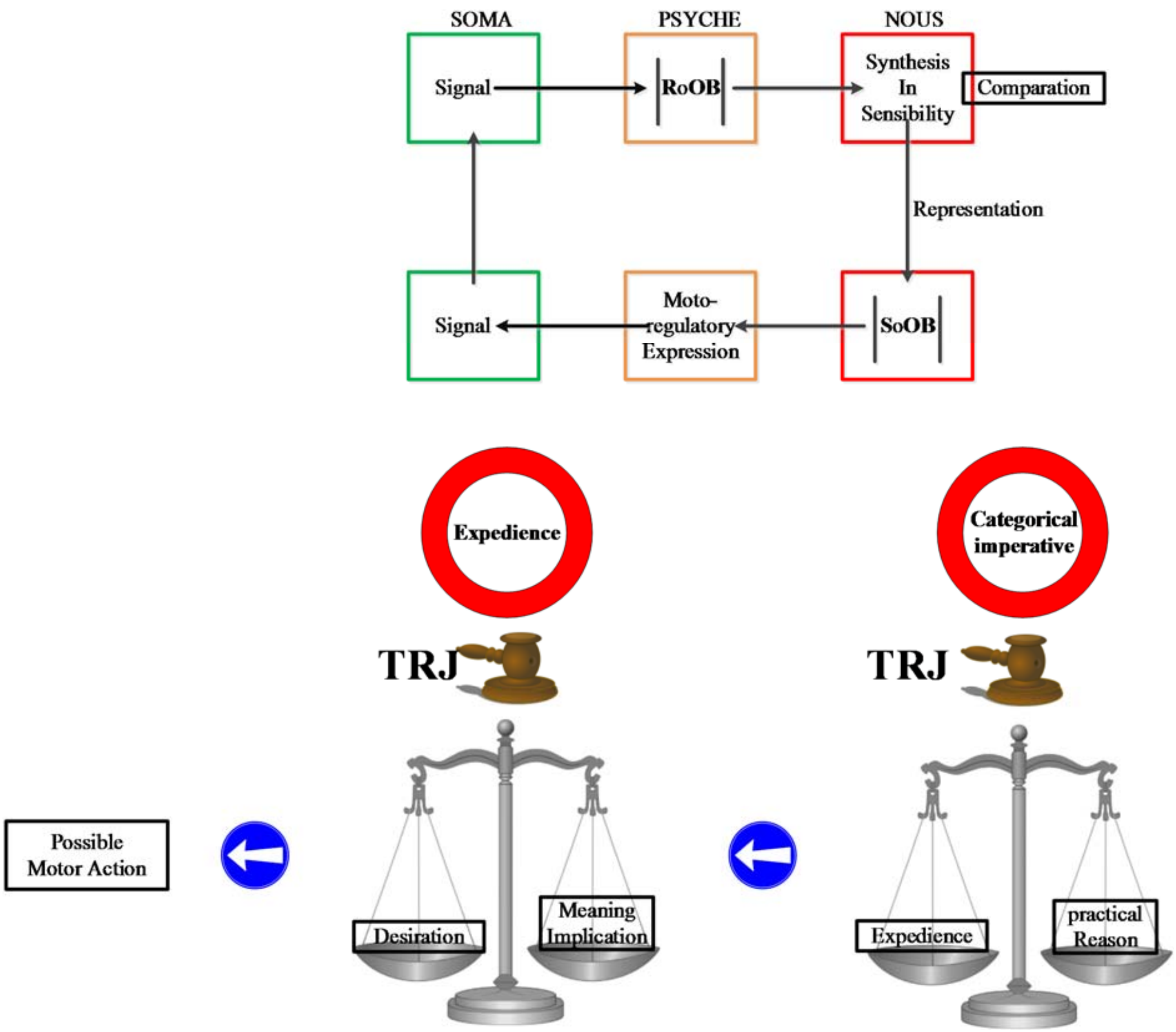

Figure 3.17. Basis for judging comparation by TRJ. TRJ judges the parástase from act of comparation by considering the property of parástase, expedience with respect to *practical* Reason on the basis of categorical imperative. TRJ also judges the determinable of motoregulatory expression, desiration with respect to meaning implication based on expedience. Thus judgment of comparation by TRJ results in possible motor action.

Therefore, TRJ judges comparation based on expedience which is then grounded by the fundamental law of acting unconditionally to achieve a state of complete equilibrium. In other words, TRJ judges the parástase when the act of comparation has reached equilibrium.

The determinable of motoregulatory expression is a parástase of possible appetite. This is called **desiration**. By meaning implication, TRJ judges desiration to be expedient, thus resulting in a possible motoregulatory expression. The connections of desiration are therefore the connections of acts of TRJ.

This shall end the discussion on the mental physics considered with comparation. In summary, comparation is logical comparison and hence in the mathematical facet-B world but requires linkage with motoregulatory expression in psyche mediated by TRJ providing semantic *context* for comparation. The basis for TRJ are expedience and desiration.

Chapter 4. Basic Tools and Techniques

As discussed, the project is based on mental physics which in turn is the application of Kantian metaphysics to mind-brain. The approach follows Bacon's investigative method (Mental Physics, pp.41) and employs set-membership theory (SMT) [Combettes, 1992]. The basic essence of SMT is that a problem may have more than one mathematical solution (> 1 satisfactory point) such that any one of them when picked makes no practical difference. The Slepian two-world model of facet-A and facet-B for principal quantities discussed earlier is an example of SMT.

In addition to these the tools for constructing the neural network are embedding field theory and method of minimal anatomies. They are both interlinked techniques and are discussed separately below.

Set-Membership Theory (SMT)

SMT produces a solution set whose characteristic is consistent with observed data and available a priori knowledge. The estimate made by SMT is governed by the notion of feasibility.

Figure 4.1 illustrates SMT. The figure (Fig.4.1a) shows the mathematical description, also called set-theoretic estimation. It is based on the point-estimation problem of guessing the value of an object h belonging in a solution space Ξ for some given observed data and some a priori knowledge. The figure (Fig.4.1b) also shows a simple practical application of the mathematics.

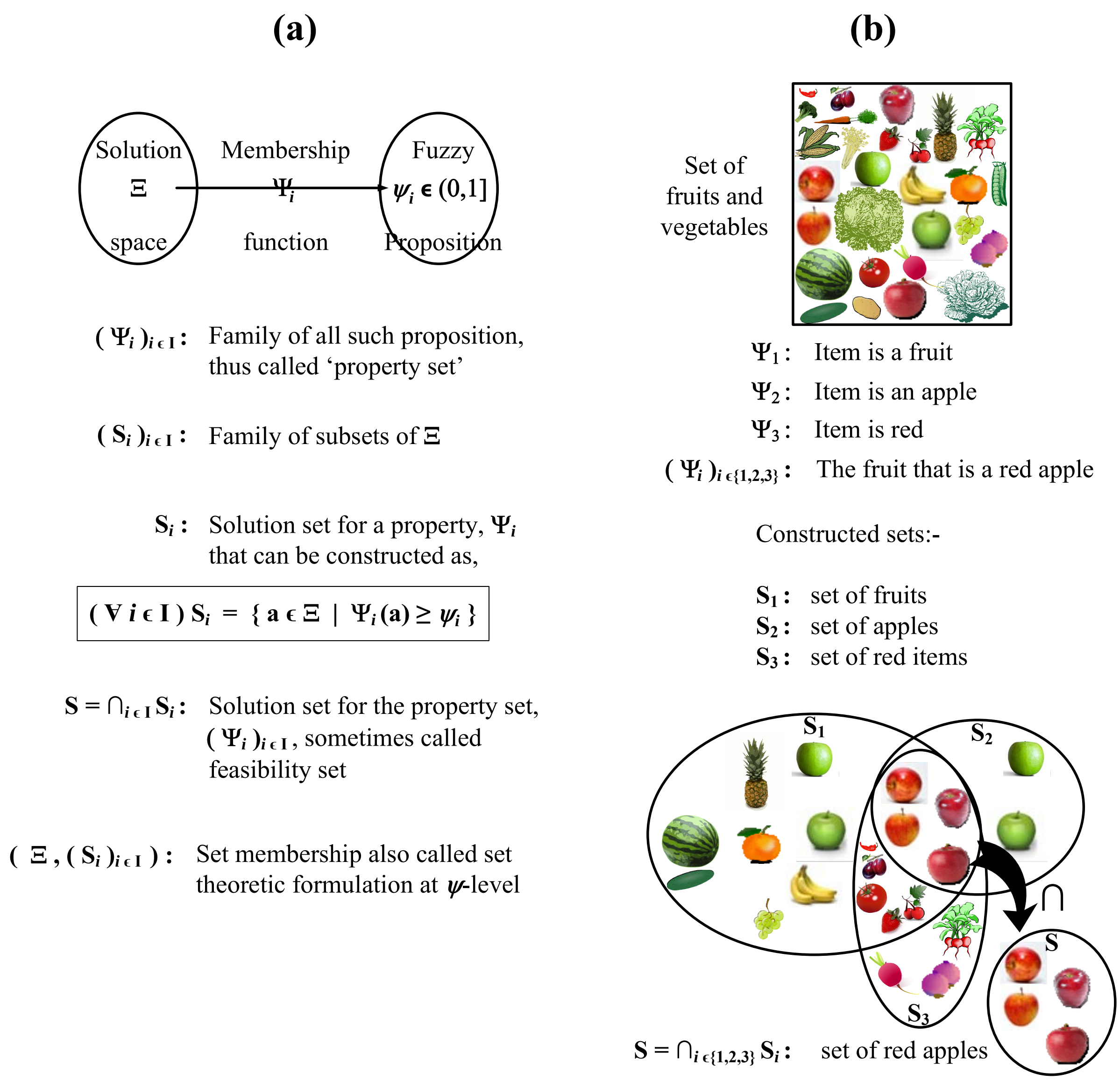

Figure 4.1. Illustration of Set-Membership Theory (SMT). (a) Mathematical description for constructing the feasibility set (solution set for the property set). The membership function or property Ψ_i is a proposition which determines the contents of its solution set S_i such that the contents are consistent with the information carried by Ψ_i at ψ-level. For crisp non-fuzzy propositions, $\psi_i \in \{0, 1\}$. (b) Given a set of fruits and vegetable and a priori knowledge that the item from the set is a fruit (Ψ_1), an apple (Ψ_2) and red (Ψ_3) in color, solution sets (S_1, S_2, S_3) for respective properties are constructed. This is followed by the construction of the feasibility set (S) which is the solution set for the property set ($(\Psi_i)_{i \in I}$) that the 'fruit is a red apple'.

There are at least two main steps for posing the set membership, (Ξ, $(S_i)_{i \in I}$). They are: 1) construction of property sets, (Ψ_i)$_{i \in I}$, and 2) selection of solution space, Ξ. These two steps are connected. There is no general technique to define membership function (a property, Ψ_i) in an objective and systematic way. In this project, property set is constructed such that it is epistemologically correct.

An important criteria of selecting the solution space is that it must be able to model available information easily and accurately. But not all information are available in most cases. Thus, the selected solution space should contain objects that are directly described from available information and reformulate the rest of the information in this space. The solution space and hence its resulting solution sets S_i should be compatible with the feasibility set, S (solution set for the property set).

The selected solution space therefore implicitly models a priori information. The constraints imposed by the selected solution space and feasibility set incorporates all available properties (information) about the problem.

Embedding Field Theory (EFT)

Theory of embedding field developed by Stephen Grossberg [Grossberg, 1969b, 1971] is a general theory of neural networks. This is derived systematically as follows. Simple psychological postulates (familiar behavioral facts) are used to derive neural networks which are then analyzed for psychological consequences. Psychological predictions are then used to derive a learning theory within the theory of embedding fields (EFT).

Mathematically, this means that EFT is the neural network or machine described by cross-correlated flows on signed (+ or excitatory, – or inhibitory) directed networks. The flows obey systems of non-linear differential equations (NLDE). Thus, deriving EFT from simple psychological postulates means derivation of NLDE.

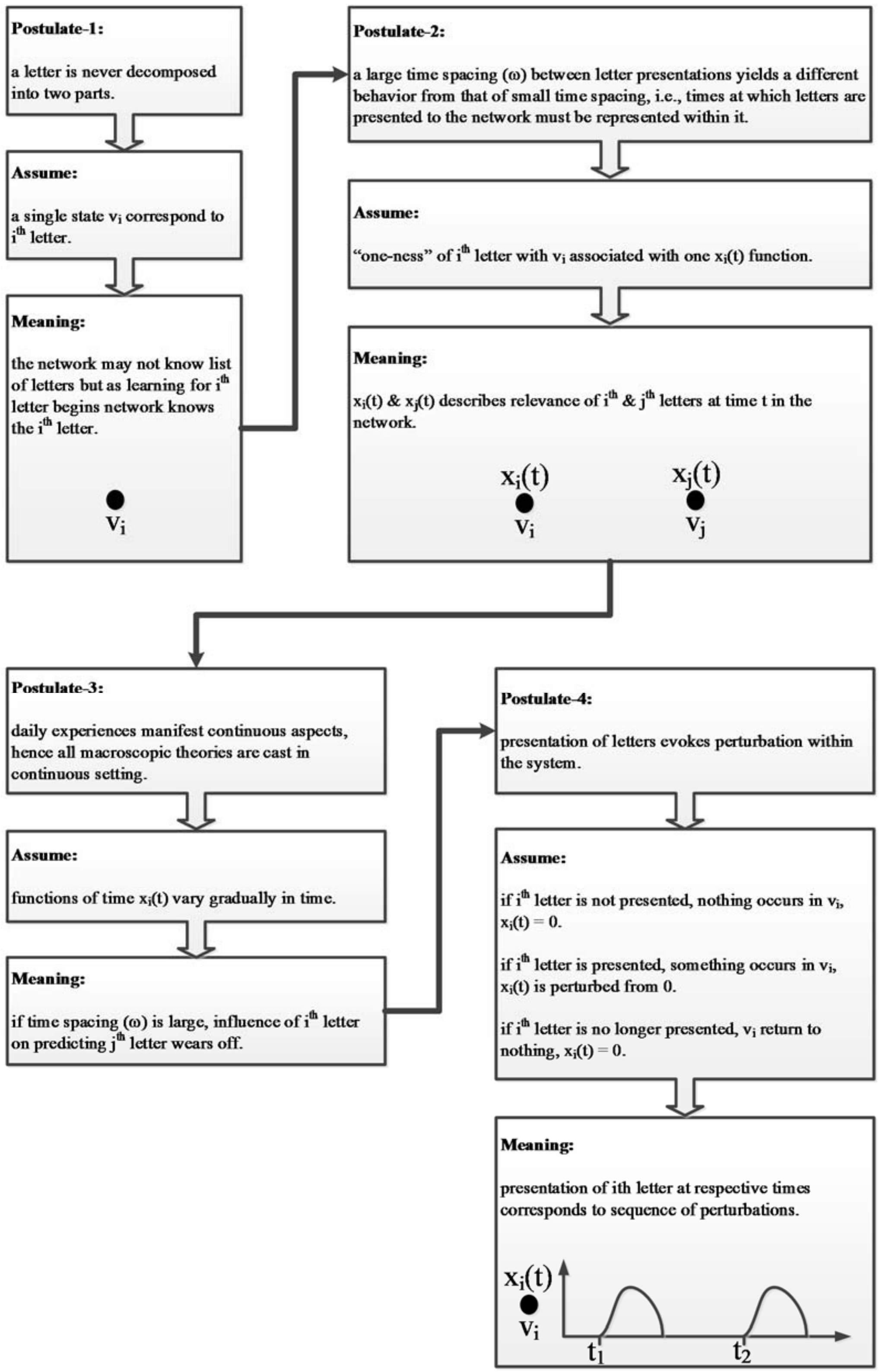

Figure 4.2. Postulates 1 to 4 and resulting derivations for the simple network. With each additional postulate the derived model acquired more capabilities. The meaning implications noted in this figure have objectively valid expression in mental physics.

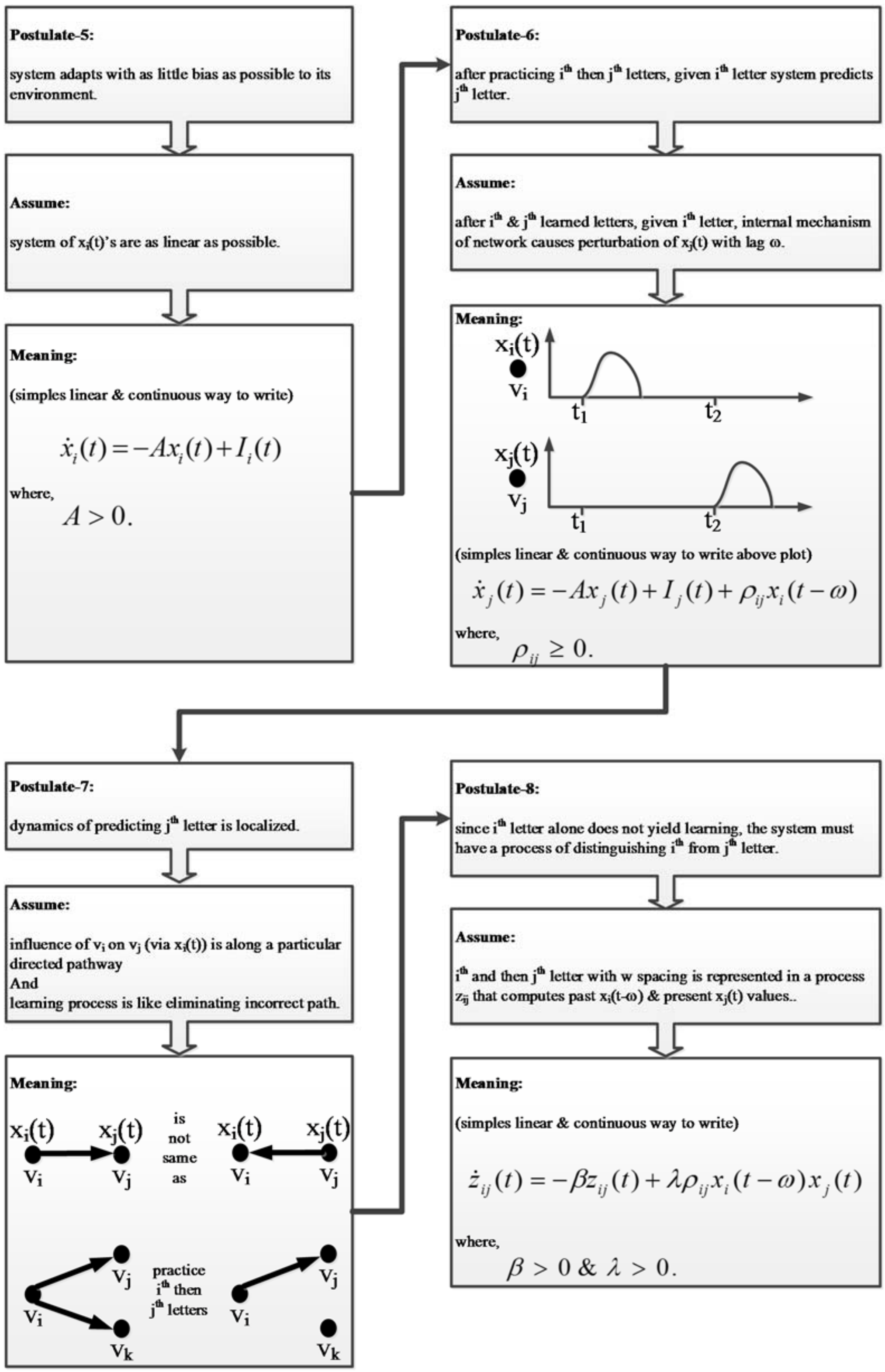

Figure 4.3. Postulates 5 to 8 and resulting derivations for the simple network. Note that this is a continuation of figure 4.2.

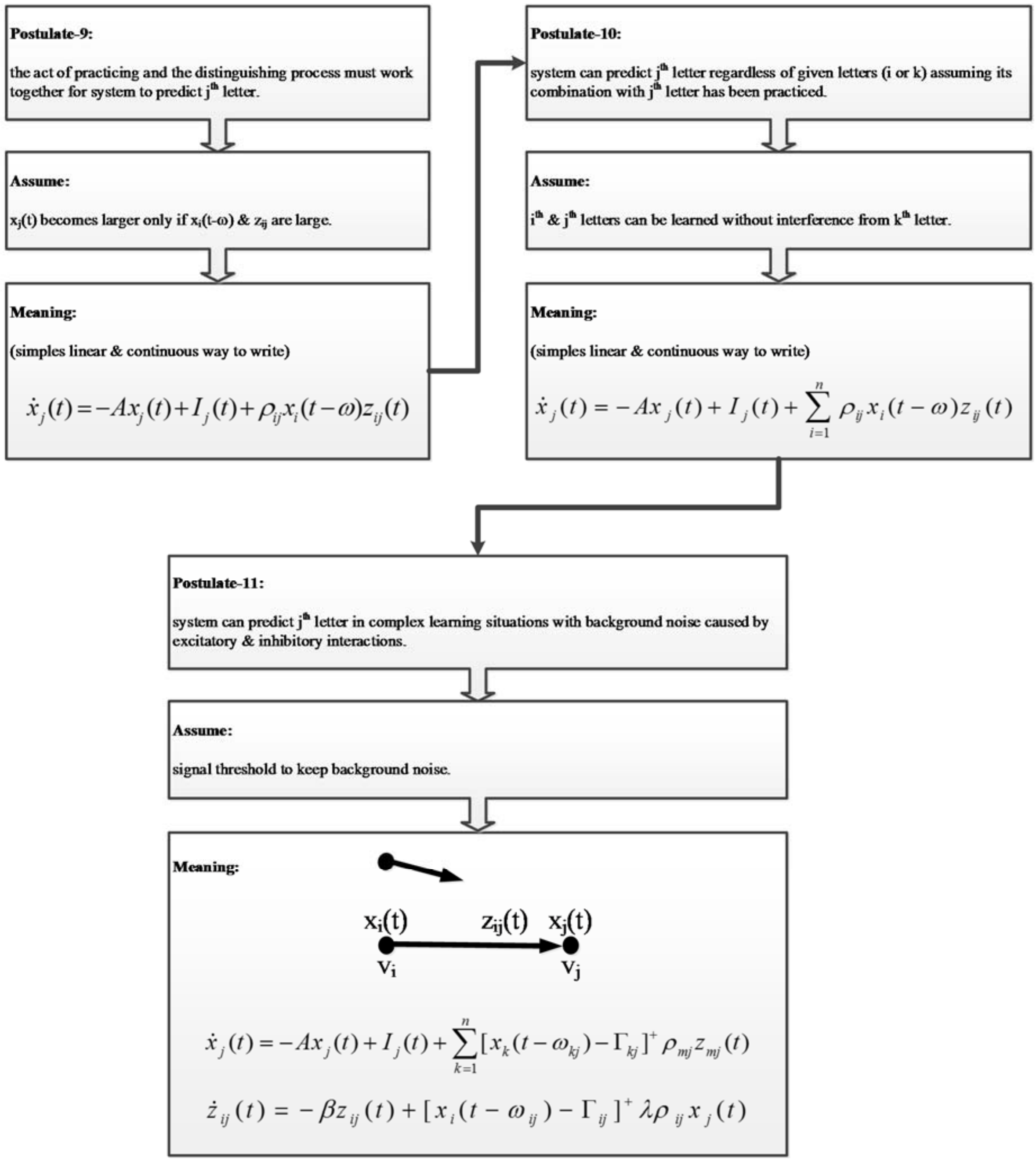

Figure 4.4. Postulates 9 to 11 and resulting derivations for the simple network. This is a continuation of figure 4.3. The non-linear differential equation (NLDE) of the finally derived simple network is the two equations resulting after postulate-11.

Figures 4.2, 4.3 and 4.4 show a step-by-step derivation of a simple network with the capability to learn and therefore exhibit learned behaviors. The specific example illustrated is Grossberg's "letter recognition" problem.

Note that though simple behavioral facts and hence empirical terminology are used to derive the network (NLDE), the NLDE variables are secondary quantities. Thus mathematical variables are not necessarily connected to empirical interpretations. However, if the output variable is defined as representing principal quantities empirical connections can be made.

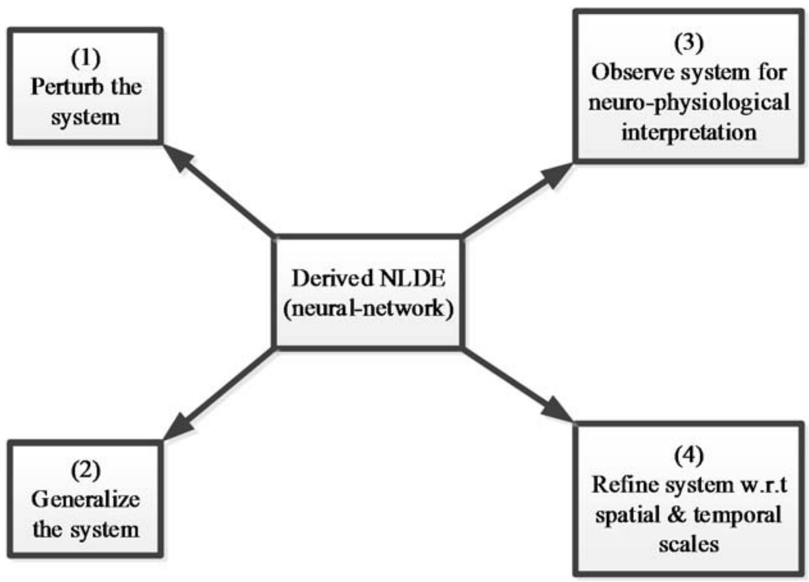

Figure 4.5. Four possible paths after deriving non-linear differential equation (NLDE).

After deriving the derived NLDE (i.e., neural network) there are at least four possible paths for analyzing it (Fig.4.5). Let us we consider system (neural network) input and output as representation of system experience and perturbation cases as representation of mathematical behavior which is qualitatively same as psychological interpretation. Then perturbing the system (Fig.4.5(1)) complicates experiences and provokes various perturbation cases.

The system may also be generalized (Fig.4.5(2)). This implies associating the system to farthest possible psychological experience. Thus, to generalize the system is to investigate the system as pure mathematical problem.

Another path is to observe system for neurophysiological interpretation (Fig.4.5(3)). However one must be careful taking this path and not make leaping interpretations because the system is derived from psychological experiences and does not incorporate microscopic neurophysiology.

Finally, the system may be refined with respect to spatial and temporal scales of the NLDE (Fig.4.5(4)). According to Grossberg, using this approach the system can make hypothesis on possible transients [Grossberg, 1971]. The discussed approaches are summarized in figure 4.6.

In this project, the derived system will be perturbed. This is because qualitative interpretation of the math and hence the psychology of complex (unrelated and related) cases are manifestations of the simple behavioral facts used for the derivation.

(1) Perturbing the system

Embedding field (neural network) shows:-

- Complex psychological phenomena are manifestations of few simpler behavioral facts.

(3) Observe for neuro-physiological interpretation

Embedding field (neural network) shows:-

- Sometimes, qualitative & quantitative agreement w.r.t neuro-physiology.
- Other times, makes new predictions.

(2) Generalizing the system

Embedding field (neural network) shows:-

- Large class of NLDE for mathematical analysis is introduced.
- Relations among alternate mathematical possibilities.

(4) Refining spatial & temporal scales of NLDE

Embedding field (neural network) shows:-

- Clarity of model scale.

Figure 4.6. Accomplishments of embedding field theory (EFT) depending on the paths taken (Fig.4.4).

Method of Minimal Anatomies (MMA)

Stephen Grossberg introduced MMA as a method of successive approximations [Grossberg, 1982]. Its principle thus has analogies in other scientific fields such as physics, (1-body to 2-body to 3-body and so on) or from thermodynamics to statistical mechanics. Thus with each successive analysis the complexity increases and is more realistic. This is consistent with Bacon's investigative method.

Grossberg's MMA answers the question of 'How to approach several levels of description relevant to understanding behavior?" The embedding field type neural component is first derived from psychological postulates (Fig.4.7). This then forms the neural unit when interconnected to form a specific anatomy. The specific anatomy or system receives input with psychological interpretation resulting in psychologically interpretable output.

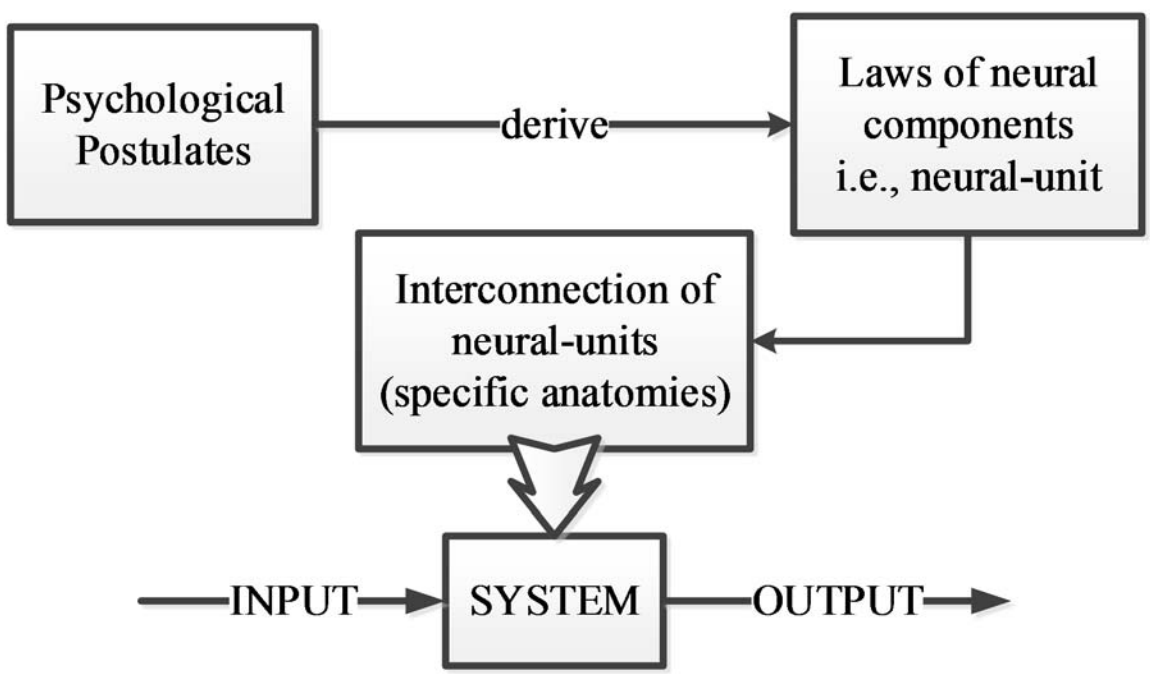

Figure 4.7. Basic description of applying embedding field theory (EFT) to derive a neural network.

It should be highlighted that though the derived components are called neural-units they are not the same as a biologists understanding of neural components. This is because the derivation is from psychological postulates and hence modelling scale (neural network) is much larger than individual neurons. Also, regardless of how precise the knowledge of laws and postulates may be, accounting for every (10^{12} nerve cells) connections and analyzing them would be impractical [Grossberg, 1982].

The above description (Fig.4.7) is basically an application of MMA. A model (network) may be considered the minimal network. For instance the derived network in figure 4.7 can be a minimal network. Other steps will build upon this minimal network resulting in a network which may then be considered minimal network for a larger model continuing this cycle to beget an even larger model.

The general MMA approach may be broken down to four basic steps (Fig.4.8). First a model is picked for considering the minimal network. This is then followed by analysis-step (Step 2) which helps in understanding the mechanism of a particular 'minimal' anatomy. In addition, at this step advantages and disadvantages of its variations can also be imagined further enhancing the understanding.

With every additional postulate (Step 4) the corresponding network will be the previous 'minimal' network with added components for the additional capabilities. Thus, the resultant network will be a hierarchy of networks with sophisticated postulates. The mechanisms of each successive 'minimal' network means that the resultant network will have a catalog of mechanisms for use in various situations.

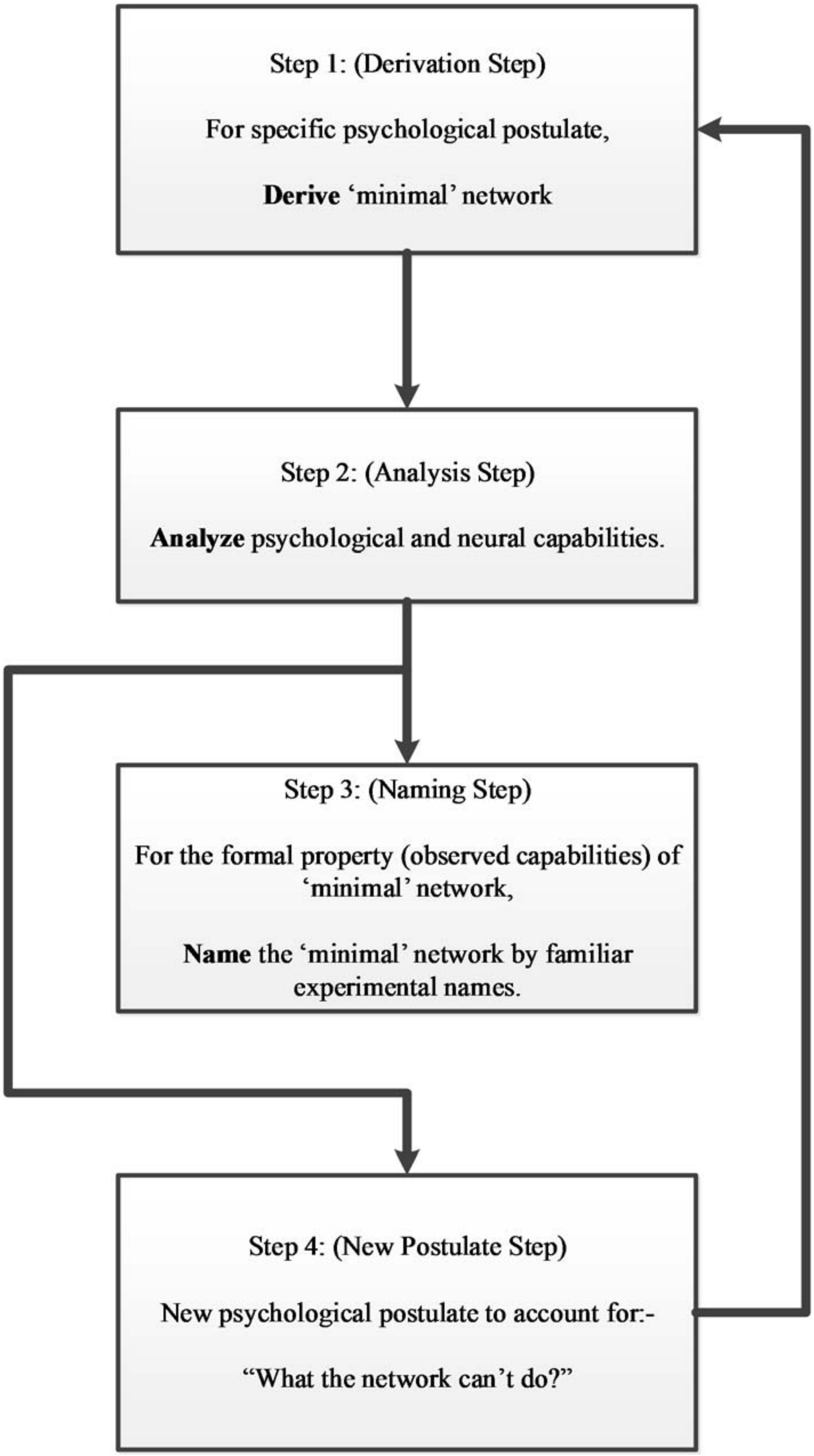

Figure 4.8. A scheme of the method of minimal anatomies approach (MMA) to design a neural network with embedding field type 'minimal' networks.

The naming-step (Step 3) answers the question of "When does a particular phenomenon first appear?" Therefore, this step, regardless of the name, will not compromise the formal correctness of the overall theory from the resultant network. The naming-step is a very useful tool for deeper insight into the resultant neural network.

Finally, one must be wary and to distinguish between postulates, mathematical properties, factual data and interpretation of network variables.

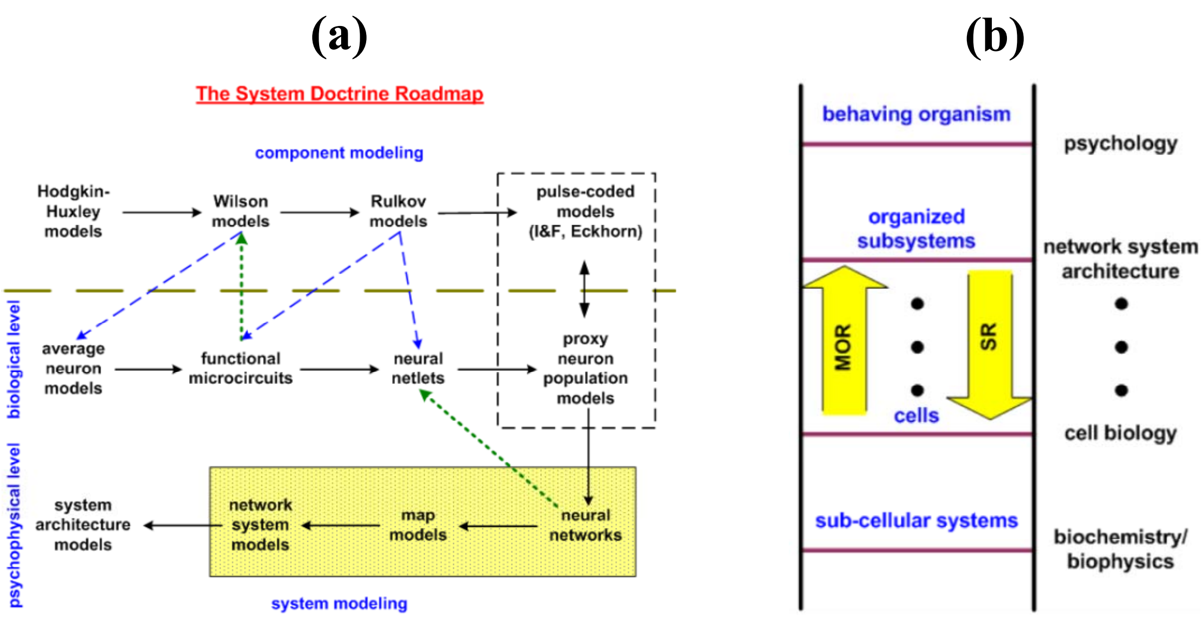

Figure 4.9. Different but similarly meaning description for neuroscience as an interdisciplinary science.

Figure (a) is the neuroscience roadmap view linking biology and psychology. The highlighted region indicates the location of this thesis with regards to the neuroscience roadmap. A map model is a network of neural networks while a network of maps comprises a network system [Wells, Ch.7, 2010].

Figure (b) is another view depicting the neuroscience ladder adopted from [Wells, 2011a] showing several rungs each representing scientific construct at various levels. Moving upward towards increasing level of abstraction from mechanism to behavior is model-order reduction (MOR). However, migration of scientific study from level of observable phenomenon down to increasingly refined scientific constructs is scientific reduction (SR).

Modelling Scale

The above description of MMA involved using EFT to build the network. However, the general idea of MMA may be used to build networks at smaller scales such as pulse-coded neural networks [Sharma, 2011]. Modelling scales for neural networks will be briefly discussed.

If we consider respective disciplines as rungs of a ladder (Fig.4.9), the objective of a neuroscientist should be to join the rungs for achieving the common goal of understanding how mind-brain works. Taking a concept from systems theory, this can be done on two accounts: model-order reduction (MOR) and scientific reduction (SR). MOR is the simplification of the amount of detail needed in obtaining computationally tractable models of ever more complex systems. Thus with MOR one moves towards increasing level of abstraction from mechanism to behavior. SR on the other hand is migrating scientific study and theory from one level of phenomena to others more directly observable by our senses but which use increasingly refined scientific constructs.

For the thesis, the modelling direction will be SR using MMA to build embedding field type minimal-anatomies neural networks to construct a map models.

Chapter 5. Building the comparation network and generation of equivalence relation

Qualitative Modelling (Comparation Network showing a relationship)

One view of building a neural network performing the process of **comparation** is to find a network exhibiting the relation properties: reflexive, symmetric and transitive. This is the view we take. This is because at the stage of the process of comparation in the **Verstandes Actus** it performs logical comparison with obscure (not conscious) parástase. Comparison made by identifying particular equivalence classes implies the process is working with conscious parástase. Thus the first postulate is,

Proposition 1: Comparation in the synthesis of equivalence relation exhibits the reflexive and symmetric relations.

Such a network is said to synthesize a compatibility relation. As was discussed earlier, comparison always involves a minimum of two items or objects. Thus,

Proposition 2: The comparation process in Verstandes Actus involves a minimum of two inputs.

Thus, the basic model will involve logical comparison of two inputs. For convenience of illustration let each input appear as a retinal-map of pixels as shown below.

Figure 5.1. The basic model (a) receiving two comparands, each represented as retinal-map matrix sized 5 x 5.

The comparation process is in facet-B and hence is in the mathematical domain. The neural network behavior determines the relationship but does so without any a priori objective knowledge. Hence, the determination (relationship or not) is made by feature definer and detector which is automatically generated. We do not build them into the model. Hence the third postulate is,

Proposition 3: Comparation compares features that are dynamically generated axiomatic features.

It was mentioned earlier that the comparation process works with obscure parástase (input) and its determination (output) is also an obscure parástase. **TRJ** (teleological reflective judgment) judges **expedience**. This gives us,

Proposition 4: The process of comparation is judged expedient when the act is not contrary to the **categorical imperative**, which regulated to achieve a state of equilibrium.

During the process of comparison when the neural network model reaches a reverberating or resonant state, we will say the model is in steady-state condition. We will consider a neural network in such a state to be in equilibrium and hence may be judged expedient.

In embedding field theory (EFT) there is a family of known and also yet to be discovered neural networks which can reach a resonant state [Wells, 2010]. They are called adaptive resonance theory (ART) networks. A typical anatomy of an ART resonator (ART-R) is shown in figure 5.2a. Based upon this basic anatomy the network model has two resonators, such that each receives a respective input element. Hence, the model receives two comparands (Fig.5.2b). However, for the process of comparation the two basic anatomies must interact and hence cannot be isolated subsystems (Fig.5.2c). Thus,

Proposition 5: The sub-processes for respective comparands are united within the process of comparation.

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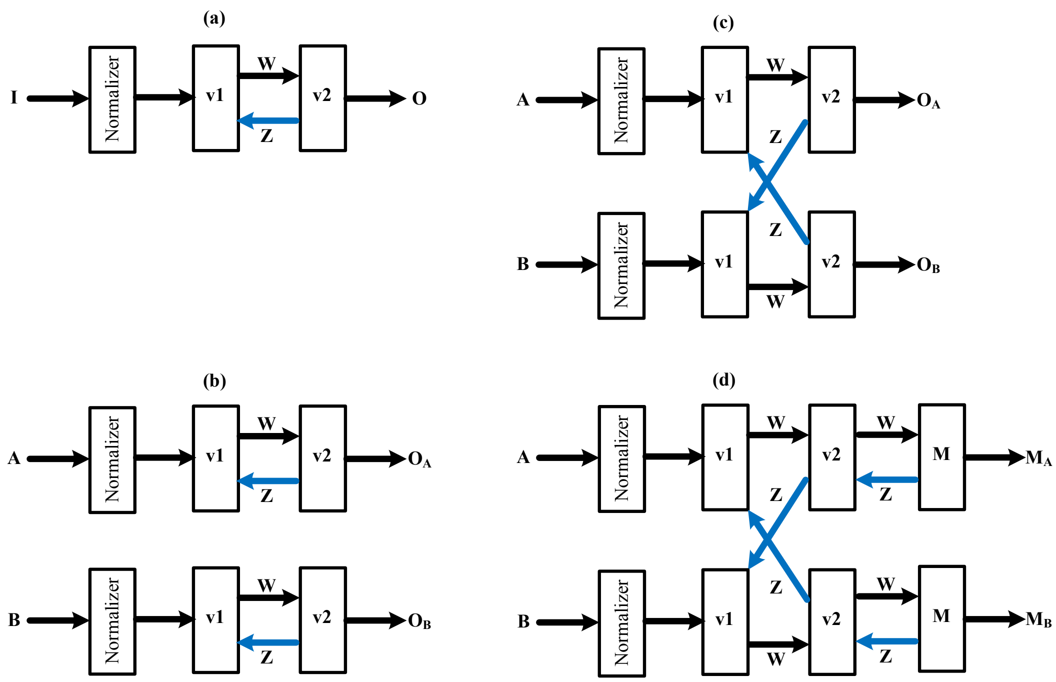

Figure 5.2. Illustration of the evolution from the basic ART-R (a) to the minimal neural network (d).

The basic ART-R (a) has a normalizer layer which then sends normalized inputs to the v1 layer. The v1 and v2 layers interact such that the nodes in v2 layers receives instar weights (W) and send out outstar weights to v1 layer. The interaction therefore plays a major role in achieving resonance.

Each ART just receiving respective comparand input (b) is insufficient. (c) Shows one approach to interaction between the two sub-networks. Here, the outstar-weighted output of the v2 layer of a sub-network feeds into the v1 layer of the other sub-network.

The comparation network is judged for expediency by interacting with M layer. Thus, this addition in the network proxies for part of TRJ. This also means that **nous-soma** connection is made. It should be noted that M_A and M_B are not motor responses but thought of as pre-motor images.

An obvious question for the above model is “how do we know that the process of comparation is expedient?” The model must have this property for at least two reasons. Firstly, since expediency is a **judicial imperative** the determination (relationship) by comparation will have no *practical* purpose if it is not expedient. Secondly, this is judged by TRJ which is a mediator between **nous** and **psyche** co-organizations. This means that the model must have link to **motoregulatory expression**. Thus, Proposition 6: The process of comparation is judged by TRJ (teleological reflective judgment).

In the model (Fig.5.2c) the judgment for resonance and hence expediency is evaluated by the addition to two more fields (Fig.5.2d). These additions are proxies for motoregulatory *emotivity* such that when they reach steady-state the process of comparation may be judged expedient. It should be noted that there is no longer a clear distinction between the process of comparation and the ability to judge expediency (a functional part of TRJ).

Comparation is a process within **sensibility** but sensibility does not judge, does not deceive and does not confuse[1] [Kant, 1798]. Recall that the **synthesis in sensibility** is transcendental, i.e., necessary for the possibility of experience. Thus the activities of the motor end of the network do not represent motor response of the **OB** but are akin to pre-motor activities. We may therefore consider that if the steady-state values of the pre-motor responses are within a solution set, the comparands have a relationship. Thus,

Proposition 7: The relationship determined by comparation is *practical* in the sense that it is not contrary to the OB's categorical imperative.

Thus meaning of the determined relationship is purely *practical*.

[1] The three anthropological characteristic of the senses may be summarized as:
senses do not confuse :- Sensuous representations comes before representations for understanding and relay themselves all together. Thus, sense perceptions (empirical parástase with consciousness) are 'inner appearances'. *senses do not control* :- Sensuous parástase offer themselves to understanding and do not have control over understanding. *senses do not deceive* :- They do not deceive because they do not judge.

Note that, Kantian anthropology is the science of man's actual behavior and has for its topic 'the subjective laws of free choice'. Free choice (arbitrum liberum) is the power of choice in an OB, which is the choice of freedom from having its (OB's) actions necessarily bound to determination by sensuous representations. This freedom is called 'practical autonomy'. Because actions are subject to conditions set in the OB's self-constructed manifold of practical rules the determined actions can opposes sensuous desire.

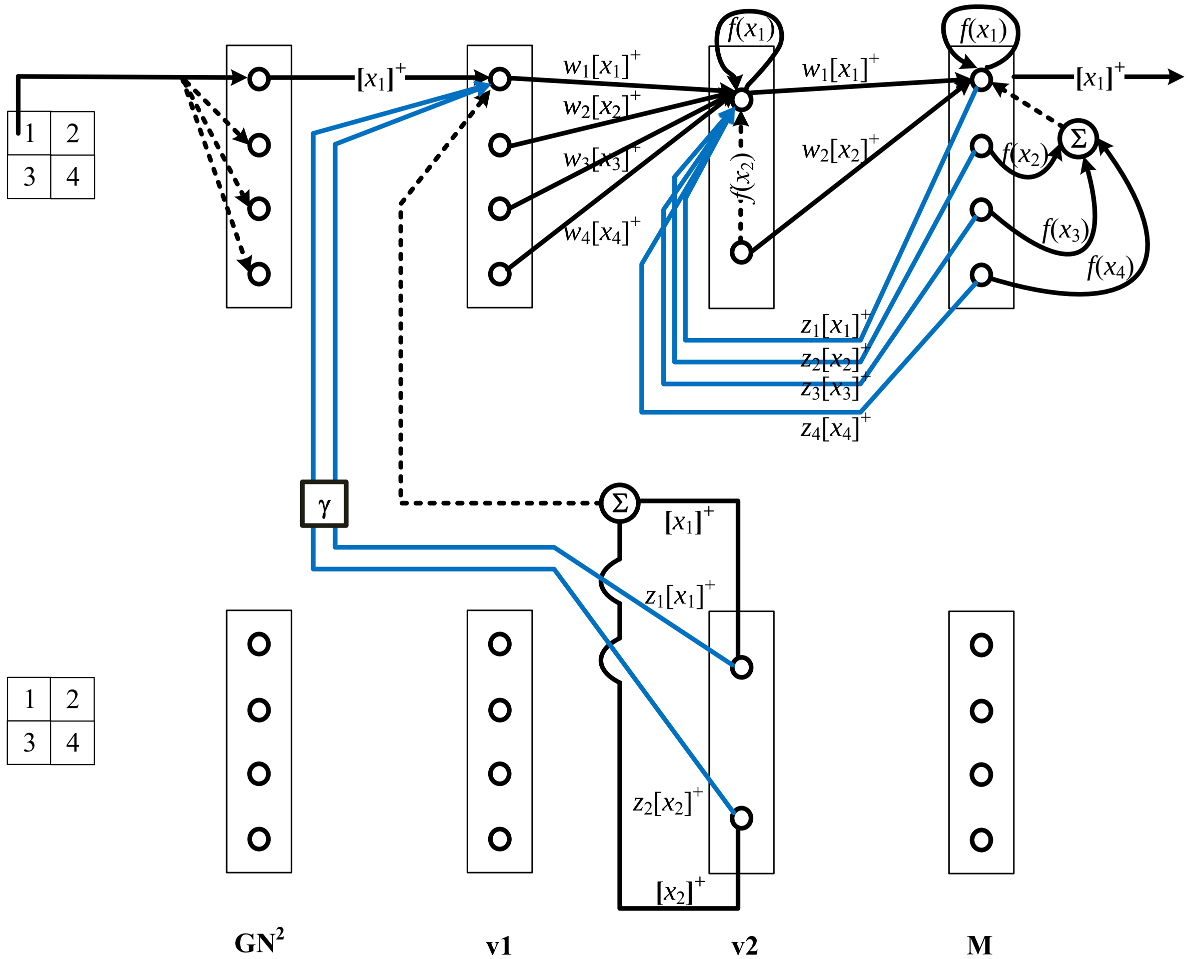

Figure 5.3. A more detailed view of the minimal neural network (Fig.5.2d). The illustration shows the connection of a single node in each layer. Given a retinal-map matrix sized 2 X 2, the first pixel excites (solid line) the first GN^2 node but inhibits (dashed lines) other nodes (of respective sub-network). The first v1 node (SNI^4) then receives excitatory inputs from the first normalized input and outstar-weighted output of all v2 nodes (other sub-network) with gain γ (solid blue line). The inhibition (dashed line) is the sum of these un-weighted v2node outputs.

The first v2 node (SNI^3) receives excitatory inputs from instar-weighted output of all v1 nodes (same sub-network), outstar-weighted output of all M nodes within the same sub-network (solid blue line) and from itself passed through the activation function ($f(\cdot)$). The rest of the v2 nodes within the same sub-network passed through $f(\cdot)$ are added to form the inhibitory input to the first v2 node. 0-1 distribution is enforced for v2 layer.

The first M node is the same kind of SNI^3 as the v2 nodes but without 0-1 distribution. Thus, its excitatory and inhibitory inputs follows a similar pattern as above but with different connectivity. The node does have any excitatory input from outstar-weighted output.

Note that *x*'s and weights *w*'s or *z*'s are labeled the same for each layer for simplicity. However, they are quantitatively different and hence don't represent for instance the same excitation.

Quantitative Model (Comparation)

The quantified (detailed) view of the figure 5.2d is shown in figure 5.3. The ART network has nodes which in general are called shunting node instars (SNI). There are numerous types of SNI's, each having a different behavior from another [Wells, 2010]. This is consistent with EFT and MMA. The general description is given above (Fig. 5.3). Below are the mathematical expressions specific to the model.

The inputs or comparands are first normalized by normalizers called a Grossberg Normalizer-2 (GN^2) [Wells, 2010]. The practical importance of having a normalizer in ART networks is elaborated in Wells' text [Wells, 2010]. The i^{th} GN^2 node is given by the differential equation,

$$\dot{x}_i^{\mathrm{GN}} = -A_o x_i^{\mathrm{GN}} + (B_o - x_i)I_i - (C_o + x_i^{\mathrm{GN}}) \sum_{\forall k \neq i} I_k,$$

where, A_o, B_o and $C_o$are non-zero parameters such that, $B_o = (n-1)C_o$. As mentioned above the comparand is a retinal-map and hence they are matrix of I_i pixels. There is a corresponding GN^2 node for each pixel. This means there will be a total of n GN^2 nodes for a retina matrix of a rows and b columns (n = $a \cdot b$). In the above equation, $I = \sum_{\forall k} I_k$ and $\omega_i = \frac{I_i}{I}$.

The normalized inputs are then received by respective v1-layer. Like the normalizer layer the v1-layer has n nodes. This layer is comprised of SNI's called SNI^4 [Wells, 2010]. It's i^{th} node is given by,

$$\dot{x}_i^{\mathrm{v1}} = -A_1 x_i^{\mathrm{v1}} + (B_1 - x_i^{\mathrm{v1}})J_i^{+} - (D_1 + x_i^{\mathrm{v1}})J^{-},$$

where, A_1, B_1 and D_1 are non-zero parameters. The excitatory J_i^+ and inhibitory J^- inputs are given by,

$$J_i^+ = x_i^{GN} + \gamma Z_{\text{v2 to v1}}[\vec{\mathbf{x}}^{\text{v2}}]^+ \quad \text{and} \quad J^- = \textstyle\sum_{\forall k}[x_k^{\text{v2}}]^+,$$

where, γ is a non-zero parameter. The Heaviside extractor $[\,\cdot\,]^+$ is given by,

$$[H]^+ = \begin{cases} H \; if \; H \geq 0 \\ 0 \; else \end{cases}.$$

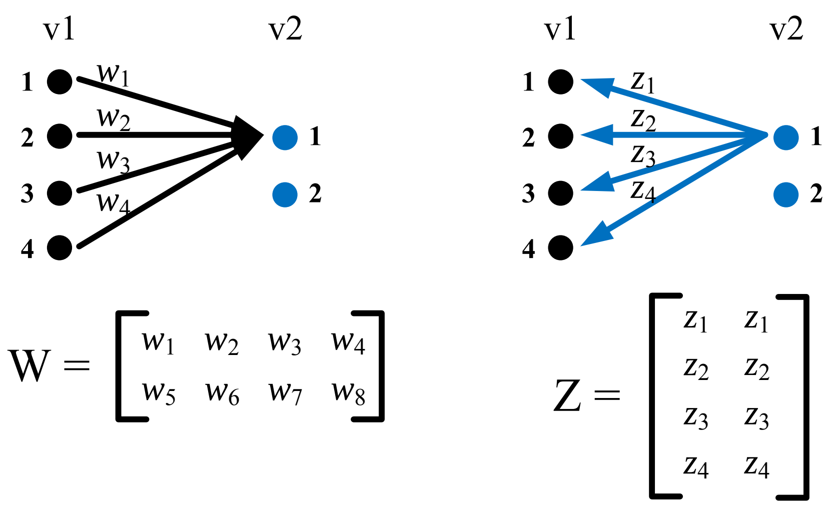

Figure 5.4. Illustration of instar (W) and oustar (Z) weights. Notice that the first row elements of W matrix corresponds to instar weights going into first v2 node (blue). But first column elements of Z matrix corresponds to outstar weights going out of the first v2 node.

$Z_{\text{v2 to v1}}$ is the outstar weight matrix from v2-layer to v1. They go hand in hand with the instar weight matrix from v1 to v2, $W_{\text{v1 to v2}}$ (Fig.5.4). They are given by the form,

$$W_{\text{v1 to v2}}(t+h) = W_{\text{v1 to v2}}(t) - \eta \cdot \left[(W_{\text{v1 to v2}}(t) - [\vec{\mathbf{x}}^{\text{v1}^{\mathrm{T}}}]^+) \cdot [\vec{\mathbf{x}}^{\text{v2}}]^+\right] \text{ and}$$

$$Z_{\text{v2 to v1}}(t+h) = Z_{\text{v2 to v1}}(t) - \eta \cdot [(Z_{\text{v2 to v1}}(t) - [\vec{\mathbf{x}}^{\text{v1}}]^+) \cdot [\vec{\mathbf{x}}^{\text{v2}}]^+],$$

where, η is the adaptation parameter and h is step size. The property of outstar weights in an ART network is that, the weights from the winning v2 nodes is an exemplar of the input.

The nodes in the v1-layer interact with v2-layer nodes. But unlike the v1-layer, the number of nodes in v2 is not restricted by the size of the retina matrix. This also means that the number of nodes in the succeeding M-layer is unrestricted. SNI[3] was chosen for the v2 nodes. They are expressed by,

$$\dot{x}_i^{\mathrm{v2}} = -A_2 + (B_2 - x_i^{\mathrm{v2}})\xi_i^{Ex} - (x_i^{\mathrm{v2}} + D_2)\xi_i^{In},$$

where, A_2, B_2 and D_2 are non-zero parameters. The excitatory ξ_i^{Ex} and inhibitory ξ_i^{In} inputs are given by,

$$\xi_i^{Ex} = W_{\mathrm{v1\ to\ v2}} \cdot [\vec{\mathbf{x}}^{\mathrm{v1}}]^+ + Z_{\mathrm{M\ to\ v2}} \cdot [\vec{\mathbf{x}}^{\mathrm{M}}]^+ + f(x_i^{\mathrm{v2}}) \text{ and}$$
$$\xi_i^{In} = \textstyle\sum_{\forall k \neq i} f(x_k).$$

It has been observed that adaptation in most ART networks necessitates a 0-1 distribution in the v2-layer [Wells, 2010]. Therefore, a 0-1 distribution is enforced for the vector, $\vec{\mathbf{x}}^{\mathrm{v2}}$ and the winning v2 node controls network adaptation.

The function $f(\cdot)$ is called the activation shape function. It is given by,

$$f(y) = \begin{cases} 0 & if\ y < 0 \\ \lambda \cdot y & if\ y \leq u^{(1)} \\ g_{max} \cdot y & if\ u^{(1)} < y \leq u^{(2)} \\ g_{max} \cdot u^{(2)} & if\ y > u^{(2)} \end{cases}.$$

where $u^{(1)}$ and $u^{(2)}$ are parameters for the activation shape function. The contrast enhancement capability of some ART networks may attenuate the absolute levels of x_i signals. Proper scaling will not alter the performance of the network apart from limiting the attenuation of the absolute levels [Wells, 2010]. Using the B parameter as the reference this is done here as,

$g_{max} = B \cdot g_{max}^{unscaled}$,

$u^{(1)} = \frac{\left(B - \frac{A}{g_{max}}\right)}{\left(1 - \frac{A}{g_{max}}\right)} \cdot u_{unscaled}^{(1)}$,

$u^{(2)} = B \cdot u_{unscaled}^{(2)}$ and

$\lambda = \frac{g_{max}}{u^{(1)}}$.

where, $g_{max}^{unscaled}$, $u_{unscaled}^{(1)}$ and $u_{unscaled}^{(2)}$ are the unscaled parameters.

The nodes for the M-layer use SNI[3] and hence is similar to the v2-layer. However, M-layer has fair distribution since 0-1 distribution is not enforced. Also, the parameters may be different and because the connections are different the expression of excitatory and inhibitory input are different.

Therefore, the minimal neural network is given by,

$$x_i^{\mathrm{M6}}(t+h) = \left[1 - h \cdot \left(A_{\mathrm{M}} + \xi_i^{Ex\_\mathrm{M6}} + \xi_i^{In\_\mathrm{M6}}\right)\right] \cdot x_i^{\mathrm{M6}} + h \cdot \left(B_{\mathrm{M}} \cdot \xi_i^{Ex\_\mathrm{M6}} - D_{\mathrm{M}} \cdot \xi_i^{In\_\mathrm{M6}}\right),$$

$$x_i^{\mathrm{M5}}(t+h) = \left[1 - h \cdot \left(A_{\mathrm{M}} + \xi_i^{Ex\_\mathrm{M5}} + \xi_i^{In\_\mathrm{M5}}\right)\right] \cdot x_i^{\mathrm{M5}} + h \cdot \left(B_{\mathrm{M}} \cdot \xi_i^{Ex\_\mathrm{M5}} - D_{\mathrm{M}} \cdot \xi_i^{In\_\mathrm{M5}}\right),$$

$$x_i^{\mathrm{v2\_4}}(t+h) = \left[1 - h\left(A_2 + \xi_i^{Ex\_4} + \xi_i^{In\_4}\right)\right] x_i^{\mathrm{v2\_4}} + h\left(B_2 \xi_i^{Ex\_4} - D_2 \xi_i^{In\_4}\right),$$

$$x_i^{\mathrm{v2\_3}}(t+h) = \left[1 - h\left(A_2 + \xi_i^{Ex\_3} + \xi_i^{In\_3}\right)\right] x_i^{\mathrm{v2\_3}} + h\left(B_2 \xi_i^{Ex\_3} - D_2 \xi_i^{In\_3}\right),$$

$x_i^{\mathrm{v1\_2}} = \frac{B_1 J_i^{\mathrm{v1\_2+}} - D_1 J^{\mathrm{v1\_2-}}}{A_1 + J_i^{\mathrm{v1\_2+}} + J^{\mathrm{v1\_2-}}}$ and

$x_i^{\mathrm{v1\_1}} = \frac{B_1 J_i^{\mathrm{v1\_1+}} - D_1 J^{\mathrm{v1\_1-}}}{A_1 + J_i^{\mathrm{v1\_1+}} + J^{\mathrm{v1\_1-}}}$.

Rather than numerically solving difference equations, steady-state solution is used for the v1 layer. This is because the v1 layer in ART is considered to be faster than v2 layer. The weights (instar & outstar) for interaction between v1 – v2 and v2 – M are adaptive. The respective expressions for the excitation and inhibitory inputs are,

$\xi_i^{Ex\_\mathrm{M6}} = W_{\mathrm{v2\_4\ to\ M6}} \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_4}}]^+ + f(x_i^{\mathrm{M6}}), \quad \xi_i^{In\_\mathrm{M6}} = \sum_{\forall k \neq i} f(x_k^{\mathrm{M6}});$

$\xi_i^{Ex\_\mathrm{M5}} = W_{\mathrm{v2\_3\ to\ M5}} \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_3}}]^+ + f(x_i^{\mathrm{M5}}), \quad \xi_i^{In\_\mathrm{M5}} = \sum_{\forall k \neq i} f(x_k^{\mathrm{M5}});$

$\xi_i^{Ex\_4} = W_{\mathrm{v1\_2\ to\ v2\_4}} \cdot [\vec{\mathbf{x}}^{\mathrm{v1\_2}}]^+ + Z_{\mathrm{M6\ to\ v2\_4}} \cdot [\vec{\mathbf{x}}^{\mathrm{M6}}]^+ + f(x_i^{\mathrm{v2\_4}}), \quad \xi_i^{In\_4} = \sum_{\forall k \neq i} f(x_k^{\mathrm{v2\_4}});$

$\xi_i^{Ex\_3} = W_{\mathrm{v1\_1\ to\ v2\_3}} \cdot [\vec{\mathbf{x}}^{\mathrm{v1\_3}}]^+ + Z_{\mathrm{M5\ to\ v2\_3}} \cdot [\vec{\mathbf{x}}^{\mathrm{M5}}]^+ + f(x_i^{\mathrm{v2\_3}}), \quad \xi_i^{In\_3} = \sum_{\forall k \neq i} f(x_k^{\mathrm{v2\_3}});$

$J_i^{\mathrm{v1\_2+}} = x_i^{\mathrm{GN\_P2}} + \gamma Z_{\mathrm{v2\_3\ to\ v1\_2}} [\vec{\mathbf{x}}^{\mathrm{v2\_3}}]^+, \quad J^{\mathrm{v1\_2-}} = \sum_{\forall k} \left[x_k^{\mathrm{v2\_3}}\right]^+$ and

$J_i^{\mathrm{v1\_1+}} = x_i^{\mathrm{GN\_P1}} + \gamma Z_{\mathrm{v2\_4\ to\ v1\_1}} [\vec{\mathbf{x}}^{\mathrm{v2\_4}}]^+, \quad J^{\mathrm{v1\_1-}} = \sum_{\forall k} \left[x_k^{\mathrm{v2\_4}}\right]^+.$

The instar (W) and outstar (Z) weights are,

$W_{\mathrm{v2\_4\ to\ M6}}(t+h) = W_{\mathrm{v2\_4\ to\ M6}} - \eta \cdot \left[(W_{\mathrm{v2\_4\ to\ M6}} - [\vec{\mathbf{x}}^{\mathrm{v2\_4}^{\mathrm{T}}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{M6}}]^+\right],$

$Z_{\mathrm{M6\ to\ v2\_4}}(t+h) = Z_{\mathrm{M6\ to\ v2\_4}} - \eta \cdot \left[(Z_{\mathrm{M6\ to\ v2\_4}} - [\vec{\mathbf{x}}^{\mathrm{v2\_4}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{M6}}]^+\right],$

$W_{\mathrm{v2\_3\ to\ M5}}(t+h) = W_{\mathrm{v2\_3\ to\ M5}} - \eta \cdot \left[(W_{\mathrm{v2\_3\ to\ M5}} - [\vec{\mathbf{x}}^{\mathrm{v2\_3}^{\mathrm{T}}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{M5}}]^+\right],$

$Z_{\mathrm{M5\ to\ v2\_3}}(t+h) = Z_{\mathrm{M5\ to\ v2\_3}} - \eta \cdot \left[(Z_{\mathrm{M5\ to\ v2\_3}} - [\vec{\mathbf{x}}^{\mathrm{v2\_3}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{M5}}]^+\right],$

$W_{\mathrm{v1\_2\ to\ v2\_4}}(t+h) = W_{\mathrm{v1\_2\ to\ v2\_4}} - \eta \cdot \left[(W_{\mathrm{v1\_2\ to\ v2\_4}} - [\vec{\mathbf{x}}^{\mathrm{v1\_2}^{\mathrm{T}}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_4}}]^+\right],$

$W_{\mathrm{v1\_1\ to\ v2\_3}}(t+h) = W_{\mathrm{v1\_1\ to\ v2\_3}} - \eta \cdot \left[(W_{\mathrm{v1\_1\ to\ v2\_3}} - [\vec{\mathbf{x}}^{\mathrm{v1\_1}^{\mathrm{T}}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_3}}]^+\right],$

$Z_{\mathrm{v2\_4\ to\ v1\_1}}(t+h) = Z_{\mathrm{v2\_4\ to\ v1\_1}} - \eta \cdot \left[(Z_{\mathrm{v2\_4\ to\ v1\_1}} - [\vec{\mathbf{x}}^{\mathrm{v1\_1}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_4}}]^+\right]$ and

$Z_{\mathrm{v2\_3\ to\ v1\_2}}(t+h) = Z_{\mathrm{v2\_3\ to\ v1\_2}} - \eta \cdot \left[(Z_{\mathrm{v2\_3\ to\ v1\_2}} - [\vec{\mathbf{x}}^{\mathrm{v1\_2}}]^+) \cdot [\vec{\mathbf{x}}^{\mathrm{v2\_3}}]^+\right].$

The weights are initialized such that, outstar weights (Z's) are set at zero. However, instar weights (W's) are set as $w_{ij} = \sigma \bullet \mathrm{rand}(0,1) + \sigma$, where rand(0,1) is a random number from uniform distribution [0,1] and σ is the initialization scale.

Finally the normalization is done only once for a given pattern. Thus its steady-state form is,

$x_i^{\mathrm{GN\_P1}} = \frac{nC_o I}{A_o + I}\left(\omega_i - \frac{1}{n}\right)$ and $x_i^{\mathrm{GN\_P2}} = \frac{nC_o I}{A_o + I}\left(\omega_i - \frac{1}{n}\right).$

The synthesis of sensibility is the noetic process that synthesizes **apprehension** in **consciousness**. Thus the OB has no conscious experience of these acts of synthesis. In other words, comparation does not have memory. Weight changes in W and Z are elastic modulations. This implies,

Proposition 8: The process of comparation does not remember its past actions.

Hence, the states of the instar and outstar weights of the above minimal neural network are not stored for succeeding acts of logical comparison. Therefore this network does not have the problem of stability-plasticity trade-off encountered in some ART networks [Wells, 2010].

Behavior of the proposed minimal neural network

The behavior of the network (Fig.5.3) was observed from simulation experiments for various set of patterns. The pattern sets used for the experiments are: uppercase English letters (A to Z), uppercase English letters versus its modified patterns (translation, rotation), 2x resolution uppercase English letters and finally Arabic numerals (0 to 9). Regardless of pattern set (experiment case), the simulations were done using the same parameters (Fig.5.5).

Unlike v2-layers, the M-layers do not have 0-1 distribution. Thus, for analysis, the activity of the average (median) node of M-layer is considered. The set-membership paradigm was employed to consider whether activities of the two M-layers differ and hence whether the network determines a relationship between the input patterns. Thus identification of feasible set solutions rather than a single “point” solution is considered.

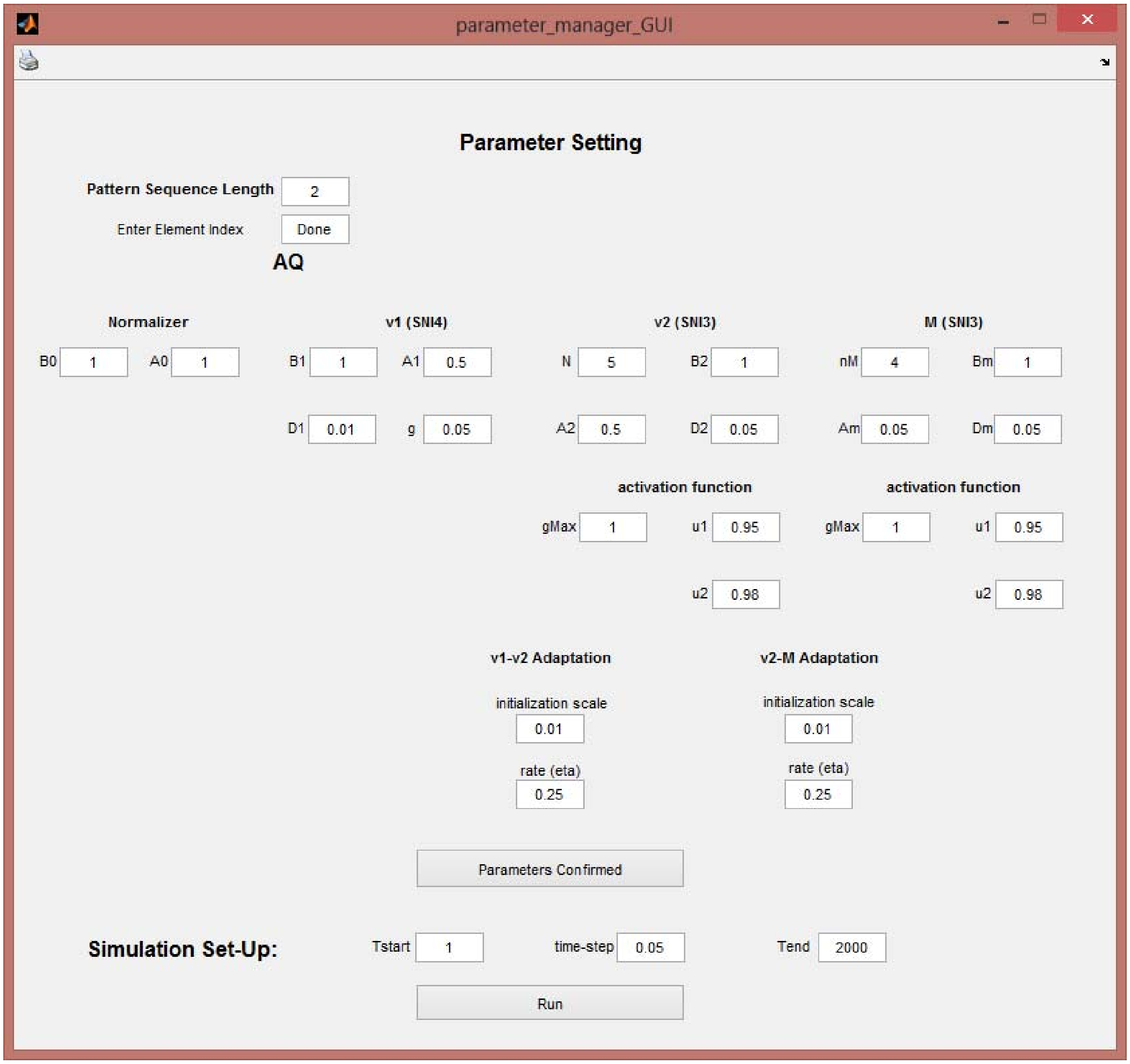

Figure 5.5. Parameters for the simulation. For a particular pattern-combo (say, AQ) in Case-1 (uppercase English letters), two (or more) desired patterns are chosen by entering their indices ranging from [1, 26] (Fig.5.6). The respective parameters are then entered. Note that $g = \gamma$ (Fig.5.3) and the activation function parameters are the unscaled values. Scaling is done as described above within the main code. Both sub-networks use same parameter values.

Though the weights of the network are not stored they are initialized for each run of pattern-combo. This is done by setting the outstar weight matrix elements at zero but the elements of the instar weight matrices are set at some very small (non-zero) random real number. The latter amount is given by initialization scale.

As governed by the functional principles of ART networks [Wells, 2010], weight adaptation occurs after resonance of the network.

Finally, the time-step (h) for the difference equations was chosen to be 0.05 but iterations are variable (usually, 2000, 3000 or 6,000 iterations).

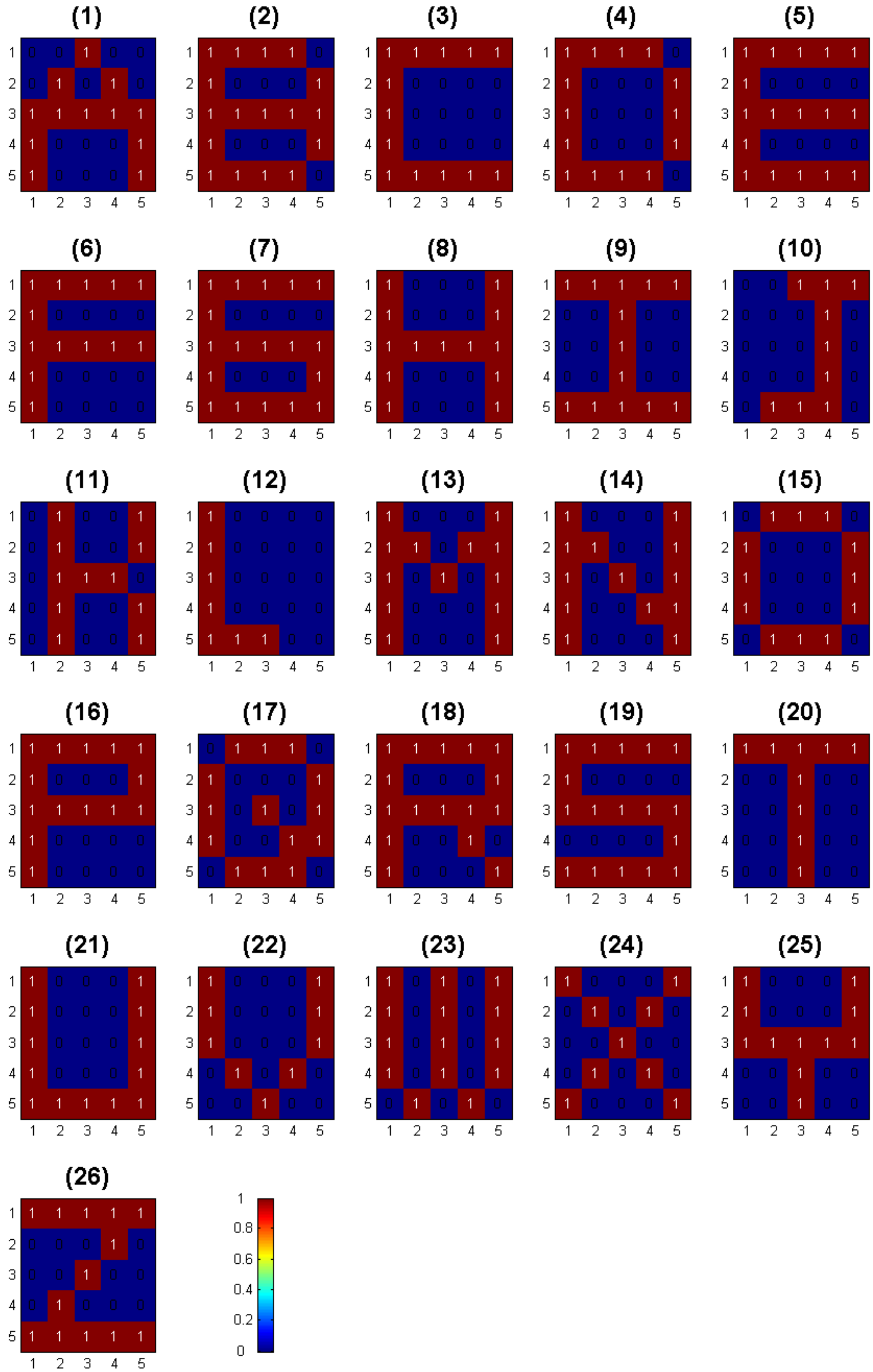

Figure 5.6. Set of upper-case English letters used for observing the network behaviors. Each alphabet is represented by the respective placement of 1's in a background of 0's.

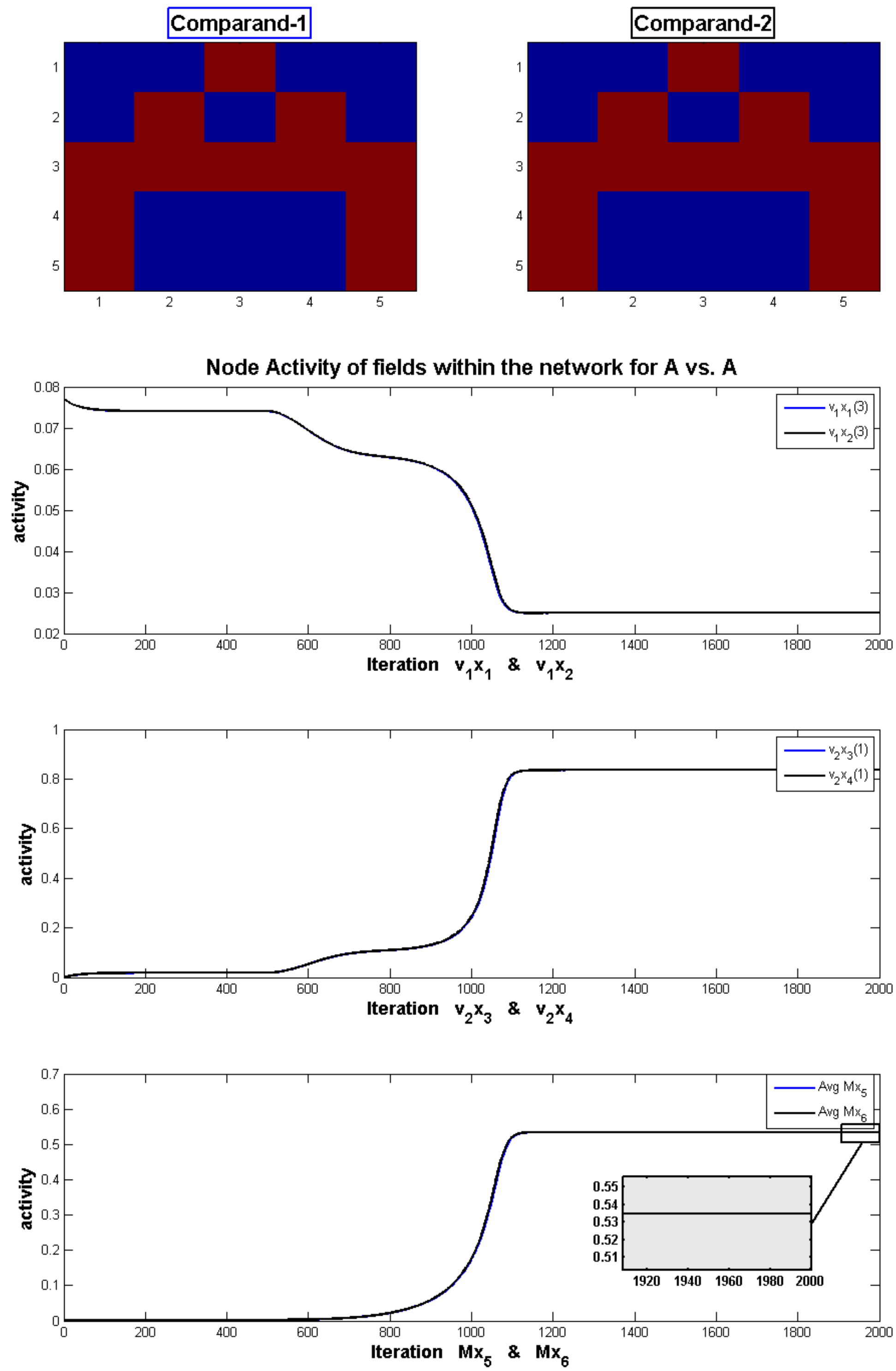

Figure 5.7. Time-series plot for patterns A versus A. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. The subplots shows the activities of node-1 in respective v1-layers and activities of winning nodes in respective v2-layers. The bottom subplot shows the activities of average (median) nodes of respective M-layers. The inset magnifies the activities of the two M-layers overlapping (≈ 0.5347) each other at final iteration.

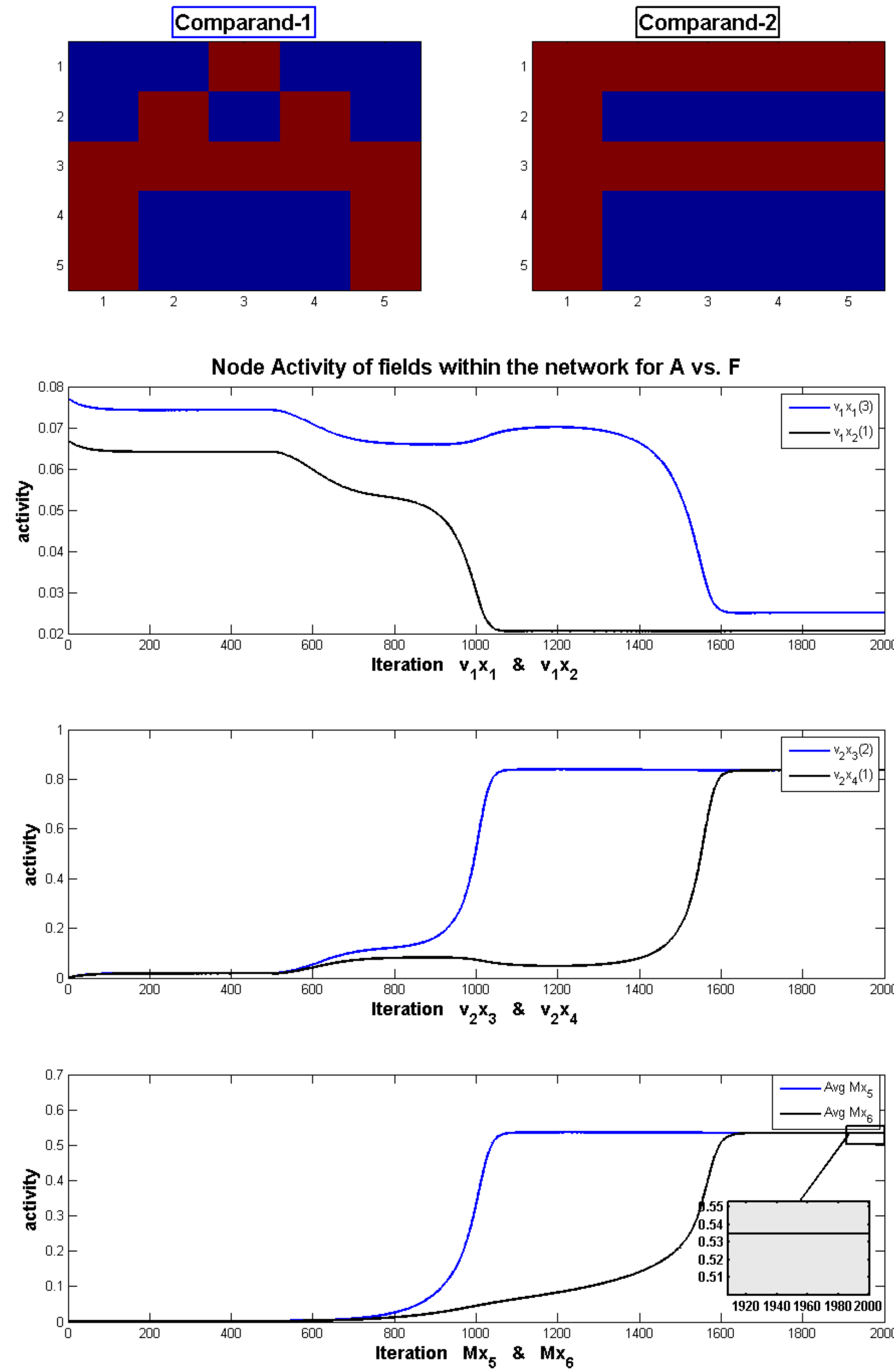

Figure 5.8. Time-series plot for patterns A versus F. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. The subplots shows the activities of node-1 in respective v1-layers and activities of winning nodes in respective v2-layers. The bottom subplot shows the activities of average (median) nodes of respective M-layers. The inset magnifies the activities of the two M-layers at final iteration which appears to overlap (0.5346 ≈ 99.9% of 0.5347).

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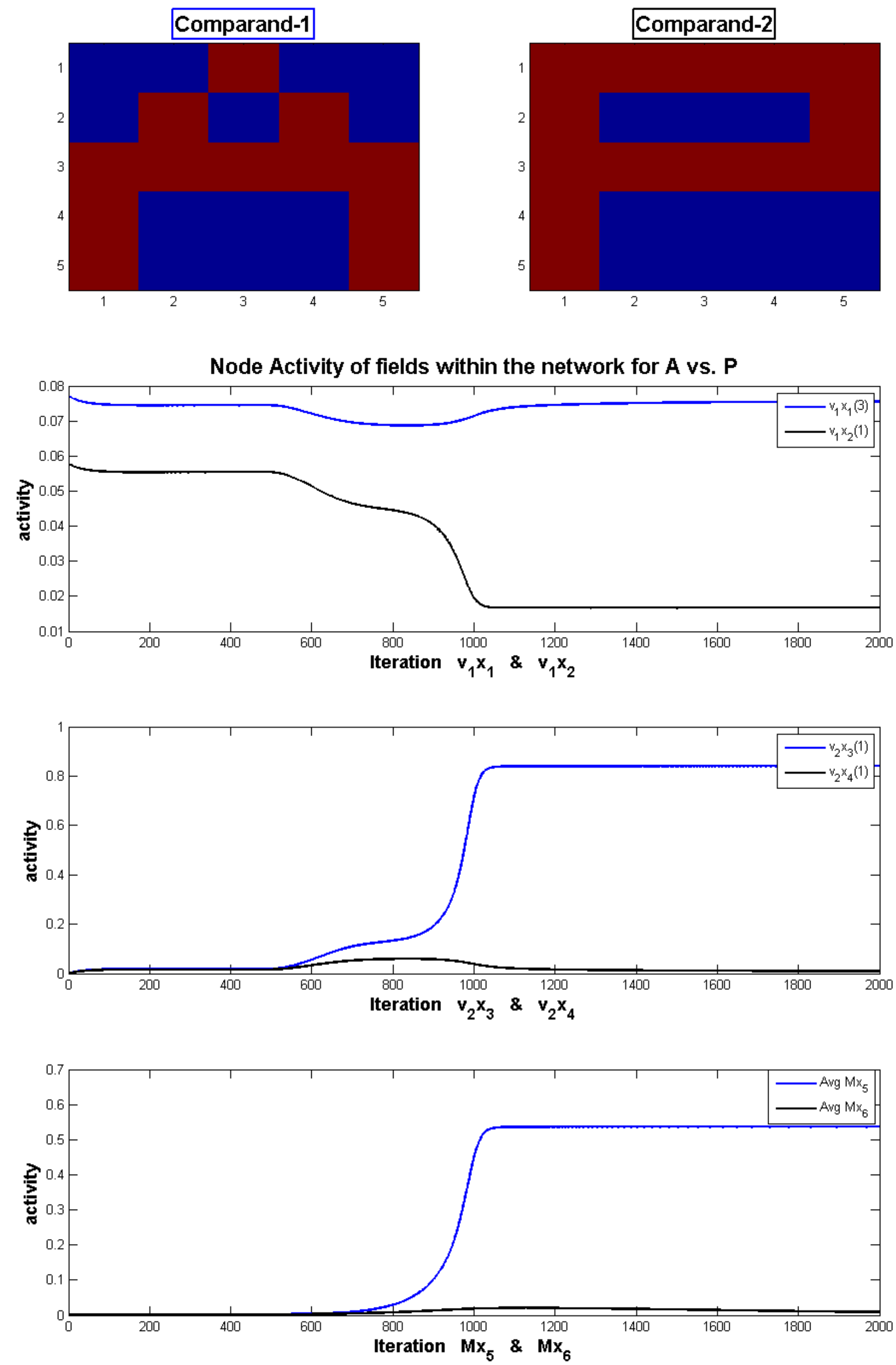

Figure 5.9. Time-series plot for patterns A versus P. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. The subplots shows the activities of node-1 in respective v1-layers and activities of winning nodes in respective v2-layers. The bottom subplot shows the activities of average (median) nodes of respective M-layers. Notice that the M-layer activities at final iteration are clearly far apart (0.0016 ≈ 0.3% of 0.5358).

Case-1, uppercase English letters (A to Z):

Network testing involved pattern-combos with two patterns in a combo such that each pattern is picked from the set of letters (Fig.5.6). It was found that the network determined relationships between some patterns and not for others. Determination of relationship depends on the expediency judged by TRJ and so the region of interest is the steady-state levels (at final iteration) of the M-layer outputs.

We say that the network determines a relationship between the patterns if the steady-state of the M-layer output falls within the same solution set. The solution set is defined such that the activity with smaller magnitude (if unequal) is ≥ 90% of the larger. In other words, the solution set is defined to contain all the "not-noticeably" different activities and hence indistinguishable patterns.

Figures 5.7 and 5.8 show that relationship was found for pattern A with itself and between patterns A and F. The steady states of M-layer average activities indicate that they fall within the solution set. On the other hand, figure 5.9 demonstrates the network's ability of finding no relationship between patterns A and P. The determination of relationship or no relationship for all the pattern-combos is shown in table 5.1.

The table shows that the network finds relationship for a pattern versus itself. It also shows that in some cases multiple patterns demonstrate relationship with the same collection of patterns. For instance, patterns A and O demonstrate relationship with any patterns within the set {A, C, F, H, I, K, M, N, O, U, Y, Z}. Notice that the determined outcome (relationship or no) for a particular pattern pair is unchanged when the pattern inputs (comparands 1 & 2) are reversed. Thus, relationship is seen in both A vs. F and F vs. A.

Input-1 patterns (5x5)	Input-2 patterns (5x5)																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A																										
B																										
C																										
D																										
E																										
F																										
G																										
H																										
I																										
J																										
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X																										
Y																										
Z																										

Table 5.1. Table illustrating similarities for Capital English letters, A to Z vs. A to Z. For a particular row, the colored (same) boxes represent similarity (for e.g. row for A). When compared to A to Z letters, if two or more rows have the same pattern of similarity, they are depicted having same colored boxes (for e.g. row for A & row for O). Two letters are defined similar if the smaller average (median) node activity of the two M-fields is ≥ 90% of the larger. This is equivalent to < 10% vigilance percentage. Note that the uncolored (white) boxes implies no similarity. The raw numerical data is given in appendix, Tables A1-1 to A1-8.

Observe that relationship is seen for A vs. C and C vs. D but not for A vs. D (table 5.1). Transitivity is therefore absent. Such state of affairs has been empirically observed in children by Piaget [Piaget, 1953a]. For instance, child (aged around 8 – 9 years) may say that a metal bar A weighs the same as another bar C, and that bar B weighs the same as metal ball D, A = C and C = D. But from past experience the child expects the relation, A < D. The child therefore says "bar B is definitely as heavy as ball D, but it will be different with A" and concludes that A ≠ D.

On the other hand, relationship is seen for A vs. C, C vs. F and A vs. F (table 5.1). Piaget has also accounted such transitive properties in children [Piaget, 1953b]. Given a tower of blocks on a table the child (aged around 6 years) is asked to build a second tower of the same height on another (lower or higher) table with block of different size. The rule of the game forbids the child from moving the tower. The child having built the tower F, builds another (third) tower C and moves it (which is allowed by the rules) over to the reference tower A. The child moves the tower C back and forth adjusting its height to A and then F. The child presupposes that C = F and C = A therefore A = F.

The network can therefore demonstrate relationship between some patterns and non-relationship for others. This ability of the network has been achieved without a priori definition of what a feature is. In other words, the network self-defines feature sets. This then begets the question, what is it that the network considers "features" and thereby recognizes a common feature among patterns shown to have a relationship? Though, this question would be a topic for future research, based on empirical observations a possible explanation would be suggested here.

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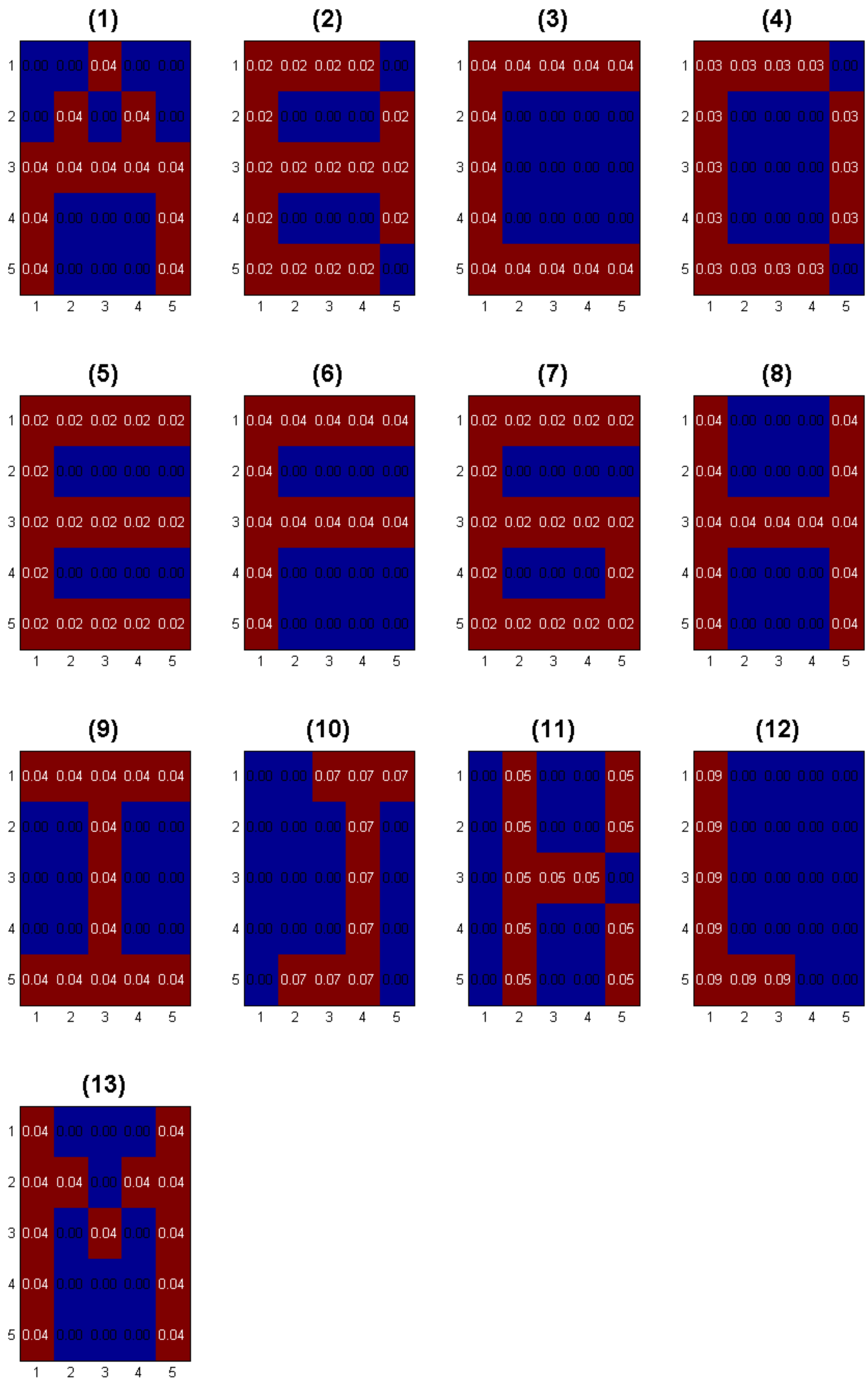

Figure 5.10. Normalized patterns (A to M) of Fig.5.6.

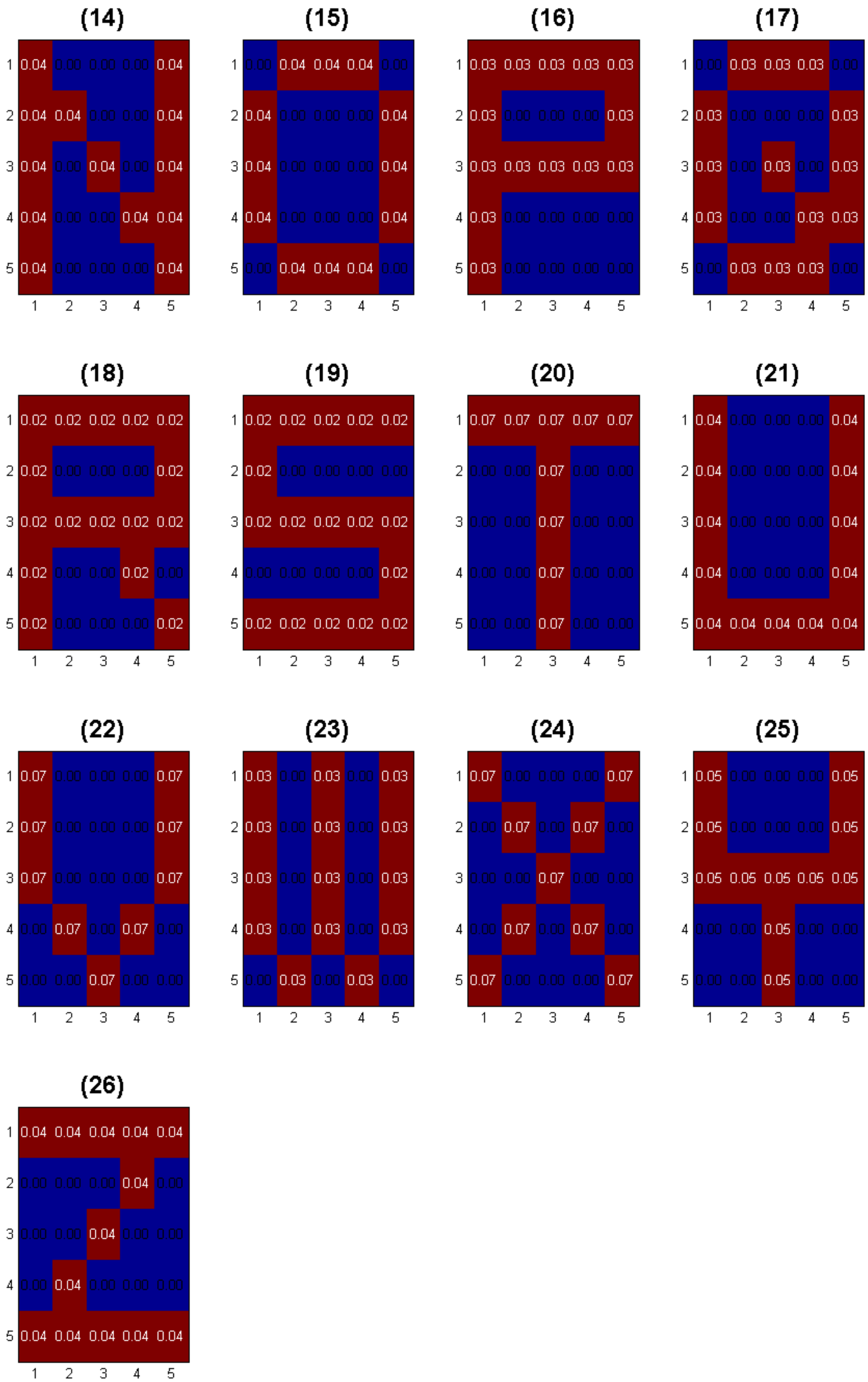

Figure 5.11. Normalized patterns (N to Z) of Fig.5.6.

Number of non zero pixels	Non zero pixel value	Cumulative pixel value	Patterns (5x5)
18	0.0154	0.2772	G
17	0.0185	0.3145	B, E, S
16	0.0221	0.3536	R
14	0.0306	0.4284	D, P, Q, W
13	0.0357	0.4641	C, F, H, I, M, N, U, Z
12	0.0417	0.5004	A, O
11	0.0486	0.5346	K, Y
9	0.0667	0.6003	J, T, V, X
7	0.0937	0.6559	L

Table 5.2. Table showing the 26 uppercase English letters arranged with respect to their number of non-zero pixels (out of 25 pixels, 5 x 5 matrix), their normalized value (2nd column) and their total (3rd column, CPV or cumulative pixel value). Note that for a particular pattern all its non-zero pixels have the same magnitude of normalized pixel value.

Subset of comparand-1 patterns (5x5)	Subset of comparand-2 patterns (5x5)
{G}	{G}
{B, E, S}	{B, E, S}
{R}	{R}
{D, P, Q W}	{C, D, F, H, I, M, N, P, Q, U, W, Z}
{C, F, H, I, M, N, U, Z}	{A, C, D, F, H, I, M, N, O, P, Q, U, W, Z}
{A, O}	{A, C, F, H, I, K, M, N, O, U, Y Z}
{K, Y}	{A, J, K, O, T, V, X, Y}
{J, T, V, X}	{J, K, L, T, V, X, Y}
{L}	{J, L, T, V, X}

Table 5.3. Table of subset of patterns derived from results in Table 5.1. Relationship is found for a given comparand-1 pattern with any comparand-2 pattern within a particular (same row) subset.

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Comparand-1 Patterns (5x5)	**Comparand-2 Patterns (5x5)**	**Largest difference w/ α**	**Smallest difference w/o α**
G	{G}	{G} α {G} : 0(0) ⇒ 0.0000	{G} $\not\alpha$ {B, E, S} : 0.1186(1) ⇒ 0.0474
B, E, S	{B, E, S}	{B, E, S} α {B, E, S} : 0(0) ⇒ 0.0000	{B, E, S} $\not\alpha$ {R} : 0.1105(1) ⇒ 0.0442
R	{R}	{R} α {R} : 0(0) ⇒ 0.0000	{R} $\not\alpha$ {B, E, S} : 0.1105(1) ⇒ 0.0442
D, P, Q, W	{C, D, F, H, I, M, N, P, Q, U W, Z}	{D, …, W} α {C, …, Z} : 0.0769(1) ⇒ 0.0307	{D, …, W} $\not\alpha$ {A, O} : 0.1439(2) ⇒ 0.0460
C, F, H, I, M, N, U, Z	{A, C, D, F, H, I, M, N, O, P, Q, U, W, Z}	{C, …, Z} α {D, …, W} : 0.0769(1) ⇒ 0.0307	{C, …, Z} $\not\alpha$ {K, Y} : 0.1319(2) ⇒ 0.0422
A, O	{A, C, F, H, I, K, M, N, O, U, Y, Z}	{A, O} α {C, …, Z} : 0.0725(1) ⇒ 0.0290	{A, O} $\not\alpha$ {J, …, X} : 0.1664(3) ⇒ 0.0416
K, Y	{A, J, K, O, T, V, X, Y}	{K, Y} α {J, …, X} : 0.1094(2) ⇒ 0.0350	{K, Y} $\not\alpha$ {C, …, Z} : 0.1319(2) ⇒ 0.0422
J, T, V, X	{J, K, L, T, V, X, Y}	{J, …, X} α {K, Y} : 0.1094(2) ⇒ 0.0350	{J, …, X} $\not\alpha$ {A, O} : 0.1664(3) ⇒ 0.0416
L	{J, L, T, V, X}	{L} α {J, …, X} : 0.0847(2) ⇒ 0.0271	{L} $\not\alpha$ {K, Y} : 0.1849(4) ⇒ 0.0425

Table 5.4. Table demonstrating the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 5x5. The first two columns shows the relationship (α) found for a given comparands-1 pattern (column-1) with any comparands-1 pattern (column-2) within a particular (same row) subset (table 5.3).

Every patterns has a corresponding cumulative pixel value, CPV (table 5.2). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on…

The third column shows the diff-fact, px (bracket) and resultant largest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has demonstrated α is < 4%. The fourth column shows the smallest diff-pc amongst those that has not demonstrated α is > 4%. The diff-pc for patterns that demonstrates α and $\not\alpha$ was determined to be largest or smallest from the table containing all the computed diff-pc values (tables A2-1 & A2-2).

Figures 5.10 and 5.11 shows the outputs of the Grossberg normalizers (GN^2, Fig.5.3) receiving respective pattern (Fig.5.6). They are therefore the normalized input to the network. Based on these normalized patterns, table 5.2 is constructed.

The table shows the grouping of patterns based upon their number of pixels (out of 25 pixels) that are not zero magnitude. The non-zero magnitudes are the normalized values (2nd column of the table). It also shows a column whose entry is the sum of normalized pixel values. We shall call this, the cumulative pixel value (CPV). Thus, CPV is a function of the number of non-zero pixels. Notice that some patterns (like patterns: B, E, S) have equal number of non-zero pixels (17) and also equal CPV (0.3145).

Table 5.3 is however a summarized or condensed table 5.1. It shows pattern groups (comparands-1) that has demonstrated relationship with any patterns within respective set (comparands-2). Thus pattern D demonstrates relationship with any pattern from the pattern set for comparands-2, {C, D, F, H, I, M, N, P Q, U, W, Z}. Furthermore, this relationship is also found for any pattern for the pattern set containing D for comparands-1, {D, P, Q, W}. Notice that the pattern sets for comparands-1 correspond to patterns having equal number of non-zero pixels.

Let us assume that the number of non-zero pixels plays an important role on how the network defines feature sets. We shall therefore consider CPV since it is a function of this number. Let us now define difference-factor (diff-fact) to be the factor of U, such that diff-fact • U = U – L where, U and L are the upper (larger magnitude) and lower CPV respectively. Finally, we define difference-percentage (diff-pc) between two patterns to be the product, diff-fact • ppx where, ppx is the parameter corresponding to px, difference of number of non-zero pixels. The ppx value is empirically determined (table 5.4).

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If we consider diff-pc to be a possible metric for feature, we observe that the network finds relationship among patterns such that diff-pc < 4% (table 5.4). On the other hand, among patterns with non-relationship, the smallest (magnitude) diff-pc appears to be always > 4%.

We shall continue to consider diff-pc as the possible measure for what the network considers as "feature" for the remaining cases. Thus discussions on the diff-pc will continue for the subsequent cases.

<u>Case-2, uppercase English letters (A to Z) versus its modified patterns:</u>

Let us now consider the case of patterns taken from uppercase English letters (case-1) versus its modifications. The modifications considered are translation and rotation.

Figures 5.12 and 5.13 respectively show that relationship was found for pattern A with itself (translated, rotated or both) and between A and F (translated, rotated or both). This outcome of finding relationships is similar to the earlier case (Fig.5.7 & 5.8).

On the other hand, figure 5.14 (unlike Fig.5.9) demonstrates relationship between patterns A and P. This observed behavior seems to be linked with the relationship found amongst patterns A and translated-A or translated-F (Fig.5.12b & Fig.5.13b). Note that for test with rotated patterns, the retinal-map size is 5x5 (Fig.5.12a, Fig.5.13a & Fig.5.14a). However the retinal-map is larger (10x10 in Fig.5.12b, Fig.5.12c, Fig.5.13b, Fig.5.13c, Fig.5.14b & Fig.5.14c) when the patterns are translated.

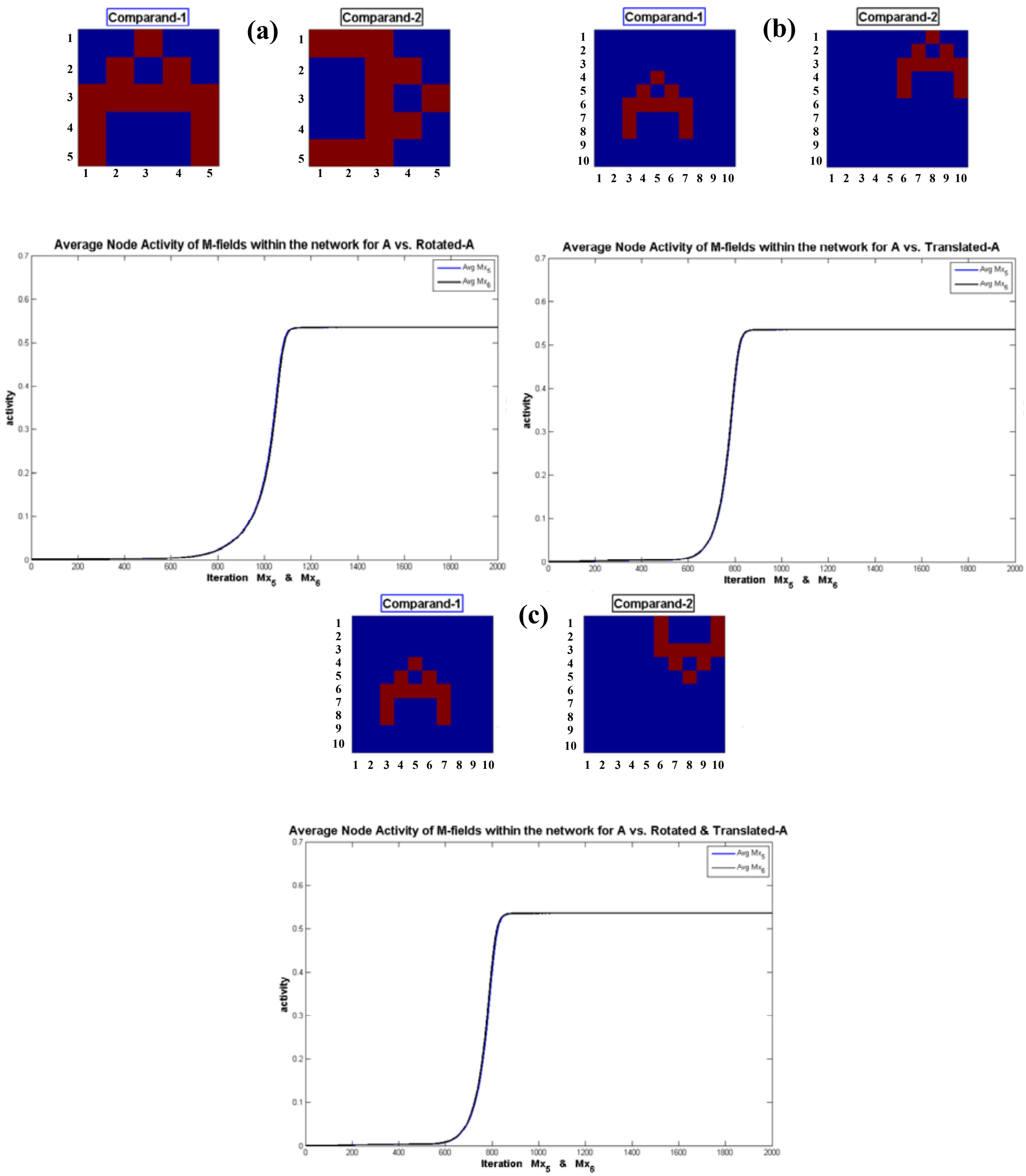

Figure 5.12. Time-series plot for patterns A versus modified-A. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a, b or c) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 5x5 for (a) and 10x10 for (b) and (c).

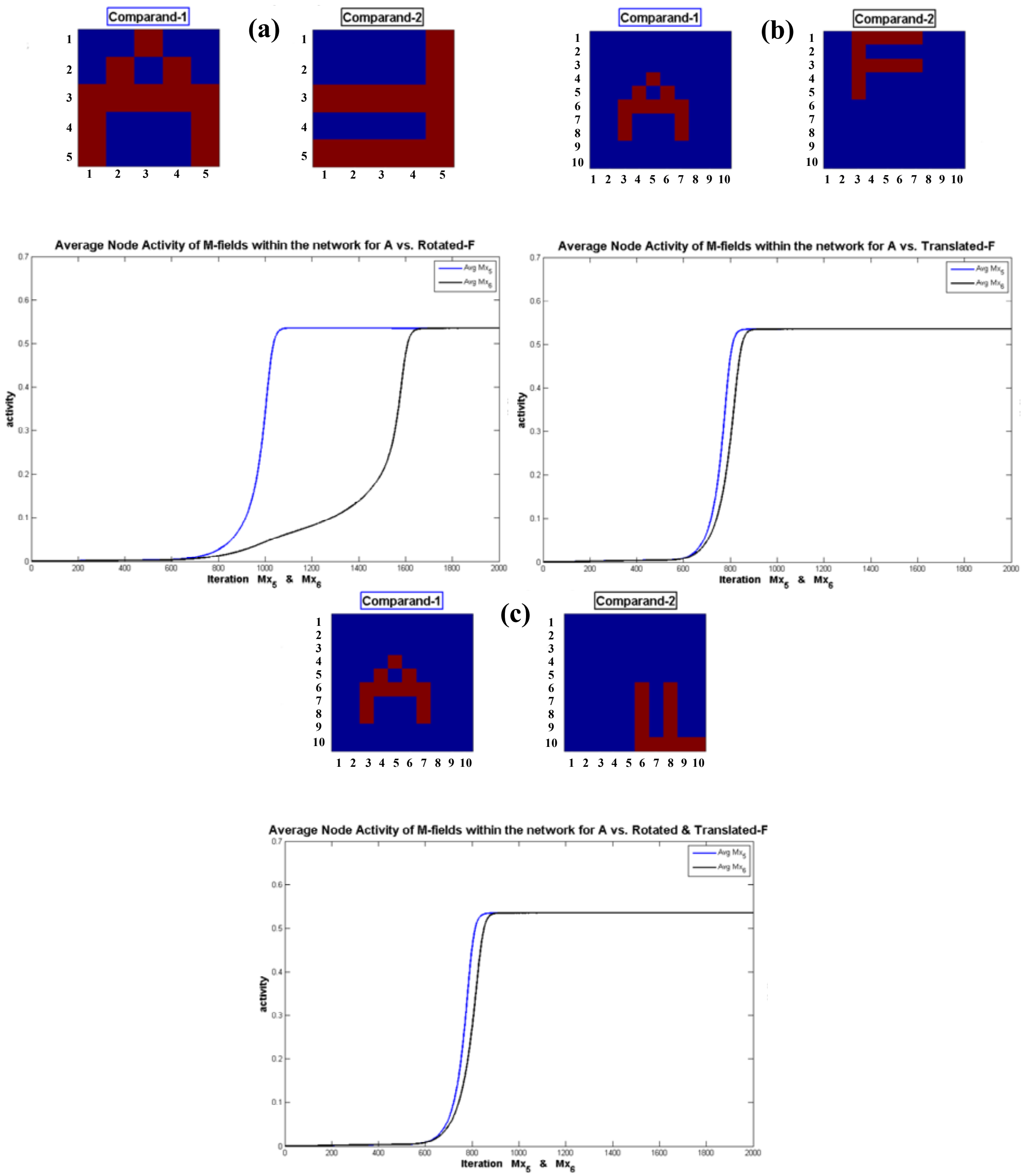

Figure 5.13. Time-series plot for patterns A versus modified-F. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a, b or c) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 5x5 for (a) and 10x10 for (b) and (c).

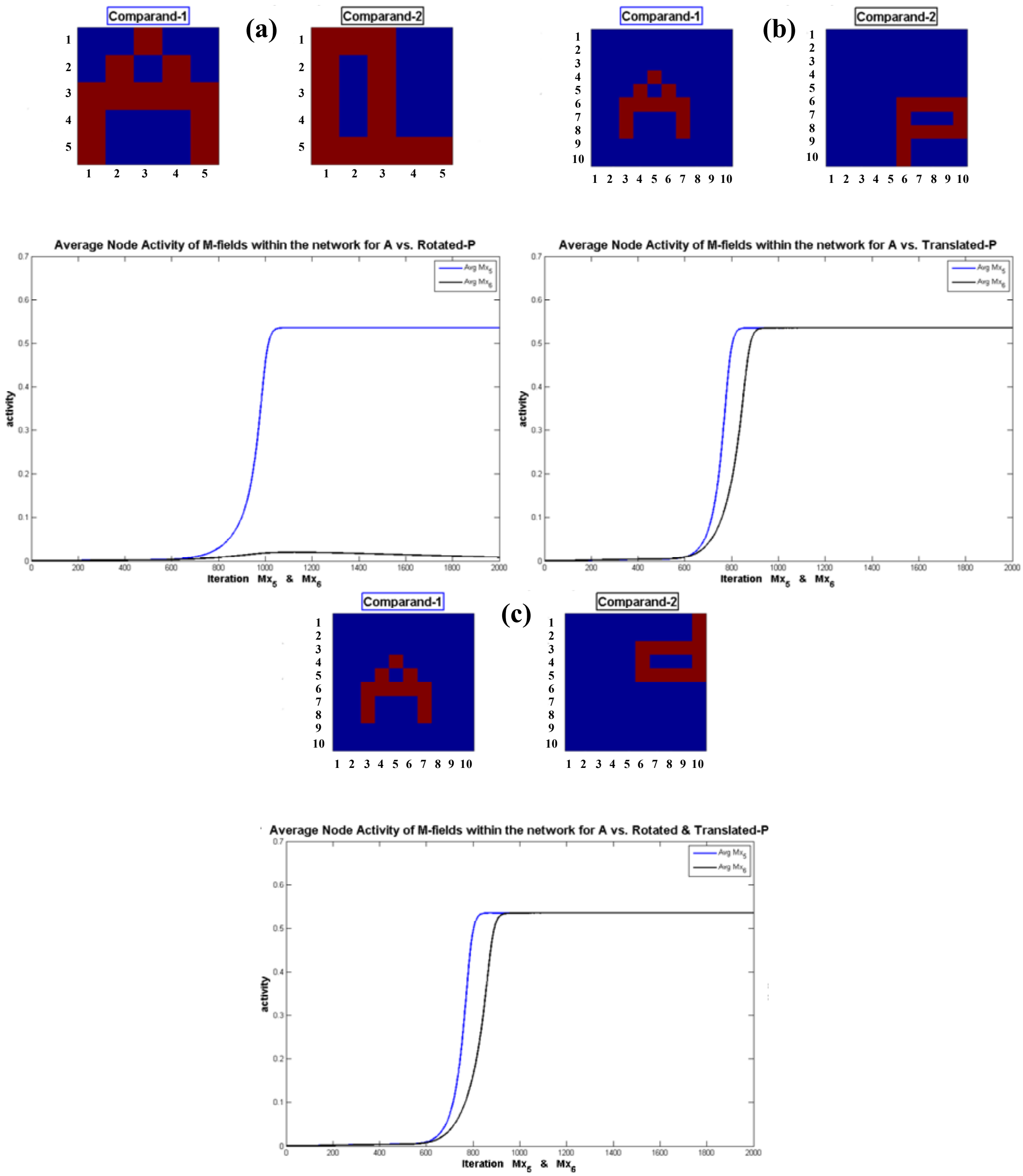

Figure 5.14. Time-series plot for patterns A versus modified-P. The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a, b or c) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 5x5 for (a) and 10x10 for (b) and (c).

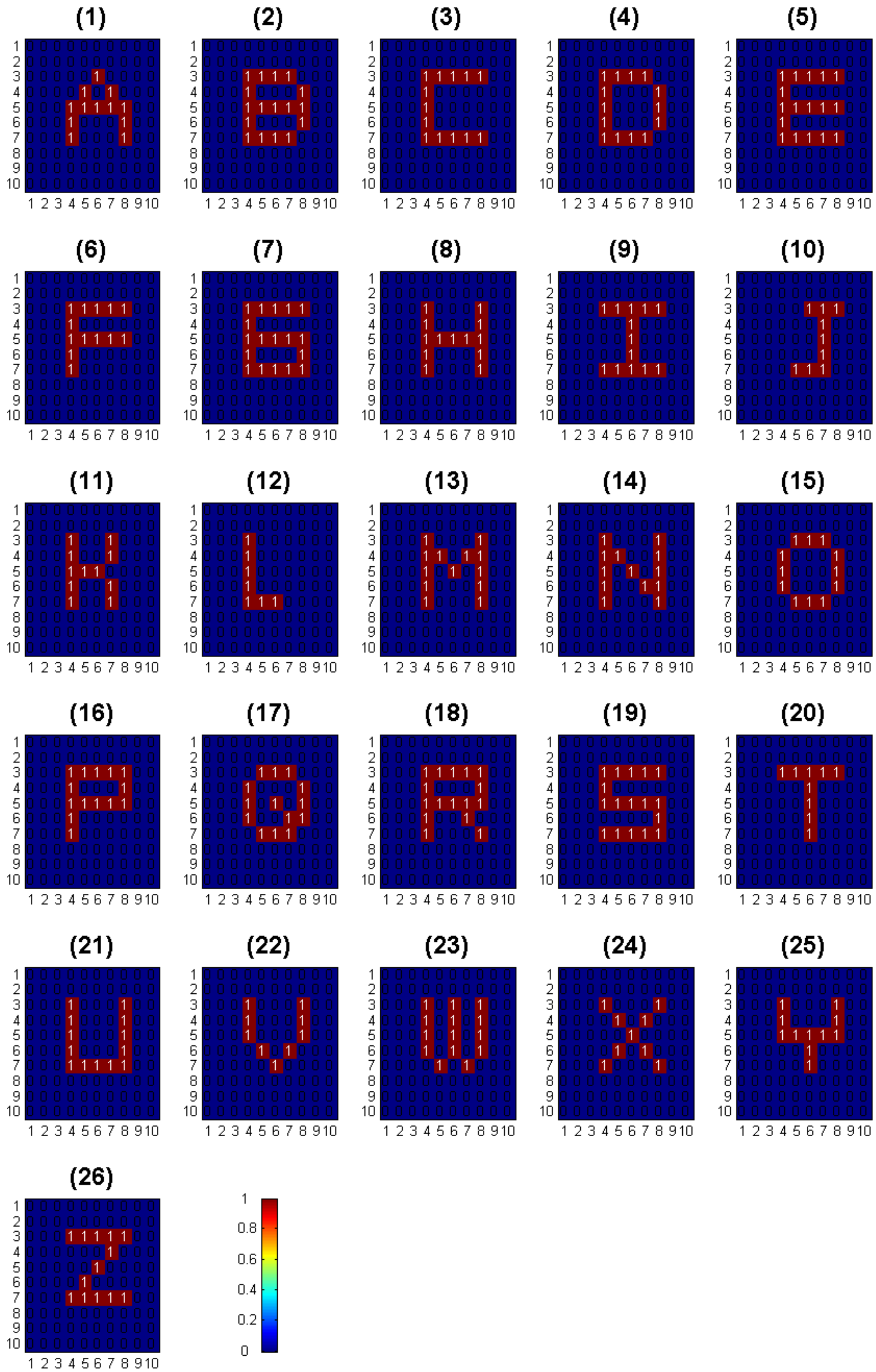

Figure 5.15. Set of upper-case English letters but with 10x10 retinal-map size. Each alphabet is represented by the respective placement of 1's in a background of 0's.

Number of non zero pixels	Non zero pixel value	Cumulative pixel value	Patterns (10x10)
18	0.0436	0.7848	G
17	0.0466	0.7922	B, E, S
16	0.0499	0.7984	R
14	0.0579	0.8685	D, P, Q, W
13	0.0628	0.8164	C, F, H, I, M, N, U, Z
12	0.0684	0.8208	A, O
11	0.0749	0.8239	K, Y
9	0.0919	0.8271	J, T, V, X
7	0.1174	0.8218	L

Table 5.5. Table showing the 26 uppercase English letters arranged with respect to their number of non-zero pixels (out of 100 pixels, 10 x 10 matrix), their normalized value (2nd column) and their total (3rd column, CPV or cumulative pixel value). Note that for a particular pattern all its non-zero pixels have the same magnitude of normalized pixel value.

Subset of comparand-1 patterns (10x10)	Subset of comparand-2 patterns (10x10)
{G}	**{A, …, Z}**
{B, E, S}	**{A, …, Z}**
{R}	**{A, …, Z}**
{D, P, Q W}	**{A, …, Z}**
{C, F, H, I, M, N, U, Z}	**{A, …, Z}**
{A, O}	**{A, …, Z}**
{K, Y}	**{A, …, Z}**
{J, T, V, X}	**{A, …, Z}**
{L}	**{A, …, Z}**

Table 5.6. Table of subset of patterns derived from simulation done with patterns from Capital English Letters of retinal size 10x10. Relationship is found for a given comparand-1 pattern with any comparand-2 pattern within a particular (same row) subset. The raw numerical data is given in appendix, Tables A3-1 to A3-8.

Comparand-1 Patterns (10x10)	Comparand-2 Patterns (10x10)	Largest difference w/ α	Smallest difference w/o α
G	{A, …, Z}	{G} α {J, …, X} : 0.0511(9) ⟹ 0.0102	-
B, E, S	{A, …, Z}	{B, E, S} α {J, …, X} : 0.0422(8) ⟹ 0.0084	-
R	{A, …, Z}	{R} α {J, …, X} : 0.0347(7) ⟹ 0.0069	-
D, P, Q, W	{A, …, Z}	{D, …, W} α {G} : 0.0318(4) ⟹ 0.0073	-
C, F, H, I, M, N, U, Z	{A, …, Z}	{C, …, Z} α {G} : 0.0387(5) ⟹ 0.0085	-
A, O	{A, …, Z}	{A, O} α {G} : 0.0439(6) ⟹ 0.0088	-
K, Y	{A, …, Z}	{K, Y} α {G} : 0.0475(7) ⟹ 0.0095	-
J, T, V, X	{A, …, Z}	{J, …, X} α {G} : 0.0511(9) ⟹ 0.0102	-
L	{A, …, Z}	{L} α {G} : 0.0450(11) ⟹ 0.0090	-

Table 5.7. Table demonstrating the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 10x10. The first two columns shows the relationship (α) found for a given comparands-1 pattern (column-1) with any comparands-1 pattern (column-2) within a particular (same row) subset (table 5.6).

Every patterns has a corresponding cumulative pixel value, CPV (table 5.5). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on…

The third column shows the diff-fact, px (bracket) and resultant largest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has demonstrated α is < 4%. Since all the patterns within the set demonstrated relationship there are no entries in the fourth column for smallest diff-pc amongst $\cancel{\alpha}$ is > 4%. The diff-pc for patterns that demonstrates α and $\cancel{\alpha}$ was determined to be largest or smallest from the table containing all the computed diff-pc values (tables A4-1 & A4-2).

The normalizer (GN^2) is a function of number of pixels of the retinal-map (n = 25 for 5x5 and n = 100 for 10x10). Thus, the normalized non-zero pixel value and hence CPV differ for respective size of retinal-map. Table 5.5 shows the normalized values and CPV of the translated patterns (Fig.5.12, Fig.5.13 & Fig.5.14) having 10x10 retinal-map size (Fig.5.15). Comparing the table with table 5.2 illustrates the difference.

Regardless of the retinal-map size, the number of non-zero pixels remain unchanged. However, the non-zero pixel values increases with the larger retinal-map size. Thus CPV's also increase for all the patterns. The result is that the spread of CPV's is narrowed with increased retinal-map size (variance = 0.0002 in 10x10 and variance = 0.0165 in 5x5 retinal-map size).

Table 5.6 shows the summarized outcome of the simulation done with pattern set made up of Capital English letters but with retinal-map size, 10x10. It shows that all patterns within the set demonstrates relationship with any pattern within the set. Applying our diff-pc as the possible metric for feature, one notices that all the diff-pc < 4% (table 5.7).

This result is interesting. It suggests a prediction made by the network. This is functionally similar to the situation when fonts "a" and "e" appear similar at a distance.

Various forms of acuity is observed, physiologically and behaviorally. The normal acuity in discriminating two point light source is about 25 seconds of arc [Guyton, pp.621, 2006]. Thus, two point light sources 10 meters away from the eye are distinguishable when they are 1.5 to 2 mm apart. Two point tactile discrimination test is commonly used for testing tactile acuity. Tactile acuity varies with skin region, skin thickness and condition. But in general, two points on skin are discriminated if they are 1 to 2 mm apart on fingers and 30 to

70 mm apart on the back [Guyton, pp.592, 2006]. Another form of acuity is the auditory temporal acuity, which is the sensitivity to amplitude modulation [Purcell & John, 2004]. It is the ability to discriminate rapid changes in sound envelope. Researchers have demonstrated that envelopes of speech signal in different spectral regions play a crucial role in speech understanding [Van Tasell et al., 1987; Shannon et al., 1995]. The above examples illustrates various forms of acuity.

The result that, all Capital English letters (5x5) when placed on a larger retinal-map size of 10x10 results in a relationship amongst all the patterns is therefore a demonstration of loss of acuity. We may refer to this loss of sharpness of discriminating patterns with increasing retinal-map size (but unchanged size of pattern) as the loss of sensory acuity.

Case-3, 2x resolution uppercase English letters (A to Z):

Continuing with the retinal-map size of 10x10 and patterns of Capital English letters, let us consider the case when these patterns fill the retinal-map (unlike Fig.5.16). Each pixels (in Fig.5.6 & Fig.5.15) is now represented by four pixels. In other words, they are 2x resolution of same pattern in 5x5 retinal-map.

Figures 5.17a and 5.17b shows relationship amongst patterns A (2x) with itself and also between A (2x) and O (2x). However no relationship was demonstrated amongst A (2x) and any other patterns within the set of 2x resolution Capital English letters (Fig.5.17c & Fig.5.17d). The determination of relationship or no relationship for all the pattern combos is shown in table 5.8. The condensed form (table 5.10) illustrates only patterns shown to demonstrate relationship.

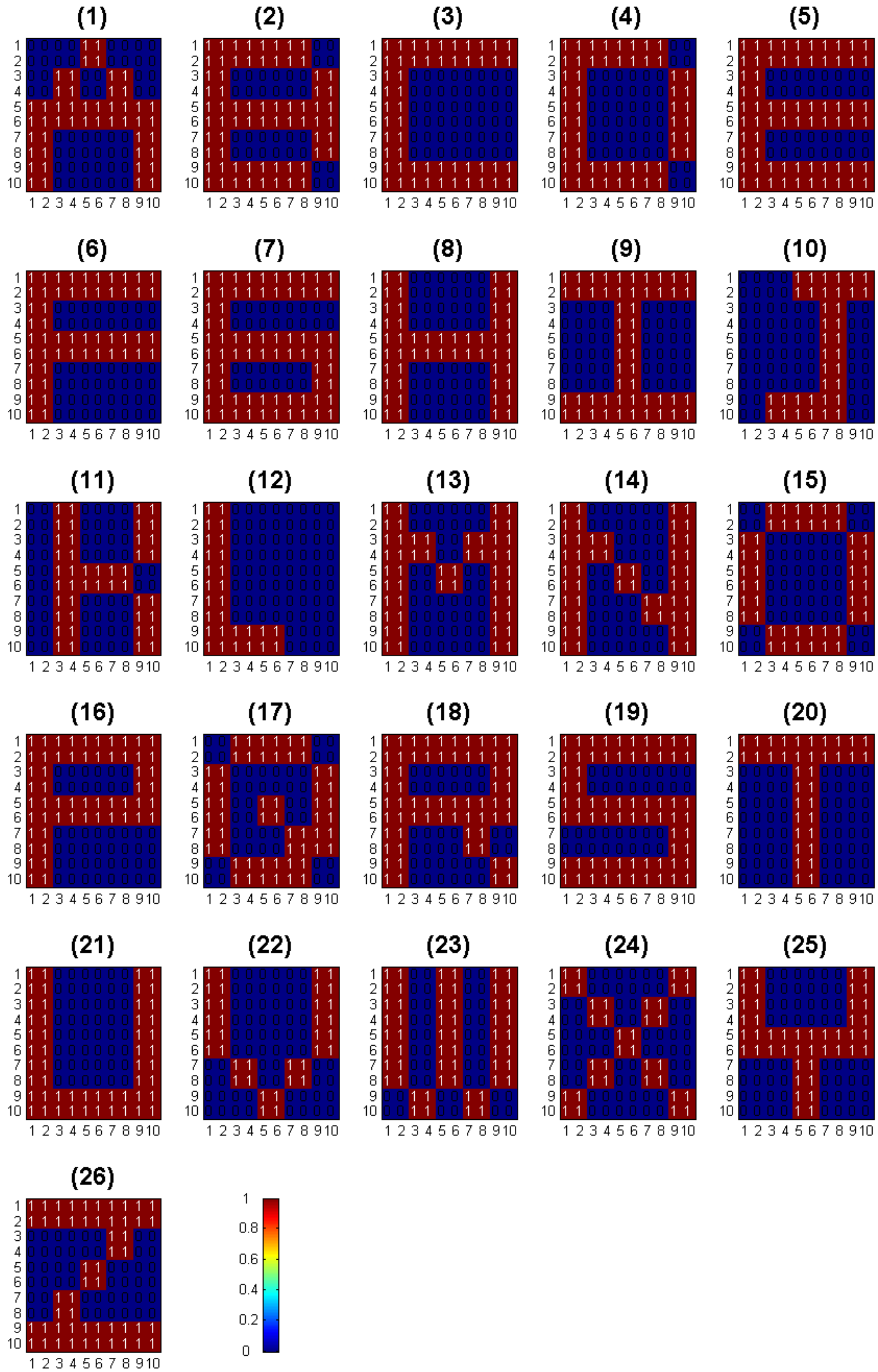

Figure 5.16. Set of 2x resolution upper-case English letters. Each alphabet is represented by the respective placement of 1's in a background of 0's.

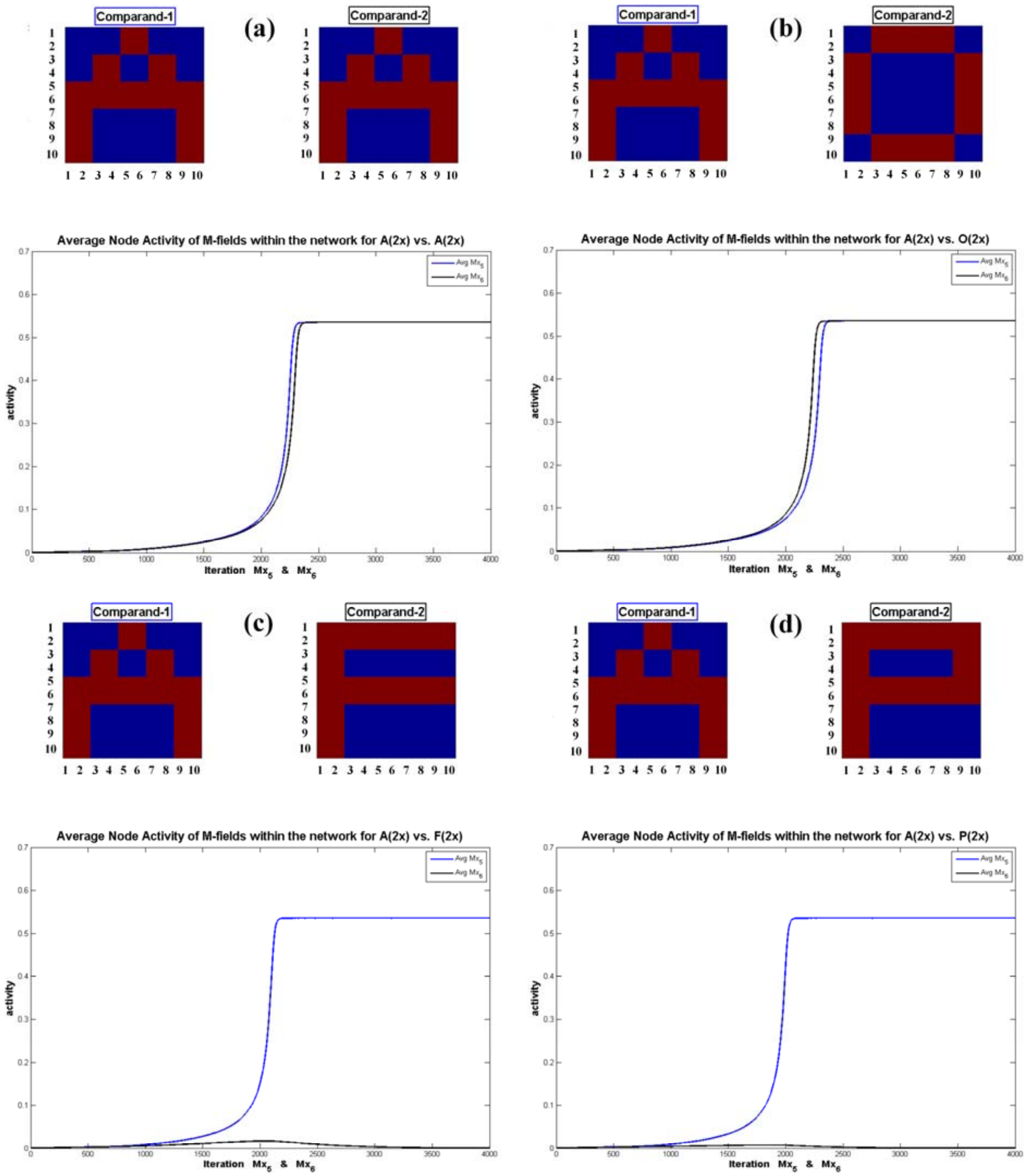

Figure 5.17. Time-series plot for 2x resolution patterns, A versus A(a), O(b), F(c) and P(d). The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a, b, c or d) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 10x10 (Fig.5.16).

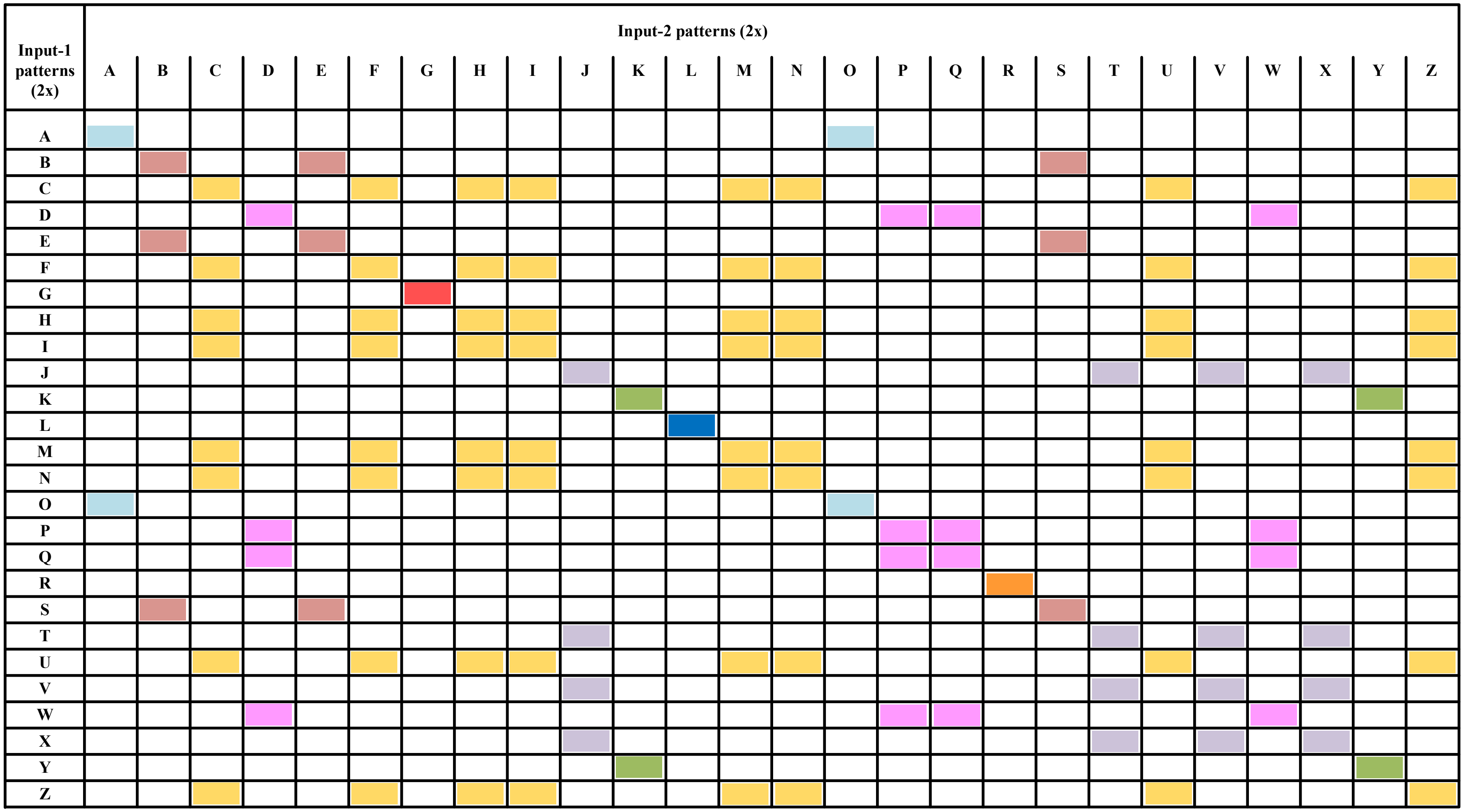

Table 5.8. Table illustrating similarities for 2x resolution Capital English letters, A to Z vs. A to Z. For a particular row, the colored (same) boxes represent similarity (for e.g. row for A). When compared to A to Z letters, if two or more rows have the same pattern of similarity, they are depicted having same colored boxes (for e.g. row for A & row for O). Two letters are defined similar if the smaller average (median) node activity of the two M-fields is ≥ 90% of the larger. This is equivalent to < 10% vigilance percentage. Note that the uncolored (white) boxes implies no similarity. The raw numerical data is given in appendix, Tables A5-1 to A5-8.

Number of non zero pixels	Non zero pixel value	Cumulative pixel value	Patterns (2x English letters)
72	0.0039	0.2808	G
68	0.0047	0.3196	B, E, S
64	0.0056	0.3584	R
56	0.0078	0.4368	D, P, Q, W
52	0.0091	0.4732	C, F, H, I, M, N, U, Z
48	0.0107	0.5136	A, O
44	0.0126	0.5544	K, Y
36	0.0175	0.6300	J, T, V, X
28	0.0251	0.7028	L

Table 5.9. Table showing the 2x resolution of the 26 uppercase English letters arranged with respect to their number of non-zero pixels (out of 100 pixels, 10 x 10 matrix), their normalized value (2nd column) and their total (3rd column, CPV or cumulative pixel value). Note that for a particular pattern all its non-zero pixels have the same magnitude of normalized pixel value.

Subset of comparand-1 patterns (2x)	Subset of comparand-2 patterns (2x)
{G}	**{G}**
{B, E, S}	**{B, E, S}**
{R}	**{R}**
{D, P, Q W}	**{D, P, Q, W}**
{C, F, H, I, M, N, U, Z}	**{C, F, H, I, M, N, U, Z}**
{A, O}	**{A, O}**
{K, Y}	**{K, Y}**
{J, T, V, X}	**{J, T, V, X}**
{L}	**{L}**

Table 5.10. Table of subset of patterns derived from simulation done with patterns from 2x resolution Capital English Letters of retinal size 10x10. Relationship is found for a given comparand-1 pattern with any comparand-2 pattern within a particular (same row) subset.

Comparand-1 Patterns (2x)	**Comparand-2 Patterns (2x)**	**Largest difference w/ α**	**Smallest difference w/o α**
G	{G}	{G} α {G} : 0(0) ⟹ 0.0000	{G} $\cancel{\alpha}$ {B, E, S} : 0.1214(4) ⟹ 0.1116
B, E, S	{B, E, S}	{B, E, S} α {B, E, S} : 0(0) ⟹ 0.0000	{B, E, S} $\cancel{\alpha}$ {R} : 0.1082(4) ⟹ 0.0995
R	{R}	{R} α {R} : 0(0) ⟹ 0.0000	{R} $\cancel{\alpha}$ {B, E, S} : 0.1082(4) ⟹ 0.0995
D, P, Q, W	{D, P, Q, W}	{D, …, W} α {D, …, W} : 0(0) ⟹ 0.0000	{D, …, W} $\cancel{\alpha}$ {C, …, Z} : 0.0769(4) ⟹ 0.0707
C, F, H, I, M, N, U, Z	{C, F, H, I, M, N, U, Z}	{C, …, Z} α {C, …, Z} : 0(0) ⟹ 0.0000	{C, …, Z} $\cancel{\alpha}$ {D, …, W} : 0.0769(4) ⟹ 0.0707
A, O	{A, O}	{A, O} α {A, O} : 0(0) ⟹ 0.0000	{A, O} $\cancel{\alpha}$ {K, Y} : 0.0735(4) ⟹ 0.0676
K, Y	{K, Y}	{K, Y} α {K, Y} : 0(0) ⟹ 0.0000	{K, Y} $\cancel{\alpha}$ {A, O} : 0.0735(4) ⟹ 0.0676
J, T, V, X	{J, T, V, X}	{J, …, X} α {J, …, X} : 0(0) ⟹ 0.0000	{J, …, X} $\cancel{\alpha}$ {L} : 0.1035(8) ⟹ 0.0828
L	{L}	{L} α {L} : 0(0) ⟹ 0.0000	{L} $\cancel{\alpha}$ {J, …, X} : 0.1035(8) ⟹ 0.0828

Table 5.11. Table demonstrating the diff-pc metric for the case of comparing patterns from 2x resolution of the 26 Capital English letters of retinal map size, 10x10. The first two columns are the same as table 5.10.

Every patterns has a corresponding cumulative pixel value, CPV (table 5.9). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (tables 5.4 & 5.7) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4, (21 to 30) → 4•0.8•3 = 9.6 and so on…

The third column shows the diff-fact, px (bracket) and resultant largest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has demonstrated α is < 4%. Since all the patterns within the set demonstrated relationship only with those having same number of non-zero pixels, all entries in the third column for largest diff-pc is zero. The fourth column shows the smallest diff-pc amongst those that has not demonstrated α is > 4%. The diff-pc for patterns that demonstrates α and $\cancel{\alpha}$ was determined to be largest or smallest from the table containing all the computed diff-pc values (tables A6-1 & A6-2).

The normalized non-zero pixel values and their corresponding CPV's are shown in table 5.9. Notice that the number of non-zero pixels have increased 4x in comparison to the same pattern with 5x5 retinal-map size (table 5.2). The non-zero pixel values and CPV's have however decreased by four-folds. The result is a widened spread of CPV's with increased number of non-zero pixels and increased retinal-map size (variance = 0.0201 in 10x10 with 4x increase in non-zero pixels and variance = 0.0165 in 5x5 retinal-map size).

Amongst the 2x resolution patterns, all patterns show relationship only with patterns having same number of non-zero pixels and hence equal CPV's (table 5.9 & table 5.10). The diff-pc amongst all other patterns are > 4% (table 5.11).

Unlike the results for the case of Capital English letters sized 5x5 placed on a larger retinal-map size of 10x10 (table 5.6), the above results for 2x resolution patterns suggests increased sensory acuity. Thus, we may say that the network has become more selective in what it considers a particular pattern-combo to have a relationship (or non-relationship).

Recall that v1-layers in both sub-networks (Fig.5.3) have equal number of nodes. Furthermore, the number of nodes in a v1-layers is equal to the size of retinal-map. Thus, to compare regular resolution Capital English letters against its higher 2x resolution patterns, both the input patterns have 10x10 retinal-map size.

Figures 5.18a and 5.18b shows no relationship amongst patterns A (1x) versus A (2x) and A (1x) versus O (1x). Since the 1x patterns have increased CPV's (table 5.5) but decreased CPV's for 2x patterns (table 5.9), none of the 1x patterns demonstrates relationship with any of the 2x patterns (Fig.5.18). The diff-pc amongst all the patterns are > 4% (table 5.12).

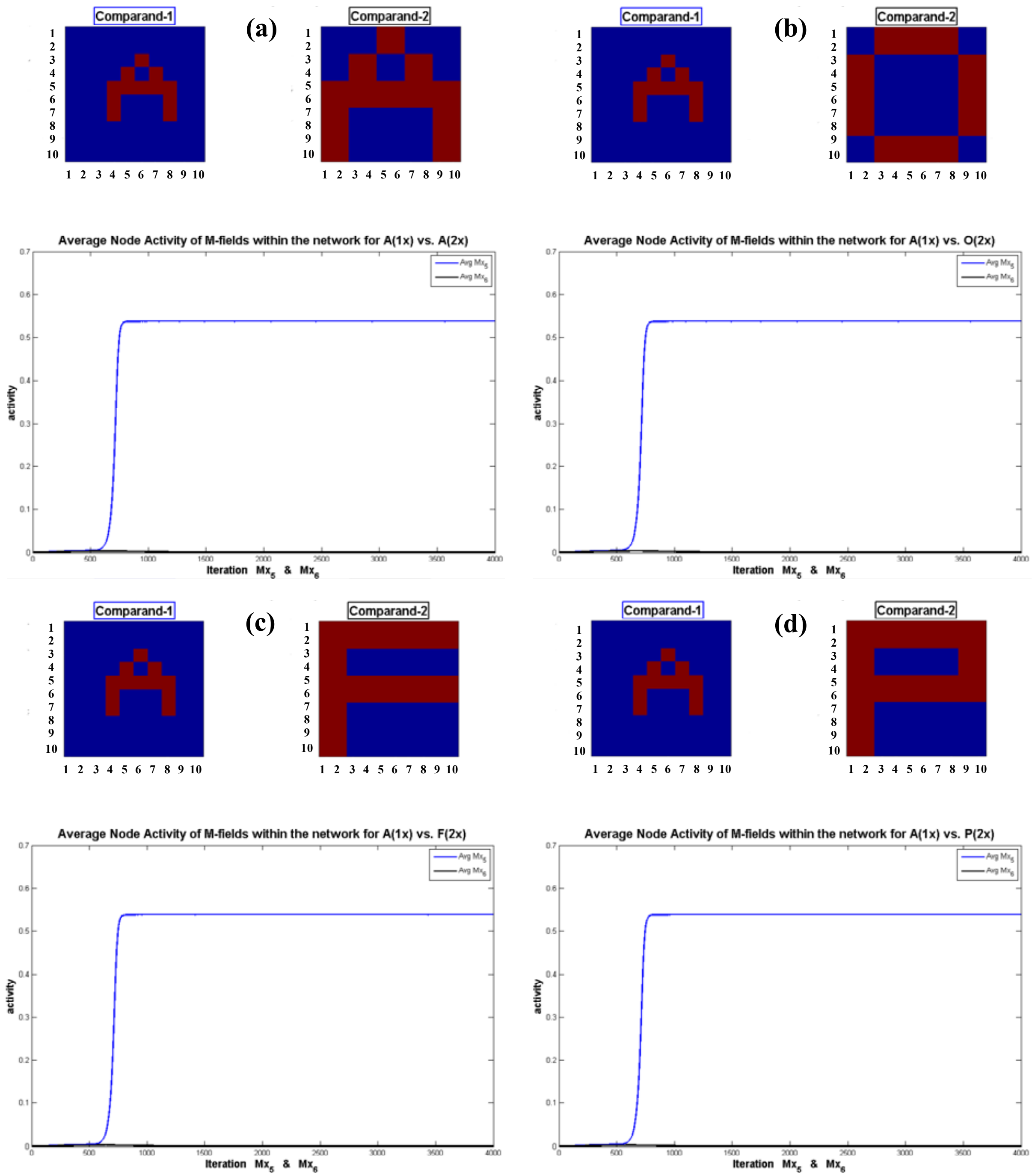

Figure 5.18. Time-series plot for 1x versus 2x resolution patterns, A versus A(a), O(b), F(c) and P(d). The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a, b, c or d) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 10x10 (Fig.5.15 & Fig.5.16).

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Comparand-1 Patterns (1x)	Comparand-2 Patterns (2x)	Largest difference w/ α	Smallest difference w/o α
G	{-}	-	{G} $\not\alpha$ {L} : 0.1045(10) ⟹ 0.0836
B, E, S	{-}	-	{B, E, S} $\not\alpha$ {L} : 0.1129(11) ⟹ 0.0903
R	{-}	-	{R} $\not\alpha$ {L} : 0.1197(12) ⟹ 0.0958
D, P, Q, W	{-}	-	{D, …, W} $\not\alpha$ {L} : 0.1330(14) ⟹ 0.1064
C, F, H, I, M, N, U, Z	{-}	-	{C, …, Z} $\not\alpha$ {L} : 0.1391(15) ⟹ 0.1113
A, O	{-}	-	{A, O} $\not\alpha$ {L} : 0.1438(16) ⟹ 0.1150
K, Y	{-}	-	{K, Y} $\not\alpha$ {L} : 0.1470(17) ⟹ 0.1176
J, T, V, X	{-}	-	{J, …, X} $\not\alpha$ {L} : 0.1503(19) ⟹ 0.1202
L	{-}	-	{L} $\not\alpha$ {J, …, X} : 0.1448(21) ⟹ 0.1158

Table 5.12. Table demonstrating the diff-pc metric for the case of comparing 1x patterns against 2x resolution of the 26 Capital English letters of retinal map size, 10x10. Since none of the 1x patterns showed any relationship with any of the 2x patterns, the entries in the comparands-2 column (2^{nd}) are empty set.

Every patterns has a corresponding cumulative pixel value, CPV (table 5.9). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (tables 5.4 & 5.7) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4, (21 to 30) → 4•0.8•3 = 9.6 and so on…

Since no relationship was demonstrated, there are no entries in the third column. The fourth column shows the diff-fact, px (bracket) and resultant smallest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has not demonstrated α is >4%. The diff-pc for patterns that demonstrates α and $\not\alpha$ was determined to be largest or smallest from the table containing all the computed diff-pc values (tables A8-1 & A8-2).

Case-4, Arabic numerals (0 to 9):

Returning to retinal-map size of 5x5, let us consider the pattern-set of Arabic numerals, 0 to 9 (Fig.5.19). Figure 5.20 shows relationship amongst 0 and 2 but not between 0 and 1. Experiment done amongst patterns from this set demonstrating relationship and no relationship is shown in table 5.12. Those patterns that showed relationships (table 5.14) has a diff-pc < 4% (table 5.15).

Finally, let us consider patterns for comparands-1 from the pattern-set of Capital English letters (Fig.5.6) and comparands-2 patterns from Arabic numerals (Fig.5.19). Figure 5.21 shows relationship for A versus 2 but not for A and 1. The determination for all the pattern-combos is shown in table 5.17. As with earlier experiments, those pattern-combos that showed relationships has a diff-pc < 4% (table 5.19).

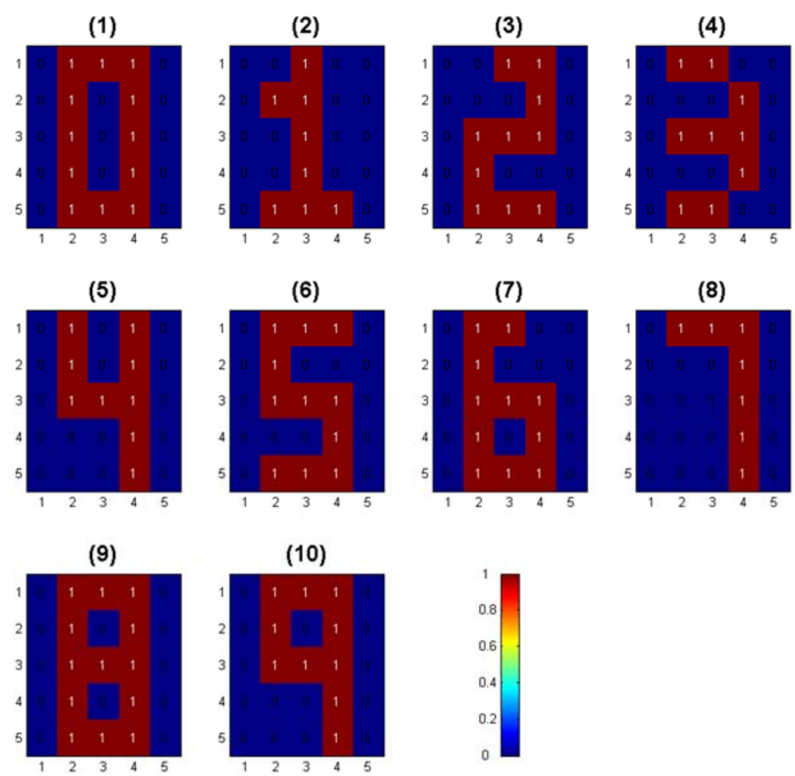


Figure 5.19. Set of Arabic numerals (0 – 9). Each alphabet is represented by the respective placement of 1's in a background of 0's.

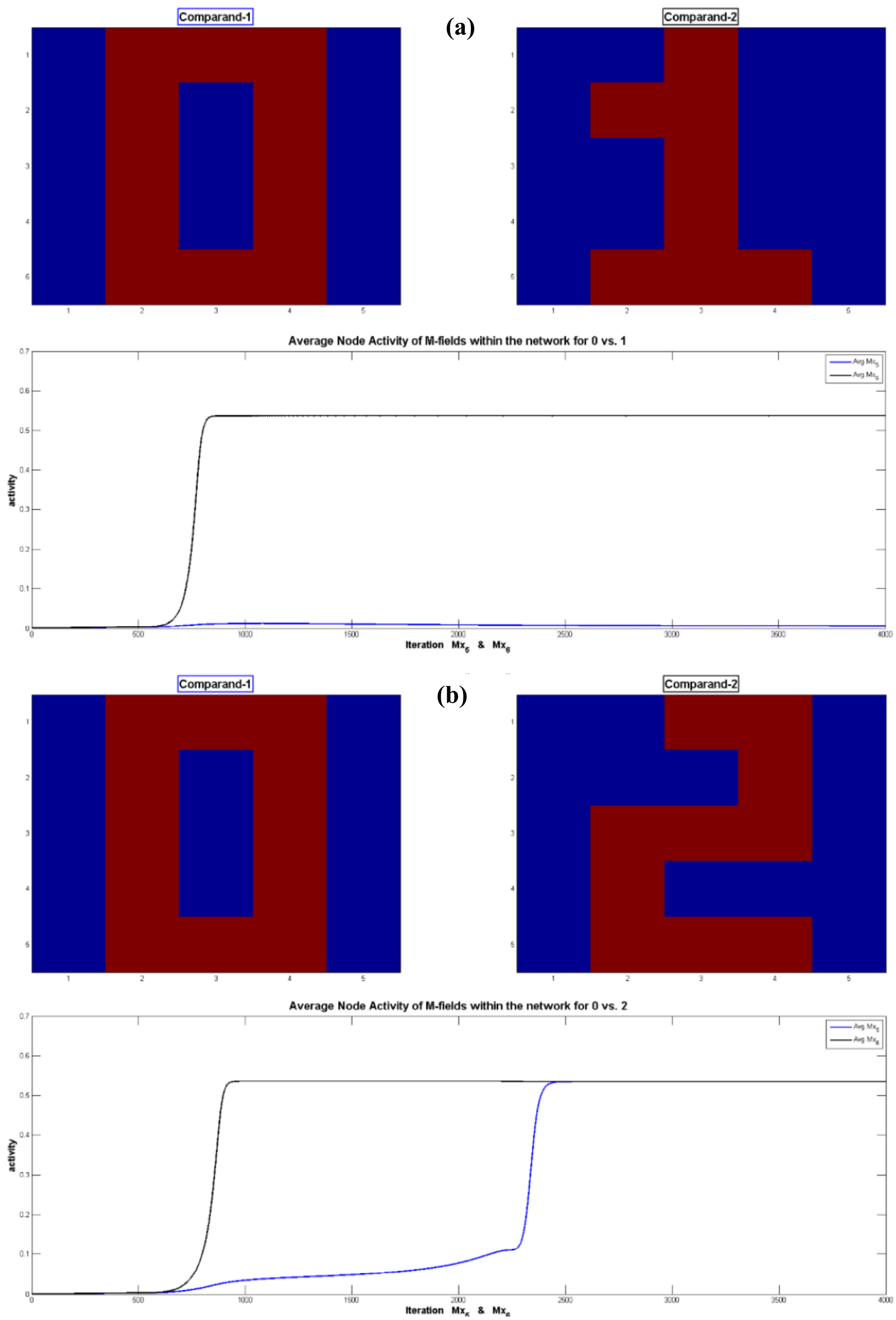


Figure 5.20. Time-series plot for numbers 0 vs. 1 (a) and 0 vs. 2 (b). The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a or b) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 5x5.

Input-1 patterns (5x5)	**Input-2 patterns (5x5)**									
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0										
1										
2										
3										
4										
5										
6										
7										
8										
9										

Table 5.13. Table illustrating similarities for pattern-set of Arabic numerals, 0 to 9. For a particular row, the colored (same) boxes represent similarity (for e.g. row for 2). When compared to 0 to 9, if two or more rows have the same pattern of similarity, they are depicted having same colored boxes (for e.g. row for 2 & row for 9). Two numeral patterns are defined similar if the smaller average (median) node activity of the two M-fields is ≥ 90% of the larger. This is equivalent to < 10% vigilance percentage. Note that the uncolored (white) boxes implies no similarity. The raw numerical data is given in appendix, Table A9.

Number of non zero pixels	**Non zero pixel value**	**Cumulative pixel value**	**Patterns (5x5)**
13	0.0357	0.4641	8
12	0.0417	0.5004	0
11	0.0486	0.5346	5, 6
10	0.0568	0.5680	2, 9
9	0.0667	0.6003	3, 4
8	0.0787	0.6296	1
7	0.0937	0.6559	7

Table 5.14. Table showing the pattern-set of Arabic numerals (0 to 9) arranged with respect to their number of non-zero pixels (out of 25 pixels, 5 x 5 matrix), their normalized value (2nd column) and their total (3rd column, CPV or cumulative pixel value). Note that for a particular pattern all its non-zero pixels have the same magnitude of normalized pixel value.

Subset of comparand-1 patterns (5x5)	**Subset of comparand-2 patterns (5x5)**
{8}	**{0, 8}**
{0}	**{0, 2, 5, 6, 8, 9}**
{5, 6}	**{0, 1, 2, 3, 4, 5, 6, 9}**
{2, 9}	**{0, 1, 2, 3, 4, 5, 6, 7, 9}**
{1, 3, 4}	**{1, 2, 3, 4, 5, 6, 7, 9}**
{7}	**{1, 2, 3, 4, 7, 9}**

Table 5.15. Table of subset of patterns derived from simulation done with patterns from Arabic Numerals, 0 to 9 of retinal size 5x5. Relationship is found for a given comparand-1 pattern with any comparand-2 pattern within a particular (same row) subset.

Comparand-1 Patterns (5x5)	**Comparand-2 Patterns (5x5)**	**Largest difference w/ α**	**Smallest difference w/o α**
8	{0, 8}	{8} α {0} : 0.0725(1) ⇒ 0.0290	{8} $\not\alpha$ {5,6} : 0.1318(2) ⇒ 0.0421
0	{0, 2, 5, 6, 8, 9}	{0} α {2, 9} : 0.1190(2) ⇒ 0.0380	{0} $\not\alpha$ {3, 4} : 0.1664(3) ⇒ 0.0416
5, 6	{0, 1, 2, 3, 4, 5, 6, 9}	{5, 6} α {1} : 0.1508(3) ⇒ 0.0377	{5, 6} $\not\alpha$ {7} : 0.1849(5) ⇒ 0.0406
2, 9	{0, 1, 2, 3, 4, 5, 6, 7, 9}	{2, 9} α {0} : 0.1190(2) ⇒ 0.0380	{2, 9} $\not\alpha$ {8} : 0.1829(3) ⇒ 0.0457
3, 4	{1, 2, 3, 4, 5, 6, 7, 9}	{3, 4} α {5, 6} : 0.1094(2) ⇒ 0.0350	{3, 4} $\not\alpha$ {0} : 0.1664(3) ⇒ 0.0416
1	{1, 2, 3, 4, 5, 6, 7, 9}	{1} α {5, 6} : 0.1508(3) ⇒ 0.0377	{1} $\not\alpha$ {0} : 0.2052(4) ⇒ 0.0471
7	{1, 2, 3, 4, 7, 9}	{7} α {2, 9} : 0.1340(3) ⇒ 0.0335	{7} $\not\alpha$ {5,6} : 0.1849(4) ⇒ 0.0425

Table 5.16. Table demonstrating the diff-pc metric for the case of comparing patterns from Arabic Numerals (0 to 9) of retinal map size, 5x5. The first two columns shows the relationship (α) found for a given comparands-1 pattern (column-1) with any comparands-1 pattern (column-2) within a particular (same row) subset (table 5.15).

Every patterns has a corresponding cumulative pixel value, CPV (table 5.14). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on…

The third column shows the diff-fact, px (bracket) and resultant largest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has demonstrated α is < 4%. The fourth column shows the smallest diff-pc amongst those that has not demonstrated α is > 4%. The diff-pc for patterns that demonstrates α and $\not\alpha$ was determined to be largest or smallest from the table containing all the computed diff-pc values (table A10).

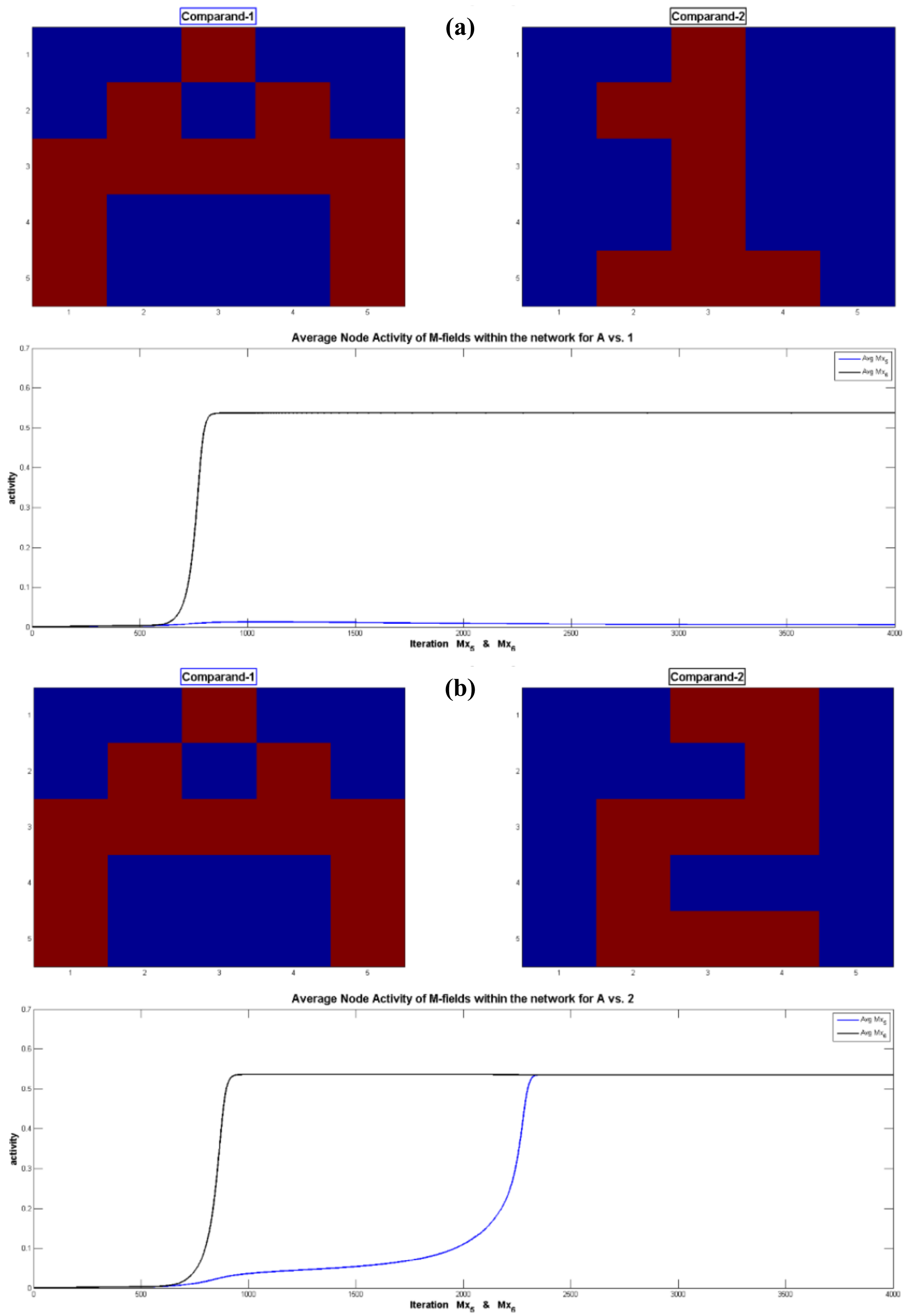


Figure 5.21. Time-series plot for Capital letter A vs. number 1 (a) and A vs. 2 (b). The top sub-network in Fig.5.3 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.3 receives comparand-2, color coded as black. Given a pattern-combo (a or b) the plots shows the activities of average (median) nodes of respective M-layers. Note that the retinal-map size is 5x5.

Input-1 patterns (5x5)	Input-2 patterns (5x5)									
	0	1	2	3	4	5	6	7	8	9
A										
B										
C										
D										
E										
F										
G										
H										
I										
J										
K										
L										
M										
N										
O										
P										
Q										
R										
S										
T										
U										
V										
W										
X										
Y										
Z										

Table 5.17. Table illustrating similarities for the case of comparing Capital English letters (A to Z) against Arabic Numerals (0 to 9). For a particular row, the colored (same) boxes represent similarity (for e.g. row for A). When compared to 0 to 9 numerals, if two or more rows have the same pattern of similarity, they are depicted having same colored boxes (for e.g. row for A & row for O). A letter-numeral pair is defined similar if the smaller average (median) node activity of the two M-fields is ≥ 90% of the larger. This is equivalent to < 10% vigilance percentage. Note that the uncolored (white) boxes implies no similarity. The raw numerical data is given in appendix, Tables A11-1 to A11-3.

Number of non zero pixels	Non zero pixel value	Cumulative pixel value	Patterns (Letters & Numbers)
18	0.0154	0.2772	G
17	0.0185	0.3145	B, E, S
16	0.0221	0.3536	R
14	0.0306	0.4284	D, P, Q, W
13	0.0357	0.4641	C, F, H, I, M, N, U, Z, 8
12	0.0417	0.5004	A, O, 0
11	0.0486	0.5346	K, Y, 5, 6
10	0.0568	0.5680	2, 9
9	0.0667	0.6003	J, T, V, X, 3, 4
8	0.0787	0.6296	1
7	0.0937	0.6559	L, 7

Table 5.18. Table showing the 26 uppercase English letters and 9 Arabic numerals arranged with respect to their number of non-zero pixels (out of 25 pixels, 5 x 5 matrix), their normalized value (2^{nd} column) and their total (3^{rd} column, CPV or cumulative pixel value). Note that for a particular pattern all its non-zero pixels have the same magnitude of normalized pixel value. Note that this table is a combination of both table 5.2 and 5.14.

Subset of comparand-1 patterns (5x5)	Subset of comparand-2 patterns (5x5)
{D, P, Q, W}	**{8}**
{C, F, H, I, M, N, U, Z}	**{0, 8}**
{A, O}	**{0, 2, 5, 6, 8, 9}**
{K, Y}	**{0, 1, 2, 3, 4, 5, 6, 9}**
{J, T, V, X}	**{1, 2, 3, 4, 5, 6, 7, 9}**
{L}	**{1, 2, 3, 4, 7, 9}**

Table 5.19. Table of subset of patterns derived from simulation done for the case of comparing Capital English letters (A to Z) against Arabic Numerals (0 to 9) with retinal-map size, 5x5. Relationship is found for a given comparand-1 pattern with any comparand-2 pattern within a particular (same row) subset.

Comparand-1 Patterns (5x5)	**Comparand-2 Patterns (5x5)**	**Largest difference w/ α**	**Smallest difference w/o α**
G	{-}	-	{G} $\not\alpha$ {8} : 0.4027(5) ⟹ 0.0885
B, E, S	{-}	-	{B, E, S} $\not\alpha$ {8} : 0.3223(4) ⟹ 0.0741
R	{-}	-	{R} $\not\alpha$ {8} : 0.2380(3) ⟹ 0.0595
D, P, Q, W	{8}	{D, …, W} α {8} : 0.0769(1) ⟹ 0.0307	{D, …, W} $\not\alpha$ {0} : 0.1439(2) ⟹ 0.0460
C, F, H, I, M, N, U, Z	{0, 8}	{C, …, Z} α {0} : 0.0725(1) ⟹ 0.0290	{C, …, Z} $\not\alpha$ {5, 6} : 0.1319(2) ⟹ 0.0422
A, O	{0, 2, 5, 6, 8, 9}	{A, O} α {2, 9} : 0.1190(2) ⟹ 0.0380	{A, O} $\not\alpha$ {3, 4} : 0.1664(3) ⟹ 0.0416
K, Y	{0, 1, 2, 3, 4, 5, 6, 9}	{K, Y} α {1} : 0.1508(3) ⟹ 0.0377	{K, Y} $\not\alpha$ {8} : 0.1319(2) ⟹ 0.0422
J, T, V, X	{1, 2, 3, 4, 5, 6, 7, 9}	{J, …, X} α {5, 6} : 0.1094(2) ⟹ 0.0350	{J, …, X} $\not\alpha$ {0} : 0.1664(3) ⟹ 0.0416
L	{1, 2, 3, 4, 7, 9}	{L} α {2, 9} : 0.1340(3) ⟹ 0.0335	{L} $\not\alpha$ {5,6} : 0.1849(4) ⟹ 0.0425

Table 5.20. Table demonstrating the diff-pc metric for the case of comparing Capital English letters (A to Z) against Arabic Numerals (0 to 9) with retinal-map size, 5x5. Since none of the G, B, E, S, and R patterns showed any relationship with any of the numeral patterns, the entries in the comparands-2 column (2^{nd}) are empty set.

Every patterns has a corresponding cumulative pixel value, CPV (table 5.18). If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on…

The third column shows the diff-fact, px (bracket) and resultant largest diff-pc amongst comparands-1 patterns and subset of comparands-2 patterns that has demonstrated α is < 4%. The fourth column shows the smallest diff-pc amongst those that has not demonstrated α is > 4%. The diff-pc for patterns that demonstrates α and $\not\alpha$ was determined to be largest or smallest from the table containing all the computed diff-pc values (table A12).

Pattern-combos	$\bar{x}_1$	$\bar{x}_2$	C.I	p-value
A vs. A	**0.5347**	**0.5357**	**[0, 0]**	**-**
A vs. F	**0.5347**	**0.5356**	**[$3.6 \cdot 10^{-5}$, $3.6 \cdot 10^{-5}$]**	**0**
A vs. P	**0.5358**	**0.0025**	**[0.5333, 0.5333]**	**$1.69 \cdot 10^{-141}$**

Table 5.21. Summarized statistical (paired t-test) result. For a given pattern-combo (comparands-1 vs. comparand-2), results includes: mean ($\bar{x}_1$ & $\bar{x}_2$) of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), confidence interval (CI) and p-value. The results are for 95% confidence and hence t*multiplier = 3.6 and alpha = 0.05. Note that p-value is not computed for cases with CI = [0, 0]. The raw numerical data is given in appendix, Tables A13-1 to A13-11.

Recall that the initial instar (W's) weights were set to random non-zero weights (and outstar weights Z's were set to zero). To test the reproducibility (consistency) of the networks determination of relationship or non-relationship, statistical tests (t-test and ANOVA f-test) were done. Considering the case of patterns from Capital English letters (case-1, Fig.5.6), data was collected from randomly independent sample of sample size = 35.

Since the initial W's are non-zero random values, one question is: Does the determined outcome (of the network, Fig.5.3) remain unchanged? For instance, does patterns A vs. A (Fig.5.7) and A vs. F (Fig.5.8) always show relationship and patterns A vs. P (Fig.5.9) always show non-relationship?

For A vs. A, the 95% confidence interval estimate for the difference in means (over n = 35) of the median M-field node activities was [0, 0] (table 5.21). The interval covers 0. Therefore, we can be fairly confident that the population means of the median M-field node activities are equal.

For A vs. F and A vs. P, the 95% confidence interval estimate for the paired-difference was [$3.6 \cdot 10^{-5}$, $3.6 \cdot 10^{-5}$] and [0.5333, 0.5333] respectively (table 5.21). Both their null hypothesis was rejected (p-values < 0.05). The difference in means for both cases was therefore statistically significant.

For A vs. F, the mean of 0.5346 (Mx6) is about 95% of 0.5347 (Mx5). Thus, the difference in means has statistical but not practical significance[2]. On the other hand, 0.0025 (Mx6) is about 0.4% of 0.5358 (Mx5) for A vs. P. Thus difference in means for this case is both statistically and practically significant.

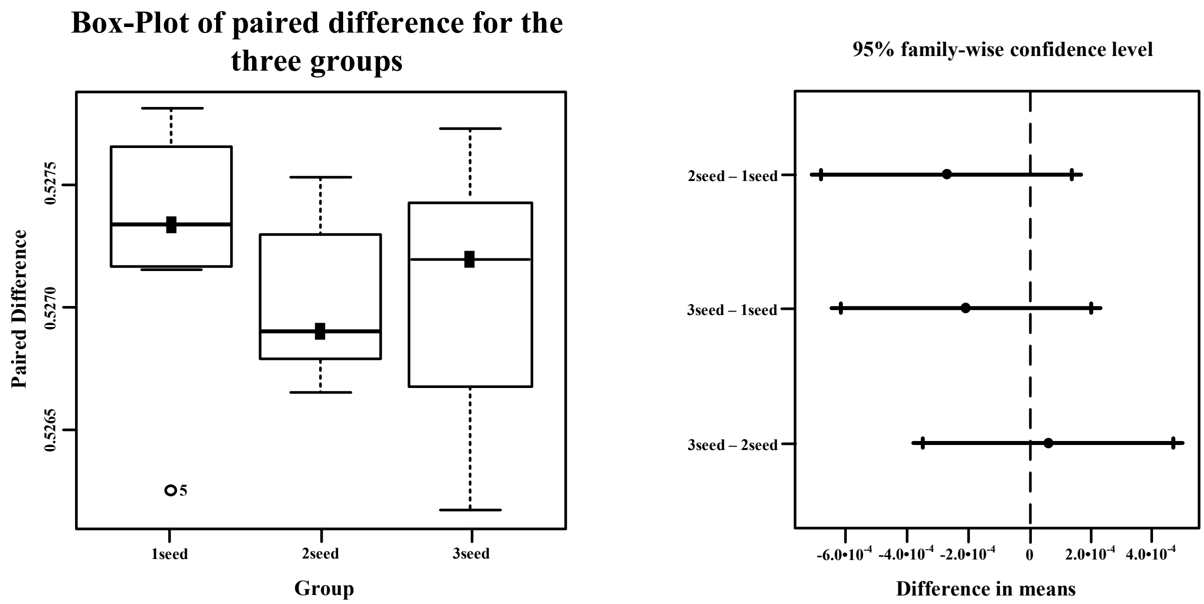
To compare response variable for different initial W weights, one-way ANOVA f-test is chosen. Three (k) groups were chosen. The groups were defined with respect to the seed (= 1, 2, 3) of the random number generator. All the groups have equal sample size, $n_k = 10$. Thus, total sample size N = 30. The response variable is the paired-difference of the means of M5 and M6-field activities at final iteration (2000) over n_k samples for respective k-group.

Figure 5.22 shows the results for A vs. P. The box-plot show more variation between the groups than variations within groups. The 95% pairwise comparison shows all three intervals crossing 0. The p-value ≈ 0.3 implies that the F-statistic (= 1.26) is not in the rejection region. Thus, with 95% confidence we can conclude that there is not enough evidence of difference in M-field outputs for different initial W weights.

---

[2] Practical significance refers to the magnitude of relationship between variables and whether or not that magnitude is important. Though statistical significance is informative, it does not necessarily mean that the relationship between the two variables has practical significance [Utts & Heckard, 2012].
Statistical significance means that the data are strong enough to reject null-hypothesis but p-value does not provide information about the magnitude of the effect. Since there is almost always at least a slight relationship between two variables, almost any null hypothesis can be rejected if the sample size is large enough.
For example, in “Height depends on month of birth” [Weber et al., 1998], the authors concluded that men born in spring is 0.6cm (1/4 inch) taller than those born in fall. Their sample size was 507,125 military recruits. Thus, statistical significance does not guarantee practical significance.

A vs. P



ANOVA Table

Source	df	Sum Sq.	Mean Sq.	F	P
Groups	2	$3.9702 \cdot 10^{-7}$	$1.9851 \cdot 10^{-7}$	1.261	0.2996
Error	27	$4.2511 \cdot 10^{-6}$	$1.5745 \cdot 10^{-7}$		
Total	29	$4.6482 \cdot 10^{-6}$			

Figure 5.22. Comparison of paired-difference (pattern-combo, A vs. P) for three (k) groups. The patterns have retinal-map size 5x5. For the ANOVA f-test the groups are defined with respect to the seed (= 1, 2, 3) of the random number generator. Each group has sample size, $n_k = 10$. Thus, $N = n_1 + n_2 + n_3 = 30$.

Paired-difference is the difference of the means of M5 and M6-field activities at final iteration (2000) over n_k samples for respective k-group. The ■ within the box indicates sample mean.

The sample means (approximate) are: 0.5273, 0.5270 and 0.5271 for groups; 1seed, 2seed and 3seed respectively. The sample standard deviations (sd) are: $4.033 \cdot 10^{-4}$, $2.785 \cdot 10^{-4}$ and $4.818 \cdot 10^{-4}$. Thus, the largest, $4.81 \cdot 10^{-4}$ > 2x smallest, $2.78 \cdot 10^{-4}$.

The 95% simultaneous confidence intervals (Tukey's procedures) indicate that all the three intervals cover 0. The pairwise intervals are; 2seed – 1 seed: [$-7.093 \cdot 10^{-4}$, $1.707 \cdot 10^{-4}$], 3seed – 1seed: [$-6.465 \cdot 10^{-4}$, $2.335 \cdot 10^{-4}$] and 3seed – 2seed: [$-3.772 \cdot 10^{-4}$, $5.028 \cdot 10^{-4}$]. The mean (●) of the respective intervals are: $-2.693 \cdot 10^{-4}$, $-2.065 \cdot 10^{-4}$ and $6.280 \cdot 10^{-5}$.

This ends the demonstration of ability of the proposed minimal neural network (Fig.5.3) in determining relationship or non-relationship between some patterns and not for others. From here onwards all the simulation results will be for the pattern-set of Capital English letters or 5x5 retinal-map size (Fig.5.6).

The results demonstrated above make a novel contribution of significance in ART network theory. The behaviors just described are emergent network properties. Nothing in the design of the networks explicitly inserted the relationship vs. no relationship characteristics just described. This means the theory did not introduce any a priori objective criterion for defining what the network treats as a feature for pattern matching. <u>The experiments just reported are the first-ever demonstration that ART is capable of self-defining feature sets</u>.

The importance of this finding must not be minimized. If a theorist deliberately introduces any objective character of a feature into the design of a network, this amounts to building objective knowledge a priori into the synthesis of apprehension. However doing so is a violation of an epistemological law of mental physics, which holds that human beings are born with no objective knowledge a priori whatsoever. It is therefore a <u>real necessity</u> that any network used in modelling the synthesis of objective perceptions (intuitions) must be capable of <u>self</u>-determining what will or will not constitute an objective feature. It can be conjectured that this ability for a network to auto-determine features is a possible explanation of how human beings come to be capable of making metaphors and analogies. This work is the first time any neural network system has demonstrated this capacity, and this is an original contribution to knowledge from this research project.

Above results describes the basic behavior of the network in terms of how pattern-combos either have relationship or not. We must now consider the three properties required for generating equivalence relations, that is, reflexive, symmetric and transitive.

Additions to the above minimal neural network

It was observed that every pattern received by the network was shown to be reflexive. In other words, when the left and right sub-networks received the same pattern the M layer output always fell within the solution-set. This behavior is due to the chosen network configuration. Referring back to the model (Fig.5.2d & Fig.5.3), recall that the sub-networks have the same architecture and parameters (Fig.5.6). Since the two similar sub-network are coupled by reciprocal inhibition, it is understandable that the network consistently shows that the relationship between patterns are reflexive. By the same argument, if a relationship is shown between two different patterns then this relationship is always symmetric. This property of the network dynamics is not a hindrance to the act of comparation because generation of equivalence relation is the mathematical act of comparation.

Therefore, if two patterns are shown by the network to have a relationship then the relationship satisfies both reflexive and symmetric properties. These two properties can be therefore be realized from a single pattern-combo. In other words, the network does not have to process another pattern-combo such that they are of same patterns or flipped patterns. If the network had to process other pattern-combos composed of different patterns, it would mean that the realization of the two relation properties would involve a logical ordering process. The network however requires an ordering processing for transitivity. The above minimal neural network does not have this capability.

Comparation is a process in synthesis in sensibility which in turn does not have memory because the obscure parástase from sensory data has not yet become a conscious or objective parástase. The obscure parástase exists however. Therefore, comparation has a 'state'. This means then, if an obscure parástase is a sequence of patterns, the comparation network will be in a 'state' whose consequence would be, a realization (or not) of equivalence relation.

One of the functions of the **pure intuition of time** (**PIT**) within the OB (Fig.3.13) is that it determines 'content' in time. In practice, this means that the **PIT** can determine which pair of elements (in a sequence) is to be processed by the comparation network. Thus we have,

Proposition 9: The comparation network interacts with the pure intuition of time (PIT) such that the PIT determines the order of sequence of pattern pairs to be processed.

Since the aim of the project is to build a comparation network generating equivalence relation and not build other nous processes of the OB, a PIT proxy was built (Fig.5.23). The PIT proxy determines the content for the comparation process by picking pattern-combos one at a time from the pattern sequence. Using results from the above observations that a pattern-combo shown to have a relationship is reflexive and also symmetric, the PIT proxy picks L unique pattern-combos, where L is the length of a pattern sequence.

If one of the pattern-combo in the sequence is shown by the comparation network not to have a relationship, then there is no point for comparation to process the remaining pattern-combos. This would mean that the M layer outputs do not fall inside the solution-set. In other words, the M layer outputs are not in equilibrium and hence not expedient.

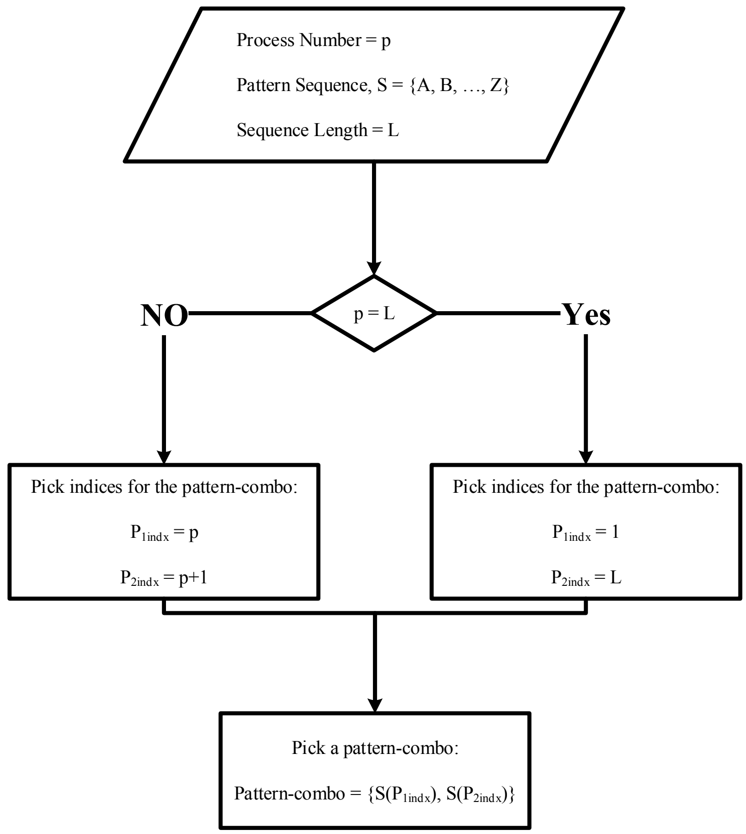


Figure 5.23. The pure intuition of time (PIT) proxy for determining content (pattern-combo) for the process of comparation network (Fig.5.3).

Since the PIT is a sub-process within the synthesis in sensibility (Fig.3.11 & Fig.3.13), like comparation the PIT is also linked to the reflective judgment (TRJ). Thus, the TRJ judge expediency based on the two pre-motor images and then stops the comparation process if one of the pattern-combo in the pattern sequence is not expedient. TRJ does not have the capability to directly stop comparation but it can indicate to PIT that a pattern-combo is not expedient. Hence,

Proposition 10: The function of PIT determining the content of the comparation process can short-circuit the order of pattern-combos based on non-expediency judged by TRJ.

The judging of M layer outputs for expediency was performed by a TRJ proxy for this particular function. Since Weber and Fechner, the concept of 'just noticeable difference' has been well known psychological phenomenon [Kandel, 2000]. Based upon this notion, the TRJ proxy was built by comparing the mismatch between the M-layer outputs against the vigilance percentage parameter, δ which is akin to difference limen or just notifiable difference.

If vectors, $\mathbf{x}_5$ and $\mathbf{x}_6$ are steady-state (last iteration) M-layer outputs then the mismatch $= \sum_{\forall i} |m_i^{(5)} - m_i^{(6)}|$ where $\mathbf{M}^{(5)}$ and $\mathbf{M}^{(6)}$ are the normalized $\mathbf{x}_5$ and $\mathbf{x}_6$ ($\mathbf{M}^{(k)} = \mathbf{x}_k$ / d, where d = max-element ($\mathbf{x}_5$, $\mathbf{x}_6$)).

Figure 5.24 shows the new minimal network model based upon the previous minimal anatomy (Fig.5.2d) incorporated with the PIT and TRJ proxies.

Behavior of the proposed minimal anatomy.

The parameters used were the same set as earlier (Fig.5.5) with the addition of vigilance percentage, δ = 0.1. The patterns comprising any desired sequence was picked from the same set of upper-case English alphabets (Fig.5.6). Because normalizer parameters are the same, the resulting normalized inputs are also unchanged (Fig.5.10 & 5.11).

The minimal network showed equivalence relationship for some pattern sets and not for others. For a pattern sequence {C, F, A, O}, the network process finds relationship between C & F (C α F) and so it continues for {F, A}, {A, O} and finally {C, O} (Fig.5.25). On the other hand, for {C, A, Y, G}, the network finds C α A and proceeds to {A, D} but finds A $\cancel{\alpha}$ Y and hence stops the process (Fig.5.26). This short-circuiting of the process is also seen in {B, D, E, P, S, G}, where the process stops at {B, D} (Fig.5.27). Notice that, if the pattern sequence was composed only of either {D, P} or {B, E, S} the network would continue the process and find relationship among the respective patterns (Fig.5.28 & 5.29).

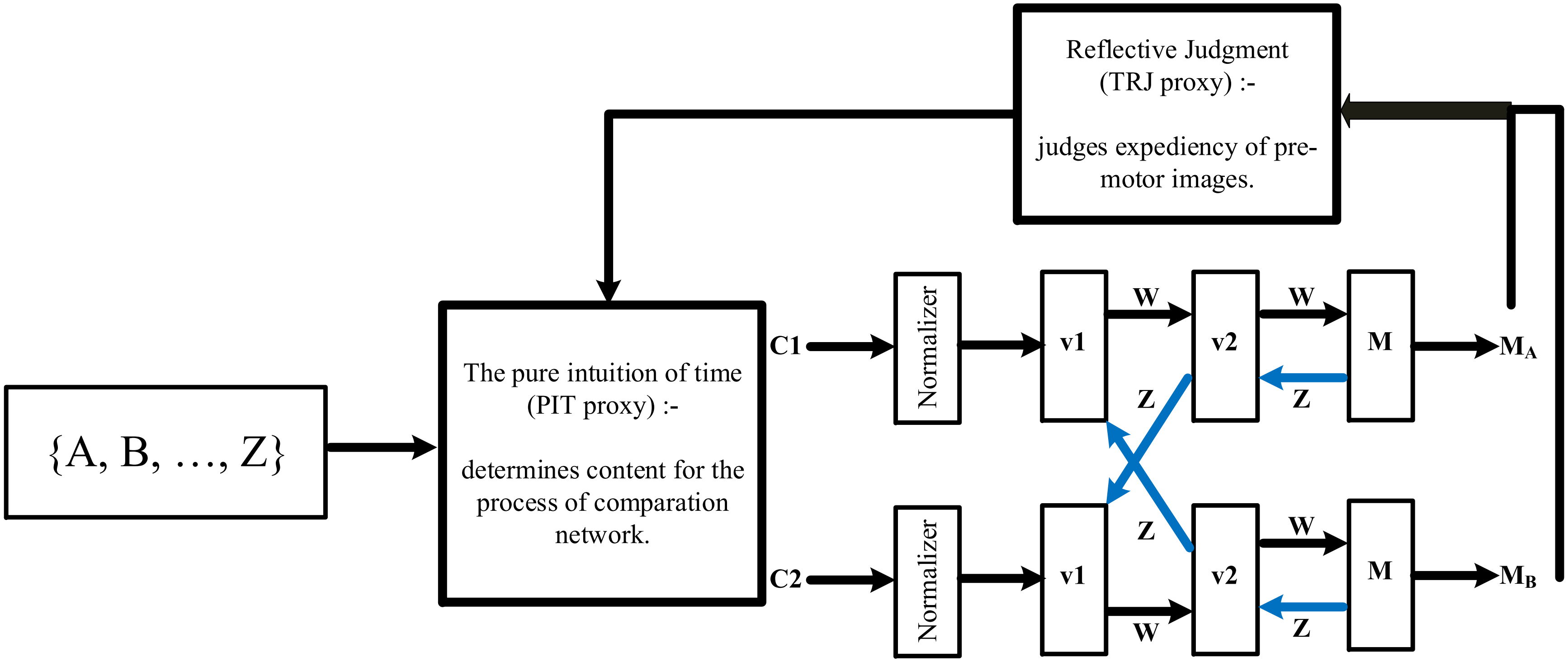


Figure 5.24. The minimal anatomy for generating equivalence relation. Notice that this is based on the previous minimal network (Fig.5.2d) with the addition of PIT proxy (Fig.5.23) determining the content (comparands, C1 & C2) from a sequence of patterns and also receives report of expediency from TRJ proxy.

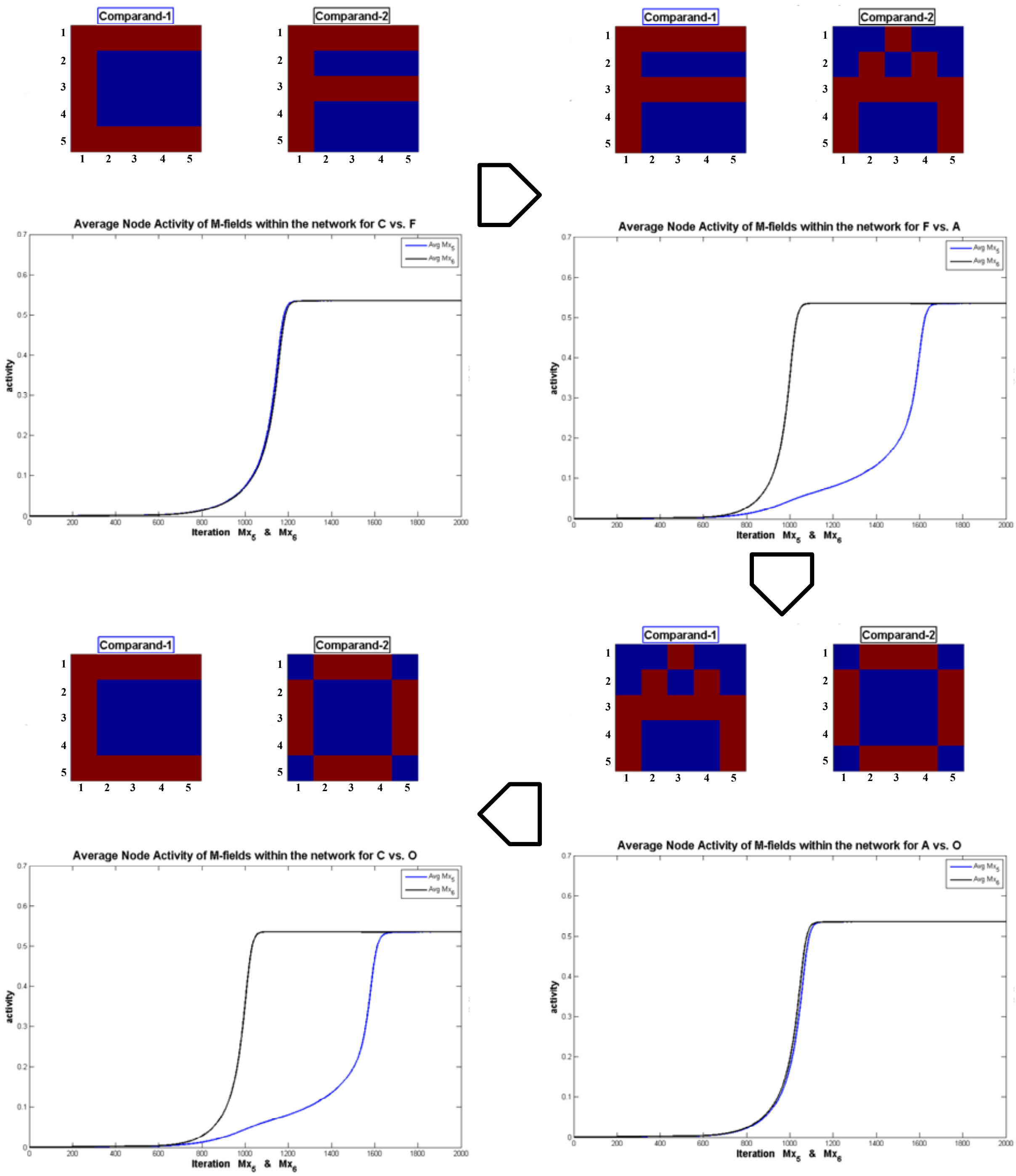


Figure 5.25. Time-series plot for the pattern sequence {C, F, A, O}. The top sub-network in Fig.5.24 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.24 receives comparand-2, color coded as black. Given a pattern-combo the plots shows the activities of average (median) nodes of respective M-layers. Clockwise from the top-left, the network proceeds from {C, F} and then {F, A}, {A, O} and finally {C, O}. Here all the patterns are shown to have a relationship.

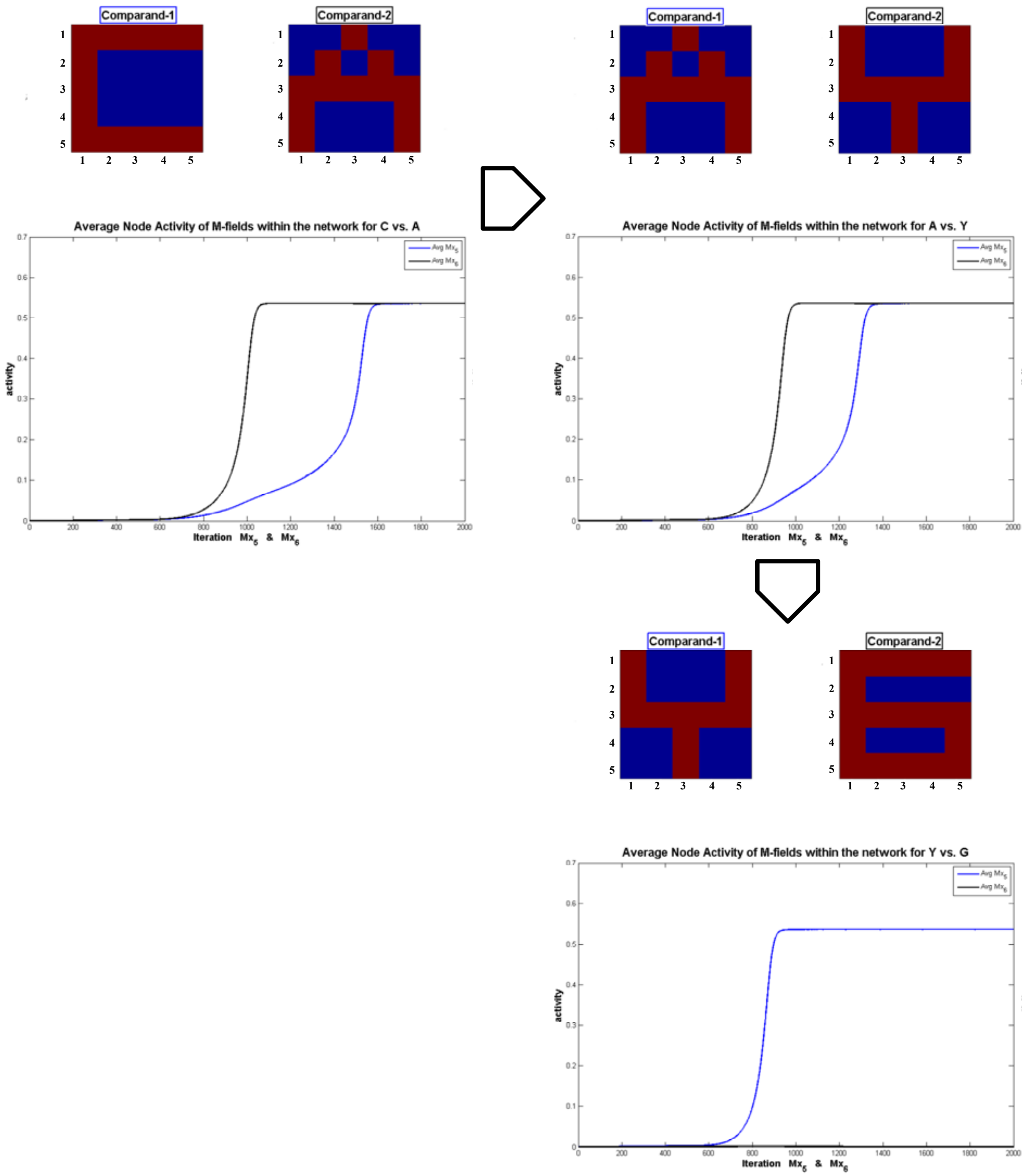


Figure 5.26. Time-series plot for the pattern sequence {C, A, Y, G}. The top sub-network in Fig.5.24 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.24 receives comparand-2, color coded as black. Given a pattern-combo the plots shows the activities of average (median) nodes of respective M-layers. Clockwise from the top-left, the network finds relationship in {C, A} and {A, Y} but not in {Y, G} and hence stopped for {C, G}.

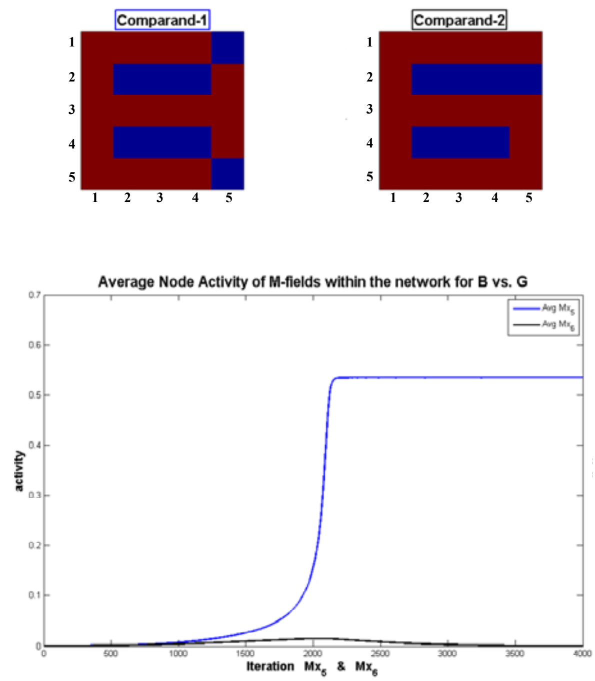


Figure 5.27. Time-series plot for the pattern sequence {B, G, D, E, P, S}. The plot shows the activities of average (median) nodes of respective M-layers for pattern-combo, {B, G}. Since there is no relationship for {B, G} it is stopped for {G, D} and succeeding pattern-combos.

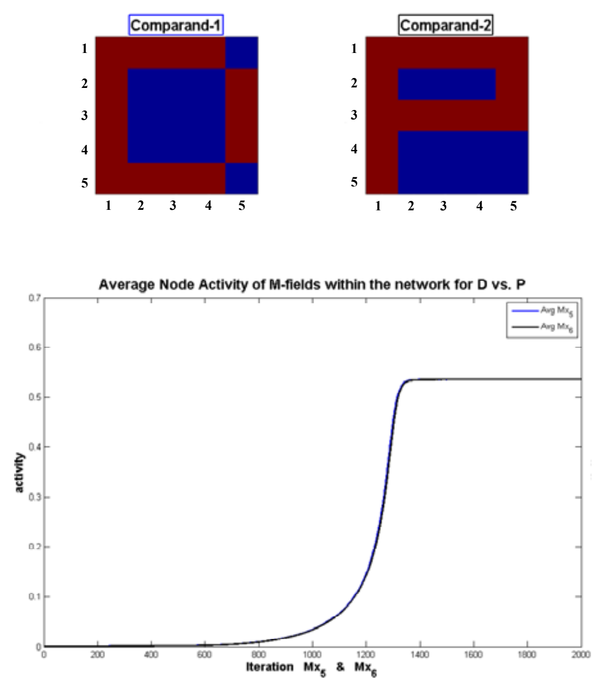


Figure 5.28. Time-series plot for the pattern sequence {D, P}. The plot shows the activities of average (median) nodes of respective M-layers for pattern-combo, {D, P}. Here all the patterns are shown to have a relationship.

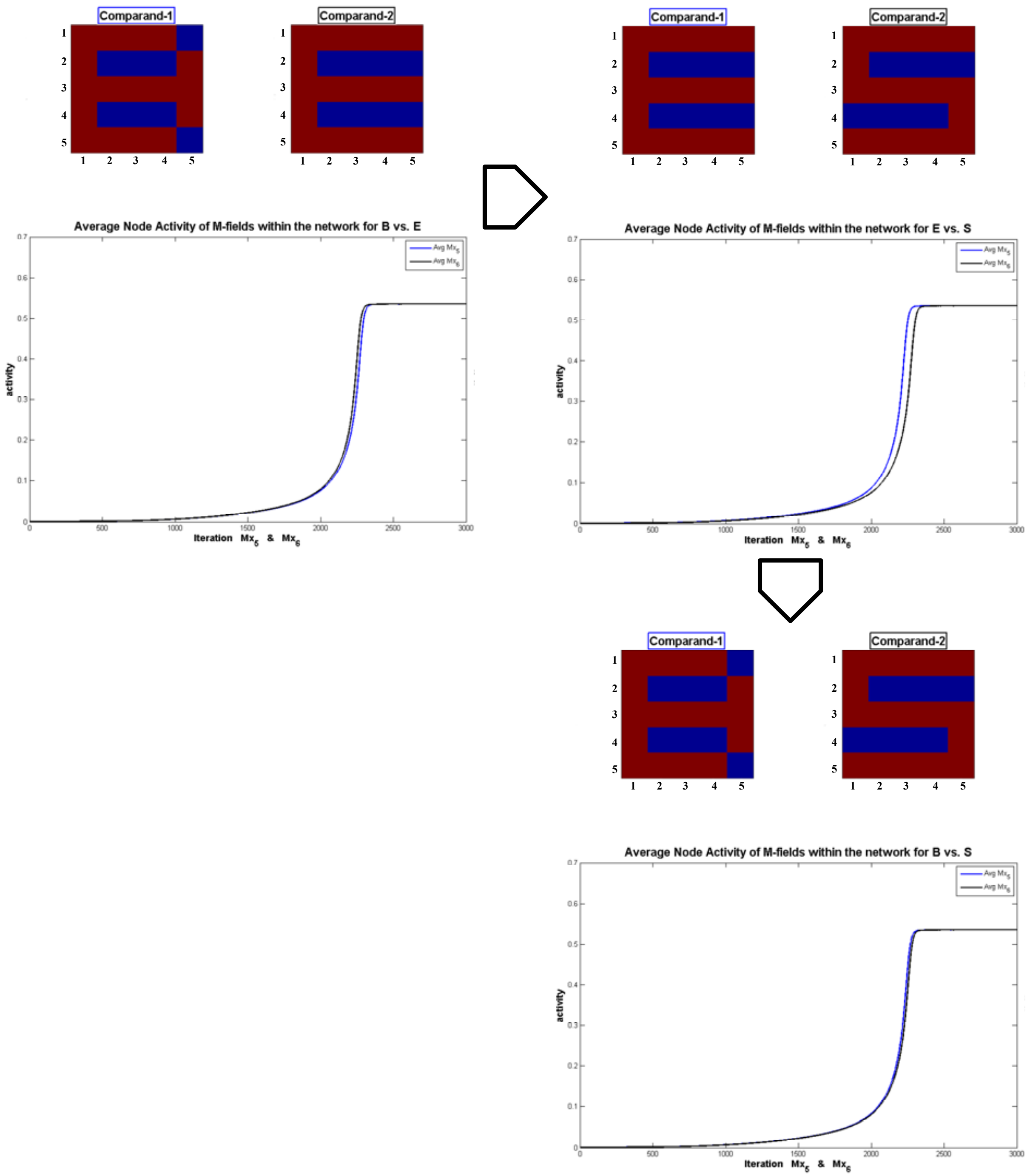


Figure 5.29. Time-series plot for the pattern sequence {B, E, S}. The top sub-network in Fig.5.24 receives comparand-1, color coded as blue. The bottom sub-network in Fig.5.24 receives comparand-2, color coded as black. Given a pattern-combo the plots shows the activities of average (median) nodes of respective M-layers. Clockwise from the top-left, the network proceeds from {B, E} and then {E, S} and finally {B, S}. Here all the patterns are shown to have a relationship.

These demonstrations do not strictly show the complete synthesis of an equivalence relation. To do that transitivity would have to be demonstrated over the whole of the candidate set of patterns. For instance, demonstrating transitivity for the set {C, F, A, O} requires, in addition to the demonstration of figure 5.25, that the following pairs have the same relationship:

C → A,
F → O.

However, recall that if a relationship is found between patterns then as a dynamic property of the network, the relationship is reflexive and also symmetric. Thus for the pairs that have been shown to have the same relationship (Fig.5.25), due to the property of the network dynamics, the following pairs will also have the same relationship:

C ← F (since, C → F),
F ← A (since, F → A),
O ← A (since, A → O), and
C ← O (since, C → O).

In other words, the relationship in the pattern-combos implies that the patterns are interchangeable, i.e., F & A are interchangeable and A & O are interchangeable. Thus, the following pairs will have the same relationship:

C → A (since, C → F & F ↔ A), and
F → O (since, F → A & A ↔ O).

Simulations (refer table 5.1) of these pattern pairs confirm this.

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The demonstrations provided here shows that the generation of equivalence relation by means of the minimal network of figure 5.24 is possible, and this is sufficient to demonstrate the Verstandes Actus of comparation. In this, the particular matter of equivalence is irrelevant, as it must be according to the laws of mental physics.

In the OB, determination of the process of the PIT is regulated by ratio-expression from practical Reason acting through determining judgment (Fig.3.11). Therefore, the complete synthesis of objective equivalence is realized by means of the overall synthesis of judgmentation.

In conclusion, the above minimal neural network (Fig.5.24) has the ability to generate equivalence relations. With the exception of pattern sequence length L = 2, if the network demonstrates relationship for the L^{th} process then the patterns within that sequence are candidates for an equivalence relation. It should be emphasized that the generation of equivalence relations is based on network dynamics without any a priori knowledge. In other words, the relationships are generated without introducing any a priori information about the patterns.

Chapter 6. Conclusion

We have shown that by using ART (EFT) we have discovered a minimal neural network anatomy that can generate equivalence relation. The model incorporates determined proxy functions for PIT and TRJ. Based on MMA, the build process led to the identification of ten postulates which were sufficient for the minimal anatomy to generate equivalence relations. The property set therefore contains these postulates:

- Comparation network exhibits reflexive and symmetric relations,
- The act of comparation involves a minimum of two inputs,
- The act compares dynamically generated axiomatic features,
- The act is judged expedient if it is not contrary to the categorical imperative,
- Comparation process comprises interacting sub-process for respective comparands,
- TRJ judges the process,
- Comparands are determined to show relationship if it is not contrary to the categorical imperative,
- The comparation process does not recall past actions,
- PIT determines the content for comparation, and
- Non-expediency of the comparation process results in PIT short-circuiting the contents.

The dynamics of this particular neural network shows that if a relationship between patterns is found, then the relationship is both reflexive and symmetric. The patterns constitute a candidate set. It is further shown that if a candidate set of patterns satisfies transitivity, then that set forms elements of an equivalence class. Therefore the neural network developed here performs comparation. It also demonstrated capability of experiencing absence of transitivity. For instance, pattern-combos {A, C} and {C, D} show relationship but not for {A, D}. In other words, the difference (in M-outputs) for {A, C} and {C, D} is smaller than Weber and Fechner's 'just noticeable difference'. But difference for {A, D} is larger and hence noticeably different.

The network also makes the prediction that, all pattern-combos will demonstrate relationship if the patterns are placed on a larger retinal-map size. This prediction of loss of sharpness of discriminating patterns with increasing retinal-map size is functionally similar to fonts 'a' and 'e' appearing indistinguishable at a distance. Thus, the difference (in M-outputs) is always smaller than the 'just noticeable difference'.

Therefore, the provided demonstrations show that generation of equivalence relation by means of minimal network (Fig.5.24) is possible. For the realization of complete synthesis of objective equivalence, the overall synthesis of judgmentation is involved.

The demonstrated results are behaviors that are emergent network properties. Nothing in the design of the network explicitly inserted the relationship vs. no relationship characteristics. In other words, no a priori objective criterion for defining features was introduced. Thus, the reported experiments are the first-ever demonstration that ART is capable of self-determining feature sets.

The model therefore does not violate epistemological law of mental physics, which holds that human beings are born with no objective knowledge a priori whatsoever. The results of this project is the first time any neural network system has demonstrated this capacity, and this is an original contribution to knowledge.

Topics for future research

Following each simulation (in chapter 5), the determined outcome (relationship or no) was analyzed for identifying the 'feature' based on the possible metric, diff-pc (difference-percentage). This metric was introduced on the premise that, the number of non-zero pixels plays an important role on the network's self-determining feature sets. Thus, diff-pc = diff-fact • ppx where, diff-fact • U = U – L (upper, U and lower, L CPV magnitudes of the two patterns) and ppx is the parameter corresponding to the difference of number of non-zero pixels. The ppx value is empirically determined. Thus, diff-pc as a metric for possible explanation of what the network considers as 'features' is based on empirical observations. In other words, diff-pc does not guarantee to explain features because it may not hold as a metric for other test-cases (not performed here). Hence, identifying the metric that would be applicable for all variants of input patterns is a topic for future research.

The input patterns (pre-normalized) for all test-cases employed in this project is binary. Binary inputs were chosen for its simplicity and convenience. Thus, implementing input with noise and real-numbered value is a topic for future research. It should however be noted that ART networks demonstrate NICE or noise-induced contrast enhancement with noisy inputs [Wells, 2010]. This NICE behavior is undesirable and can be avoided by changing the quenching threshold. This can be done by making the distance between the lower ($u^{(1)}$) and upper ($u^{(2)}$) parameters of the activation shape function smaller.

Recall that the weights (instars, W and outstars, Z) of the neural network are adaptive. The weights adapt from their respective initial values. For the next pattern-combo the weights begin adapting again from re-initialized values (not from their respective adapted weight values). This is because comparation does not have memory since the OB has no conscious experience of acts in synthesis of sensibility. This property may be incorporated (but without re-initialization for every succeeding pattern-combo) in elastic weights. The elastic weights are so called because the adapted weights decay after the input (stimulus) to the network is removed, and hence has a short-term memory like effect. This elastic function was studied by Grossberg in a simple dipole-network [Grossberg, 1972b] and has also been applied in other network [Sharma, 2011]. The incorporation of elastic weight is hence another research question.

The aim for the current project was to discover an EFT based minimal neural network to generate equivalence relations for the function of comparation. Thus, the main-body of the discovered minimal anatomy (Fig. 5.24) employs ART based neural network for comparation and proxy functions for noetic processes; TRJ and PIT. Thus, another topic for future research is to design EFT based neural network for the proxy functions.

Piaget's study of intellectual development of the study discovered that the earliest cognitive operation grows out of handling things. The operations can be divided precisely into three categories which correspond to Bourbaki's 'mother structures'; algebraic, order and topological structures. Piaget says,

> "these facts (that the earliest cognitive operations in intellectual development of the child can be precisely divided into categories; of "reversibility", of "reciprocity" or of "continuity" and of "separation") suggests that the mother (Bourbaki's) structures correspond to coordinations that are necessary to all intellectual activity, though they are very elementary, even rudimentary, and quite

> lacking in generality in the earliest stages of intellectual development. It would, in fact, not be difficult to show that in these very early stages intellectual operations grow directly out of sensory-motor coordinations and that intentional sensory-motor acts *cannot* be understood apart from structures" [Piaget, 1970].

The psycho-functional abilities at the sensory-motor stage begin with mathematical sensibility. This is the ability of making parástase structured in spatio-temporal form by re-presentations of data of senses to form intuitions and affective perceptions. This is done by Verstandes-Actus (acts of understanding).

Comparation is the first in the three-step process for logical synthesis of the Verstandes-Actus. Reflexion is the second process. Mathematically, just as the act of comparation correspond to generating equivalence relations, the act of reflexion is to generating congruence relations. Thus, with respect to the research aim to develop EFT neural networks based on mental physics, minimal neural network anatomy for reflexion is the next topic for future research.

This project provides a theoretical foundation for the noetic model and hence building on this we can continue our journey in understanding "how brain-mind works" Though the current modelling scale is more towards the psychological end, the findings from such research must correspond to empirical findings from both psychological and biological studies. Thus the collaborative interdisciplinary activities play a critical role in developing such models.

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Appendix

For A to Z (5x5)		
Tables 5.1 & 5.3	↔	M-field outputs: **Tables A1-1 to A1-8**
Table 5.4	↔	diff-pc metric : **Tables A2-1 to A2-2**
For A to Z (5x5 pattern on 10x10 retina)		
Table 5.6	↔	M-field outputs: **Tables A3-1 to A3-8**
Table 5.7	↔	diff-pc metric : **Tables A4-1 to A4-2**
For A to Z (2x)		
Tables 5.8 & 5.10	↔	M-field outputs: **Tables A5-1 to A5-8**
Table 5.11	↔	diff-pc metric : **Tables A6-1 to A6-2**
For A to Z (1x vs. 2x)		
		M-field outputs: **Tables A7-1 to A7-8**
Table 5.12	↔	diff-pc metric : **Tables A8-1 to A8-2**
For 0 to 9 (5x5)		
Tables 5.13 & 5.15	↔	M-field outputs: **Table A9**
Table 5.16	↔	diff-pc metric : **Table A10**
For A to Z vs. 0 to 9 (5x5)		
Tables 5.17 & 5.19	↔	M-field outputs: **Tables A11-1 to A11-3**
Table 5.20	↔	diff-pc metric : **Table A12**
For A to Z (5x5)		
Table 5.21	↔	t-test: **Tables A13-1 to A13-11**

Figure A1. Guideline for referring raw data against the results shown in chapter 5. In addition figures A2 and A3-1 are histograms for statistical t-test and ANOVA f-test respectively. Figures A3-2 and A3-3 are the f-test results for A vs. A and A vs. F (results for A vs. P is shown in Ch.5).

Input-1 patterns (5x5)		Input-2 patterns (5x5) A	B	C	D	E	F	G	H	I	J	K	L	M
A	M (x5)	0.5347	0.5358	0.5347	0.5358	0.5358	0.5347	0.5358	0.5347	0.5347	0.0064	0.5347	0.0057	0.5347
	M (x6)	0.5347	$3.93\cdot10^{-4}$	0.5346	0.0016	$3.915\cdot10^{-4}$	0.5346	$2.45\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5347	0.5374	0.5346
	Miss.	0	3.9971	0.0002693	3.9882	3.9971	0.0002693	3.9982	0.0002693	0.0002693	3.9526	0.0003441	3.9572	0.0002693
B	M (x5)	$3.865\cdot10^{-4}$	0.5346	$4.102\cdot10^{-4}$	$4.315\cdot10^{-4}$	0.5346	$4.075\cdot10^{-4}$	0.5349	$4.065\cdot10^{-4}$	$4.112\cdot10^{-4}$	$3.58\cdot10^{-4}$	$3.747\cdot10^{-4}$	$3.432\cdot10^{-4}$	$4.09\cdot10^{-4}$
	M (x6)	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	$4.795\cdot10^{-4}$	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	Miss.	3.9971	0	3.9969	3.9968	0	3.997	3.9964	3.997	3.9969	3.9973	3.9972	3.9974	3.9969
C	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.087\cdot10^{-4}$	0.5346	0.5346	$4.08\cdot10^{-4}$	0.5346	$2.612\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.997	0	3.998	0	0	3.9781	3.9761	3.9789	0
D	M (x5)	0.0016	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0016	0.0016	0.0015	0.5346
	M (x6)	0.5358	$4.317\cdot10^{-4}$	0.5346	0.5346	$4.312\cdot10^{-4}$	0.5346	$2.73\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	Miss.	3.9882	3.9968	0.0002244	0	3.9968	0.0002244	3.998	0.0002244	0.0002244	3.988	3.9878	3.9886	0.0002244
E	M (x5)	$3.892\cdot10^{-4}$	0.5346	$4.14\cdot10^{-4}$	$4.315\cdot10^{-4}$	0.5346	$4.102\cdot10^{-4}$	0.5349	$4.147\cdot10^{-4}$	$4.072\cdot10^{-4}$	$3.502\cdot10^{-4}$	$3.757\cdot10^{-4}$	$3.447\cdot10^{-4}$	$4.1\cdot10^{-4}$
	M (x6)	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	$4.75\cdot10^{-4}$	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	Miss.	3.9971	0	3.9969	3.9968	0	3.9969	3.9965	3.9969	3.997	3.9974	3.9972	3.9974	3.9969
F	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.12\cdot10^{-4}$	0.5346	0.5346	$4.062\cdot10^{-4}$	0.5346	$2.572\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.997	0	3.9981	0	0	3.976	3.7481	3.9789	0
G	M (x5)	$2.455\cdot10^{-4}$	$4.745\cdot10^{-4}$	$2.565\cdot10^{-4}$	$2.73\cdot10^{-4}$	$4.85\cdot10^{-4}$	$2.60\cdot10^{-4}$	0.5345	$2.547\cdot10^{-4}$	$2.535\cdot10^{-4}$	$2.247\cdot10^{-4}$	$2.412\cdot10^{-4}$	$2.307\cdot10^{-4}$	$2.57\cdot10^{-4}$
	M (x6)	0.5358	0.5349	0.5356	0.5354	0.5349	0.5356	0.5345	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	Miss.	3.9982	3.9965	3.9981	3.998	3.9964	3.9981	0	3.9981	3.9981	3.9983	3.9982	3.9983	3.9981

Table A1-1. Experimental data of Comparation network with Capital English letters, A to G vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	M (x5)	0.5347	0.5347	0.5358	0.5358	0.5358	0.5358	0.0062	0.5347	0.0062	0.5358	0.0063	0.5347	0.5347
	M (x6)	0.5346	0.5347	0.0016	0.0016	$6.29 \cdot 10^{-4}$	$3.877 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.0016	0.5366	0.5347	0.5346
	Miss.	0.0002693	0	3.9882	3.9882	3.9953	3.9971	3.9536	0.0002693	3.9535	3.9882	3.9532	0.0003441	0.0002693
B	M (x5)	$4.072 \cdot 10^{-4}$	$3.862 \cdot 10^{-4}$	$4.315 \cdot 10^{-4}$	$4.315 \cdot 10^{-4}$	$4.237 \cdot 10^{-4}$	0.5346	$3.575 \cdot 10^{-4}$	$4.085 \cdot 10^{-4}$	$3.685 \cdot 10^{-4}$	$4.327 \cdot 10^{-4}$	$3.545 \cdot 10^{-4}$	$3.705 \cdot 10^{-4}$	$4.09 \cdot 10^{-4}$
	M (x6)	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	Miss.	3.997	3.9971	3.9968	3.9968	3.9968	0	3.9973	3.9969	3.9973	3.9968	3.9974	3.9972	3.9969
C	M (x5)	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0029	0.5346	0.0029	0.5346	0.0029	0.0032	0.5346
	M (x6)	0.5346	0.5347	0.5346	0.5346	$6.39 \cdot 10^{-4}$	$4.08 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	Miss.	0	0.0002693	0.0002244	0.0002244	3.9952	3.997	3.9781	0	3.9782	0.0002244	3.9782	3.9761	0
D	M (x5)	0.5346	0.0016	0.5346	0.5346	0.5354	0.5354	0.0016	0.5346	0.0016	0.5346	0.0016	0.0016	0.5346
	M (x6)	0.5346	0.5358	0.5346	0.5346	$5.967 \cdot 10^{-4}$	$4.317 \cdot 10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	Miss.	0.0002244	3.9882	0	0	3.9955	3.9968	3.988	0.0002244	3.988	0	3.988	3.9879	0.0002244
E	M (x5)	$4.097 \cdot 10^{-4}$	$3.87 \cdot 10^{-4}$	$4.317 \cdot 10^{-4}$	$4.32 \cdot 10^{-4}$	$4.282 \cdot 10^{-4}$	0.5346	$3.562 \cdot 10^{-4}$	$4.142 \cdot 10^{-4}$	$3.62 \cdot 10^{-4}$	$4.315 \cdot 10^{-4}$	$3.512 \cdot 10^{-4}$	$3.747 \cdot 10^{-4}$	$4.077 \cdot 10^{-4}$
	M (x6)	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	Miss.	3.9969	3.9971	3.9968	3.9968	3.9968	0	3.9973	3.9969	3.9973	3.9968	3.9974	3.9972	3.997
F	M (x5)	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0029	0.5346	0.0029	0.5346	0.0029	0.0032	0.5346
	M (x6)	0.5346	0.5347	0.5346	0.5346	$6.395 \cdot 10^{-4}$	$4.092 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	Miss.	0	0.0002693	0.0002244	0.0002244	3.9952	3.9969	3.9781	0	3.9782	0.0002244	3.9781	3.9761	0
G	M (x5)	$2.617 \cdot 10^{-4}$	$2.502 \cdot 10^{-4}$	$2.727 \cdot 10^{-4}$	$2.767 \cdot 10^{-4}$	$3.320 \cdot 10^{-4}$	$4.772 \cdot 10^{-4}$	$2.282 \cdot 10^{-4}$	$2.565 \cdot 10^{-4}$	$2.272 \cdot 10^{-4}$	$2.78 \cdot 10^{-4}$	$2.325 \cdot 10^{-4}$	$2.342 \cdot 10^{-4}$	$2.56 \cdot 10^{-4}$
	M (x6)	0.5356	0.5358	0.5354	0.5354	0.5351	0.5349	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	Miss.	3.998	3.9981	3.998	3.9979	3.9975	3.9964	3.9983	3.9981	3.9983	3.9979	3.9983	3.9983	3.9981

Table A1-2. Experimental data of Comparation network with Capital English letters, A to G vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5) A	B	C	D	E	F	G	H	I	J	K	L	M
H	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0033	0.0028	0.5346
	M (x6)	0.5347	$4.087\cdot10^{-4}$	0.5346	0.5346	$4.085\cdot10^{-4}$	0.5346	$2.542\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.9969	0	3.9981	0	0	3.9781	3.9757	3.9789	0
I	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.105\cdot10^{-4}$	0.5346	0.5346	$4.082\cdot10^{-4}$	0.5346	$2.552\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.997	0	3.9981	0	0	3.9781	3.9759	3.9789	0
J	M (x5)	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	M (x6)	0.0063	$3.562\cdot10^{-4}$	0.0029	0.0016	$3.507\cdot10^{-4}$	0.0029	$2.335\cdot10^{-4}$	0.0029	0.0029	0.5348	0.5347	0.5350	0.0029
	Miss.	3.953	3.9973	3.9781	3.988	3.9974	3.9782	3.9983	3.9782	3.9782	0	0.0009198	0.0013607	3.9781
K	M (x5)	0.5347	0.5361	0.5360	0.5360	0.5361	0.5360	0.5361	0.5360	0.5360	0.5347	0.5347	0.0199	0.5360
	M (x6)	0.5347	$3.745\cdot10^{-4}$	0.0032	0.0016	$3.762\cdot10^{-4}$	0.0032	$2.452\cdot10^{-4}$	0.0033	0.0032	0.5348	0.5347	0.5373	0.0033
	Miss.	0.0003441	3.9972	3.976	3.9879	3.9972	3.9761	3.9982	3.9753	3.9762	0.0009198	0	3.8518	3.9755
L	M (x5)	0.5374	0.5375	0.5374	0.5374	0.5375	0.5374	0.5375	0.5374	0.5374	0.5350	0.5373	0.5350	0.5374
	M (x6)	0.0057	$3.487\cdot10^{-4}$	0.0028	0.0015	$3.395\cdot10^{-4}$	0.0028	$2.19\cdot10^{-4}$	0.0028	0.0028	0.5348	0.0242	0.5350	0.0028
	Miss.	3.9573	3.9974	3.9789	3.9886	3.9975	3.9789	3.9984	3.9789	3.9789	0.0013607	3.8198	0	3.9789
M	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0033	0.0028	0.5346
	M (x6)	0.5347	$4.08\cdot10^{-4}$	0.5346	0.5346	$4.09\cdot10^{-4}$	0.5346	$2.547\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.997	0	0.0002244	3.9969	0	3.9981	0	0	3.9782	3.9754	3.9789	0
N	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.08\cdot10^{-4}$	0.5346	0.5346	$4.075\cdot10^{-4}$	0.5346	$2.557\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.997	0	0.0002244	3.997	0	3.9981	0	0	3.9781	3.9761	3.9789	0

Table A1-3. Experimental data of Comparation network with Capital English letters, H to N vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
	M (x5)	**0.5346**	**0.5346**	**0.5346**	**0.5346**	**0.5356**	**0.5356**	**0.0029**	**0.5346**	**0.0029**	**0.5346**	**0.0029**	**0.0033**	**0.5346**
H	**M (x6)**	**0.5346**	**0.5347**	**0.5346**	**0.5346**	$6.372\cdot10^{-4}$	$4.12\cdot10^{-4}$	**0.5366**	**0.5346**	**0.5366**	**0.5346**	**0.5366**	**0.5360**	**0.5346**
	Miss.	**0**	**0.0002693**	**0.0002244**	**0.0002244**	**3.9952**	**3.9969**	**3.9781**	**0**	**3.9782**	**0.0002244**	**3.9781**	**3.9757**	**0**
	M (x5)	**0.5346**	**0.5346**	**0.5346**	**0.5346**	**0.5356**	**0.5356**	**0.0029**	**0.5346**	**0.0029**	**0.5346**	**0.0029**	**0.0032**	**0.5346**
I	**M (x6)**	**0.5346**	**0.5347**	**0.5346**	**0.5346**	$6.385\cdot10^{-4}$	$4.122\cdot10^{-4}$	**0.5366**	**0.5346**	**0.5366**	**0.5346**	**0.5366**	**0.5360**	**0.5346**
	Miss.	**0**	**0.0002693**	**0.0002244**	**0.0002244**	**3.9952**	**3.9969**	**3.9781**	**0**	**3.9781**	**0.0002244**	**3.9782**	**3.9764**	**0**
	M (x5)	**0.5366**	**0.5366**	**0.5367**	**0.5367**	**0.5367**	**0.5367**	**0.5348**	**0.5366**	**0.5348**	**0.5367**	**0.5348**	**0.5348**	**0.5366**
J	**M (x6)**	**0.0029**	**0.0062**	**0.0016**	**0.0016**	$5.665\cdot10^{-4}$	$3.58\cdot10^{-4}$	**0.5348**	**0.0029**	**0.5348**	**0.0016**	**0.5348**	**0.5347**	**0.0029**
	Miss.	**3.9781**	**3.9535**	**3.988**	**3.988**	**3.9958**	**3.9973**	**0**	**3.9781**	**0**	**3.988**	**0**	**0.0009198**	**3.9781**
	M (x5)	**0.5360**	**0.5347**	**0.5360**	**0.5360**	**0.5361**	**0.5361**	**0.5347**	**0.5360**	**0.5347**	**0.5360**	**0.5347**	**0.5347**	**0.5360**
K	**M (x6)**	**0.0033**	**0.5347**	**0.0016**	**0.0016**	$6.032\cdot10^{-4}$	$3.7\cdot10^{-4}$	**0.5348**	**0.0033**	**0.5348**	**0.0016**	**0.5348**	**0.5347**	**0.0032**
	Miss.	**3.9753**	**0.0003441**	**3.9878**	**3.9879**	**3.9955**	**3.9878**	**0.0009198**	**3.9752**	**0.0009198**	**3.9879**	**0.0009198**	**0**	**3.9762**
	M (x5)	**0.5374**	**0.5374**	**0.5374**	**0.5374**	**0.5375**	**0.5375**	**0.5350**	**0.5374**	**0.5350**	**0.5374**	**0.5350**	**0.5373**	**0.5374**
L	**M (x6)**	**0.0028**	**0.0057**	**0.0015**	**0.0015**	$5.427\cdot10^{-4}$	$3.512\cdot10^{-4}$	**0.5348**	**0.0028**	**0.5348**	**0.0015**	**0.5348**	**0.0243**	**0.0028**
	Miss.	**3.9788**	**3.9573**	**3.9886**	**3.9885**	**3.996**	**3.9974**	**0.0013607**	**3.9789**	**0.0013607**	**3.9886**	**0.0013607**	**3.819**	**3.9789**
	M (x5)	**0.5346**	**0.5346**	**0.5346**	**0.5346**	**0.5356**	**0.5356**	**0.0029**	**0.5346**	**0.0029**	**0.5346**	**0.0029**	**0.0033**	**0.5346**
M	**M (x6)**	**0.5346**	**0.5347**	**0.5346**	**0.5346**	$6.37\cdot10^{-4}$	$4.11\cdot10^{-4}$	**0.5366**	**0.5346**	**0.5366**	**0.5346**	**0.5366**	**0.5360**	**0.5346**
	Miss.	**0**	**0.0002693**	**0.0002244**	**0.0002244**	**3.9952**	**3.9969**	**3.9781**	**0**	**3.9782**	**0.0002244**	**3.9781**	**3.9756**	**0**
	M (x5)	**0.5346**	**0.5346**	**0.5346**	**0.5346**	**0.5356**	**0.5356**	**0.0029**	**0.5346**	**0.0029**	**0.5346**	**0.0029**	**0.0032**	**0.5346**
N	**M (x6)**	**0.5346**	**0.5347**	**0.5346**	**0.5346**	$6.355\cdot10^{-4}$	$4.077\cdot10^{-4}$	**0.5366**	**0.5346**	**0.5366**	**0.5346**	**0.5366**	**0.5360**	**0.5346**
	Miss.	**0**	**0.0002693**	**0.0002244**	**0.0002244**	**3.9953**	**3.997**	**3.9781**	**0**	**3.9781**	**0.0002244**	**3.9781**	**3.9758**	**0**

Table A1-4. Experimental data of Comparation network with Capital English letters, H to N vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5) A	B	C	D	E	F	G	H	I	J	K	L	M
O	M (x5)	0.5347	0.5358	0.5347	0.5358	0.5358	0.5347	0.5358	0.5347	0.5347	0.0063	0.5347	0.0058	0.5347
	M (x6)	0.5347	$3.922\cdot10^{-4}$	0.5346	0.0016	$3.87\cdot10^{-4}$	0.5346	$2.522\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5347	0.5374	0.5346
	Miss.	0	3.9971	0.0002693	3.9882	3.9971	0.0002693	3.9981	0.0002693	0.0002693	3.9533	0.0003441	3.9572	0.0002693
P	M (x5)	0.0016	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0016	0.0016	0.0015	0.5346
	M (x6)	0.5358	$4.322\cdot10^{-4}$	0.5346	0.5346	$4.322\cdot10^{-4}$	0.5346	$2.777\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	Miss.	3.9882	3.9968	0.0002244	0	3.9968	0.0002244	3.9979	0.0002244	0.0002244	3.988	3.9879	3.9885	0.0002244
Q	M (x5)	0.0016	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0016	0.0016	0.0015	0.5346
	M (x6)	0.5358	$4.317\cdot10^{-4}$	0.5346	0.5346	$4.32\cdot10^{-4}$	0.5346	$2.772\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	Miss.	3.9882	3.9968	0.0002244	0	3.9968	0.0002244	3.9979	0.0002244	0.0002244	3.988	3.9878	3.9885	0.0002244
R	M (x5)	$6.257\cdot10^{-4}$	0.5351	$6.395\cdot10^{-4}$	$5.97\cdot10^{-4}$	0.5351	$6.395\cdot10^{-4}$	0.5351	$6.387\cdot10^{-4}$	$6.385\cdot10^{-4}$	$5.7\cdot10^{-4}$	$6.01\cdot10^{-4}$	$5.45\cdot10^{-4}$	$6.407\cdot10^{-4}$
	M (x6)	0.5358	$4.335\cdot10^{-4}$	0.5356	0.5354	$4.312\cdot10^{-4}$	0.5356	$3.335\cdot10^{-4}$	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	Miss.	3.9953	3.9968	3.9952	3.9955	3.9968	3.9952	3.9975	3.9952	3.9952	3.9958	3.9955	3.9959	3.9952
S	M (x5)	$3.935\cdot10^{-4}$	0.5346	$4.097\cdot10^{-4}$	$4.32\cdot10^{-4}$	0.5346	$4.09\cdot10^{-4}$	0.5349	$4.1\cdot10^{-4}$	$4.09\cdot10^{-4}$	$3.58\cdot10^{-4}$	$3.722\cdot10^{-4}$	$3.49\cdot10^{-4}$	$4.172\cdot10^{-4}$
	M (x6)	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	$4.742\cdot10^{-4}$	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	Miss.	3.9971	0	3.9969	3.9968	0	3.9969	3.9965	3.9969	3.9969	3.9973	3.9972	3.9974	3.9969
T	M (x5)	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	M (x6)	0.0062	$3.59\cdot10^{-4}$	0.0029	0.0016	$3.557\cdot10^{-4}$	0.0029	$2.297\cdot10^{-4}$	0.0029	0.0029	0.5348	0.5347	0.5350	0.0029
	Miss.	3.9535	3.9973	3.9781	3.988	3.9879	3.9781	3.9983	3.9781	3.9781	0	0.0009198	0.0013607	3.9781
U	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.092\cdot10^{-4}$	0.5346	0.5346	$4.075\cdot10^{-4}$	0.5346	$2.612\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.997	0	3.998	0	0	3.9781	3.976	3.9788	0

Table A1-5. Experimental data of Comparation network with Capital English letters, O to U vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
O	M (x5)	0.5347	0.5347	0.5358	0.5358	0.5358	0.5358	0.0062	0.5347	0.0063	0.5358	0.0062	0.5347	0.5347
	M (x6)	0.5346	0.5347	0.0016	0.0016	$6.257\cdot10^{-4}$	$3.872\cdot10^{-4}$	0.5366	0.5346	0.5366	0.0016	0.5366	0.5347	0.5346
	Miss.	0.0002693	0	3.9882	3.9882	3.9953	3.9971	3.9537	0.0002693	3.9531	3.9882	3.9535	0.0003441	0.0002693
P	M (x5)	0.5346	0.0016	0.5346	0.5346	0.5354	0.5354	0.0016	0.5346	0.0016	0.5346	0.0016	0.0016	0.5346
	M (x6)	0.5346	0.5358	0.5346	0.5346	$5.97\cdot10^{-4}$	$4.315\cdot10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	Miss.	0.0002244	3.9882	0	0	3.9955	3.9968	3.988	0.0002244	3.988	0	3.988	3.9878	0.0002244
Q	M (x5)	0.5346	0.0016	0.5346	0.5346	0.5354	0.5354	0.0016	0.5346	0.0016	0.5346	0.0016	0.0016	0.5346
	M (x6)	0.5346	0.5358	0.5346	0.5346	$5.995\cdot10^{-4}$	$4.312\cdot10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	Miss.	0.0002244	3.9882	0	0	3.9955	3.9968	3.988	0.0002244	3.988	0	3.988	3.9878	0.0002244
R	M (x5)	$6.395\cdot10^{-4}$	$6.287\cdot10^{-4}$	$6.032\cdot10^{-4}$	$6.047\cdot10^{-4}$	0.5346	0.5351	$5.652\cdot10^{-4}$	$6.35\cdot10^{-4}$	$5.635\cdot10^{-4}$	$5.922\cdot10^{-4}$	$5.64\cdot10^{-4}$	$6.082\cdot10^{-4}$	$6.377\cdot10^{-4}$
	M (x6)	0.5356	0.5358	0.5354	0.5354	0.5346	$4.312\cdot10^{-4}$	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	Miss.	3.9952	3.9953	3.9955	3.9955	0	3.9968	3.9958	3.9953	3.9958	3.9956	3.9958	3.9955	3.9952
S	M (x5)	$4.075\cdot10^{-4}$	$3.925\cdot10^{-4}$	$4.32\cdot10^{-4}$	$4.32\cdot10^{-4}$	$4.315\cdot10^{-4}$	0.5346	$3.517\cdot10^{-4}$	$4.145\cdot10^{-4}$	$3.63\cdot10^{-4}$	$4.322\cdot10^{-4}$	$3.505\cdot10^{-4}$	$3.825\cdot10^{-4}$	$4.087\cdot10^{-4}$
	M (x6)	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	Miss.	3.997	3.9971	3.9968	3.9968	3.9968	0	3.9974	3.9969	3.9973	3.9968	3.9974	3.9971	3.9969
T	M (x5)	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	M (x6)	0.0029	0.0062	0.0016	0.0016	$5.745\cdot10^{-4}$	$3.557\cdot10^{-4}$	0.5348	0.0029	0.5348	0.0016	0.5348	0.5347	0.0029
	Miss.	3.9781	3.9535	3.988	3.988	3.9957	3.9973	0	3.9781	0	3.988	0	0.0009198	3.9782
U	M (x5)	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0029	0.5346	0.0029	0.5346	0.0029	0.0034	0.5346
	M (x6)	0.5346	0.5347	0.5346	0.5346	$6.40\cdot10^{-4}$	$4.082\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	Miss.	0	0.0002693	0.0002244	0.0002244	3.9952	3.997	3.9782	0	3.9782	0.0002244	3.9781	3.9746	0

Table A1-6. Experimental data of Comparation network with Capital English letters, O to U vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5)												
		A	B	C	D	E	F	G	H	I	J	K	L	M
V	M (x5)	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	M (x6)	0.0063	$3.575 \cdot 10^{-4}$	0.0029	0.0016	$3.502 \cdot 10^{-4}$	0.0029	$2.36 \cdot 10^{-4}$	0.0029	0.0029	0.5348	0.5347	0.5350	0.0029
	Miss.	3.9533	3.9973	3.9781	3.988	3.9974	3.9782	3.9982	3.9781	3.9781	0	0.0009198	0.0013607	3.9781
W	M (x5)	0.0016	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0016	0.0016	0.0015	0.5346
	M (x6)	0.5358	$4.315 \cdot 10^{-4}$	0.5346	0.5346	$4.322 \cdot 10^{-4}$	0.5346	$2.757 \cdot 10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	Miss.	3.9882	3.9968	0.0002244	0	3.9968	0.0002244	3.9979	0.0002244	0.0002244	3.988	3.9879	3.9886	0.0002244
X	M (x5)	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	M (x6)	0.0062	$3.63 \cdot 10^{-4}$	0.0029	0.0016	$3.625 \cdot 10^{-4}$	0.0029	$2.267 \cdot 10^{-4}$	0.0029	0.0029	0.5348	0.5347	0.5350	0.0029
	Miss.	3.9535	3.9973	3.9781	3.988	3.9973	3.9781	3.9983	3.9781	3.9782	0	0.0009198	0.0013607	3.9781
Y	M (x5)	0.5347	0.5361	0.5360	0.5360	0.5361	0.5360	0.5361	0.5360	0.5360	0.5347	0.5347	0.0201	0.5360
	M (x6)	0.5347	$3.732 \cdot 10^{-4}$	0.0032	0.0016	$3.74 \cdot 10^{-4}$	0.0032	$2.375 \cdot 10^{-4}$	0.0032	0.0033	0.5348	0.5347	0.5373	0.0033
	Miss.	0.0003441	3.9972	3.9763	3.9878	3.9972	3.9765	3.9982	3.9762	3.9754	0.0009198	0	3.8506	3.9754
Z	M (x5)	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0029	0.0032	0.0028	0.5346
	M (x6)	0.5347	$4.122 \cdot 10^{-4}$	0.5346	0.5346	$4.102 \cdot 10^{-4}$	0.5346	$2.59 \cdot 10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	Miss.	0.0002693	3.9969	0	0.0002244	3.9969	0	3.9981	0	0	3.9781	3.9759	3.9789	0

Table A1-7. Experimental data of Comparation network with Capital English letters, V to Z vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5)												
		N	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**
V	**M (x5)**	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	M (x6)	0.0029	0.0062	0.0016	0.0016	$5.69 \cdot 10^{-4}$	$3.627 \cdot 10^{-4}$	0.5348	0.0029	0.5348	0.0016	0.5348	0.5347	0.0029
	Miss.	3.9781	3.9537	3.988	3.988	3.9958	3.9973	0	3.9782	0	3.988	0	0.0009198	3.9781
W	**M (x5)**	0.5346	0.0016	0.5346	0.5346	0.5354	0.5354	0.0016	0.5346	0.0016	0.5346	0.0016	0.0016	0.5346
	M (x6)	0.5346	0.5358	0.5346	0.5346	$6.042 \cdot 10^{-4}$	$4.317 \cdot 10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	Miss.	0.0002244	3.9882	0	0	3.9955	3.9968	3.988	0.0002244	3.988	0	3.988	3.9878	0.0002244
X	**M (x5)**	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	M (x6)	0.0029	0.0062	0.0016	0.0016	$5.685 \cdot 10^{-4}$	$3.517 \cdot 10^{-4}$	0.5348	0.0029	0.5348	0.0016	0.5348	0.5347	0.0029
	Miss.	3.9781	3.9535	3.988	3.988	3.9958	3.9974	0	3.9781	0	3.988	0	0.0009198	3.9781
Y	**M (x5)**	0.5360	0.5347	0.5360	0.5360	0.5361	0.5361	0.5347	0.5360	0.5347	0.5360	0.5347	0.5347	0.5360
	M (x6)	0.0034	0.5347	0.0016	0.0016	$6.06 \cdot 10^{-4}$	$3.812 \cdot 10^{-4}$	0.5348	0.0032	0.5348	0.0016	0.5348	0.5347	0.0032
	Miss.	3.9748	0.0003441	3.9878	3.9879	3.9955	3.9972	0.0009198	3.9763	0.0009198	3.9878	0.0009198	0	3.9765
Z	**M (x5)**	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0029	0.5346	0.0029	0.5346	0.0029	0.0032	0.5346
	M (x6)	0.5346	0.5347	0.5346	0.5346	$6.382 \cdot 10^{-4}$	$4.112 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	Miss.	0	0.0002693	0.0002244	0.0002244	3.9952	3.9969	3.9781	0	3.9781	0.0002244	3.9781	3.9764	0

Table A1-8. Experimental data of Comparation network with Capital English letters, V to Z vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Comparand-1 Patterns (5x5)		Comparand-2 Patterns (5x5)				
		G	**B, E, S**	**R**	**D, P, Q, W**	**C, F, H, I, M, N, U, Z**
G	α	0	-	-	-	-
	~~α~~	-	0.1186 (1) ⟹ 0.0474	0.2160 (2) ⟹ 0.0691	0.3529 (4) ⟹ 0.0811	0.4027 (5) ⟹ 0.0885
B, E, S	α	-	0	-	-	-
	~~α~~	0.1186 (1) ⟹ 0.0474	-	0.1105 (1) ⟹ 0.0442	0.2658 (3) ⟹ 0.0664	0.3223 (4) ⟹ 0.0741
R	α	-	-	0	-	-
	~~α~~	0.2160 (2) ⟹ 0.0691	0.1105 (1) ⟹ 0.0442	-	0.1746 (2) ⟹ 0.0558	0.2380 (3) ⟹ 0.0595
D, P, Q, W	α	-	-	-	0	0.0769 (1) ⟹ 0.0307
	~~α~~	0.3529 (4) ⟹ 0.0811	0.2659 (3) ⟹ 0.0664	0.1746 (2) ⟹ 0.0558	-	-
C, F, H, I, M, N, U, Z	α	-	-	-	0.0769 (1) ⟹ 0.0307	0
	~~α~~	0.4027 (5) ⟹ 0.0885	0.3223 (4) ⟹ 0.0741	0.2380 (3) ⟹ 0.0595	-	-
A, O	α	-	-	-	-	0.0725 (1) ⟹ 0.0290
	~~α~~	0.4460 (6) ⟹ 0.0892	0.3715 (5) ⟹ 0.0817	0.2933 (4) ⟹ 0.0674	0.1439 (2) ⟹ 0.0460	-
K, Y	α	-	-	-	-	-
	~~α~~	0.4814 (7) ⟹ 0.0962	0.4117 (6) ⟹ 0.0823	0.3385 (5) ⟹ 0.0744	0.1987 (3) ⟹ 0.0496	0.1319 (2) ⟹ 0.0422
J, T, V, X	α	-	-	-	-	-
	~~α~~	0.5382 (9) ⟹ 0.1076	0.4760 (8) ⟹ 0.0952	0.4109 (7) ⟹ 0.0821	0.2864 (5) ⟹ 0.0630	0.2269 (4) ⟹ 0.0521
L	α	-	-	-	-	-
	~~α~~	0.5773 (11) ⟹ 0.1154	0.5205 (10) ⟹ 0.1041	0.4608 (9) ⟹ 0.0921	0.3469 (7) ⟹ 0.0693	0.2924 (6) ⟹ 0.0584

Table A2-1. Demonstration (Part-1) of the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 5x5. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship (~~α~~, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A1-1 to A1-8.

Comparand-1 Patterns (5x5)		Comparand-2 Patterns (5x5)			
		A, O	K, Y	J, T, V, X	L
G	α	-	-	-	-
	$\cancel{\alpha}$	0.4460 (6) ⟹ 0.0892	0.4814 (7) ⟹ 0.0962	0.5382 (9) ⟹ 0.1076	0.5773 (11) ⟹ 0.1154
B, E, S	α	-	-	-	-
	$\cancel{\alpha}$	0.3715 (5) ⟹ 0.0817	0.4117 (6) ⟹ 0.0823	0.4760 (8) ⟹ 0.0952	0.5205 (10) ⟹ 0.1041
R	α	-	-	-	-
	$\cancel{\alpha}$	0.2933 (4) ⟹ 0.0674	0.3385 (5) ⟹ 0.0744	0.4109 (7) ⟹ 0.0821	0.4608 (9) ⟹ 0.0921
D, P, Q, W	α	-	-	-	-
	$\cancel{\alpha}$	0.1439 (2) ⟹ 0.0460	0.1987 (3) ⟹ 0.0496	0.2864 (5) ⟹ 0.0630	0.3469 (7) ⟹ 0.0693
C, F, H, I, M, N, U, Z	α	0.0725 (1) ⟹ 0.0290	-	-	-
	$\cancel{\alpha}$	-	0.1319 (2) ⟹ 0.0422	0.2269 (4) ⟹ 0.0521	0.2924 (6) ⟹ 0.0584
A, O	α	0	0.0640 (1) ⟹ 0.0256	-	-
	$\cancel{\alpha}$	-	-	0.1664 (3) ⟹ 0.0416	0.2371 (5) ⟹ 0.0521
K, Y	α	0.0640 (1) ⟹ 0.0256	0	0.1094 (2) ⟹ 0.0350	-
	$\cancel{\alpha}$	-	-	-	0.1849 (4) ⟹ 0.0425
J, T, V, X	α	-	0.1094 (2) ⟹ 0.0350	0	0.0848 (2) ⟹ 0.0271
	$\cancel{\alpha}$	0.1664 (3) ⟹ 0.0416	-	-	-
L	α	-	-	0.0848 (2) ⟹ 0.0271	0
	$\cancel{\alpha}$	0.2371 (5) ⟹ 0.0521	0.1849 (4) ⟹ 0.0425	-	-

Table A2-2. Demonstration (Part-2) of the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 5x5. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship ($\cancel{\alpha}$, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A1-1 to A1-8.

Input-1 patterns (10x10)		Input-2 patterns (10x10)												
		A	B	C	D	E	F	G	H	I	J	K	L	M
A	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0	0.001301	0.0003289	0.0006131	0.001301	0.0003289	0.0014879	0.0003289	0.0003289	0.0012856	0.0003663	0.0024958	0.0003289
B	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.001301	0	0.0009795	0.0006879	0	0.0009795	0.0001795	0.0009795	0.0009795	0.0025788	0.0016747	0.0038034	0.0009795
C	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0
D	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0006131	0.0006879	0.0002916	0	0.0006879	0.0002916	0.0008674	0.0002916	0.0002916	0.0018986	0.0009794	0.0031085	0.0002916
E	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.001301	0	0.0009795	0.0006879	0	0.0009795	0.0001795	0.0009795	0.0009795	0.0025788	0.0016747	0.0038034	0.0009795
F	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0
G	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0014879	0.0001795	0.001159	0.0008674	0.0001795	0.001159	0	0.001159	0.001159	0.0027656	0.0018616	0.0039828	0.001159

Table A3-1. Experimental data of Comparation network with Capital English letters, A to G vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0003289	0	0.0006131	0.0006131	0.0010991	0.001301	0.0012856	0.0003289	0.0012856	0.0006131	0.0012856	0.0003663	0.0003289
B	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0009795	0.001301	0.0006879	0.0006879	0.0002094	0	0.0025788	0.0009795	0.0025788	0.0006879	0.0025788	0.0016747	0.0009795
C	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0
D	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0002916	0.0006131	0	0	0.0004860	0.0006879	0.0018986	0.0002916	0.0018986	0	0.0018986	0.0009794	0.0002916
E	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0009795	0.001301	0.0006879	0.0006879	0.0002094	0	0.0025788	0.0009795	0.0025788	0.0006879	0.0025788	0.0016747	0.0009795
F	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0
G	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.001159	0.0014879	0.0008674	0.0008674	0.0003889	0.0001795	0.0027656	0.001159	0.0027656	0.0008674	0.0027656	0.0018616	0.001159

Table A3-2. Experimental data of Comparation network with Capital English letters, A to G vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10)												
		A	B	C	D	E	F	G	H	I	J	K	L	M
H	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0
I	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0
J	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0012856	0.0025788	0.0016071	0.0018986	0.0025788	0.0016071	0.0027656	0.0016071	0.0016071	0	0.0009044	0.001218	0.0016071
K	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003663	0.0016747	0.0006953	0.0009794	0.0016747	0.0006953	0.0018616	0.0006953	0.0006953	0.0009044	0	0.0021296	0.0006953
L	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0024958	0.0038034	0.0028246	0.0031085	0.0038034	0.0028246	0.0039828	0.0028246	0.0028246	0.001218	0.0021296	0	0.0028246
M	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0
N	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0

Table A3-3. Experimental data of Comparation network with Capital English letters, H to N vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
H	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0
I	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0
J	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0016071	0.0012856	0.0018986	0.0018986	0.0023769	0.0025788	0	0.0016071	0	0.0018986	0	0.0009044	0.0016071
K	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0006953	0.0003663	0.0009794	0.0009794	0.0014728	0.0016747	0.0009044	0.0006953	0.0009044	0.0009794	0.0009044	0	0.0006953
L	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0028246	0.0024958	0.0031085	0.0031085	0.0035867	0.0038034	0.001218	0.0028246	0.001218	0.0031085	0.001218	0.0021296	0.0028246
M	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0
N	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0

Table A3-4. Experimental data of Comparation network with Capital English letters, H to N vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10) A	B	C	D	E	F	G	H	I	J	K	L	M
O	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0	0.001301	0.0003289	0.0006131	0.001301	0.0003289	0.0014879	0.0003289	0.0003289	0.0012856	0.0003663	0.0024958	0.0003289
P	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0006131	0.0006879	0.0002916	0	0.0006879	0.0002916	0.0008674	0.0002916	0.0002916	0.0018986	0.0009794	0.0031085	0.0002916
Q	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0006131	0.0006879	0.0002916	0	0.0006879	0.0002916	0.0008674	0.0002916	0.0002916	0.0018986	0.0009794	0.0031085	0.0002916
R	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0010991	0.0002094	0.0007776	0.0004860	0.0002094	0.0007776	0.0003889	0.0007776	0.0007776	0.0023769	0.0014728	0.0035867	0.0007776
S	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.001301	0	0.0009795	0.0006879	0	0.0009795	0.0001795	0.0009795	0.0009795	0.0025788	0.0016747	0.0038034	0.0009795
T	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0012856	0.0025788	0.0016071	0.0018986	0.0025788	0.0016071	0.0027656	0.0016071	0.0016071	0	0.0009044	0.001218	0.0016071
U	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0

Table A3-5. Experimental data of Comparation network with Capital English letters, O to U vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
O	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0003289	0	0.0006131	0.0006131	0.0010991	0.001301	0.0012856	0.0003289	0.0012856	0.0006131	0.0012856	0.0003663	0.0003289
P	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0002916	0.0006131	0	0	0.0004860	0.0006879	0.0018986	0.0002916	0.0018986	0	0.0018986	0.0009794	0.0002916
Q	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0002916	0.0006131	0	0	0.0004860	0.0006879	0.0018986	0.0002916	0.0018986	0	0.0018986	0.0009794	0.0002916
R	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0007776	0.0010991	0.0004860	0.0004860	0	0.0002094	0.0023769	0.0007776	0.0023769	0.0004860	0.0023769	0.0014728	0.0007776
S	M (x5)	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0009795	0.001301	0.0006879	0.0006879	0.0002094	0	0.0025788	0.0009795	0.0025788	0.0006879	0.0025788	0.0016747	0.0009795
T	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0016071	0.0012856	0.0018986	0.0018986	0.0023769	0.0025788	0	0.0016071	0	0.0018986	0	0.0009044	0.0016071
U	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0

Table A3-6. Experimental data of Comparation network with Capital English letters, O to U vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10)												
		A	B	C	D	E	F	G	H	I	J	K	L	M
V	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0012856	0.0025788	0.0016071	0.0018986	0.0025788	0.0016071	0.0027656	0.0016071	0.0016071	0	0.0009044	0.001218	0.0016071
W	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0006131	0.0006879	0.0002916	0	0.0006879	0.0002916	0.0008674	0.0002916	0.0002916	0.0018986	0.0009794	0.0031085	0.0002916
X	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0012856	0.0025788	0.0016071	0.0018986	0.0025788	0.0016071	0.0027656	0.0016071	0.0016071	0	0.0009044	0.001218	0.0016071
Y	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003663	0.0016747	0.0006953	0.0009794	0.0016747	0.0006953	0.0018616	0.0006953	0.0006953	0.0009044	0	0.0021296	0.0006953
Z	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5350	0.5348	0.5349	0.5349	0.5348	0.5349	0.5348	0.5349	0.5349	0.5351	0.5350	0.5353	0.5349
	Miss.	0.0003289	0.0009795	0	0.0002916	0.0009795	0	0.001159	0	0	0.0016071	0.0006953	0.0028246	0

Table A3-7. Experimental data of Comparation network with Capital English letters, V to Z vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (10x10)		Input-2 patterns (10x10)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
V	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0016071	0.0012856	0.0018986	0.0018986	0.0023769	0.0025788	0	0.0016071	0	0.0018986	0	0.0009044	0.0016071
W	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0002916	0.0006131	0	0	0.0004860	0.0006879	0.0018986	0.0002916	0.0018986	0	0.0018986	0.0009794	0.0002916
X	M (x5)	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351	0.5351
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0016071	0.0012856	0.0018986	0.0018986	0.0023769	0.0025788	0	0.0016071	0	0.0018986	0	0.0009044	0.0016071
Y	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0.0006953	0.0003663	0.0009794	0.0009794	0.0014728	0.0016747	0.0009044	0.0006953	0.0009044	0.0009794	0.0009044	0	0.0006953
Z	M (x5)	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349
	M (x6)	0.5349	0.5350	0.5349	0.5349	0.5348	0.5348	0.5351	0.5349	0.5351	0.5349	0.5351	0.5350	0.5349
	Miss.	0	0.0003289	0.0002916	0.0002916	0.0007776	0.0009795	0.0016071	0	0.0016071	0.0002916	0.0016071	0.0006953	0

Table A3-8. Experimental data of Comparation network with Capital English letters, V to Z vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 3000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

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Comparand-1 Patterns (10x10)		Comparand-2 Patterns (10x10)				
		G	B, E, S	R	D, P, Q, W	C, F, H, I, M, N, U, Z
G	α	0	0.0093 (1) ⟹ 0.0037	0.0170 (2) ⟹ 0.0055	0.0318 (4) ⟹ 0.0073	0.0387 (5) ⟹ 0.0085
	~~α~~	-	-	-	-	-
B, E, S	α	0.0093 (1) ⟹ 0.0037	0	0.0078 (1) ⟹ 0.0031	0.0227 (3) ⟹ 0.0057	0.0296 (4) ⟹ 0.0068
	~~α~~	-	-	-	-	-
R	α	0.0170 (2) ⟹ 0.0055	0.0078 (1) ⟹ 0.0031	0	0.0151 (2) ⟹ 0.0048	0.0220 (3) ⟹ 0.0055
	~~α~~	-	-	-	-	-
D, P, Q, W	α	0.0318 (4) ⟹ 0.0073	0.0227 (3) ⟹ 0.0057	0.0151 (2) ⟹ 0.0048	0	0.0071 (1) ⟹ 0.0028
	~~α~~	-	-	-	-	-
C, F, H, I, M, N, U, Z	α	0.0387 (5) ⟹ 0.0085	0.0296 (4) ⟹ 0.0068	0.0220 (3) ⟹ 0.0055	0.0071 (1) ⟹ 0.0028	0
	~~α~~	-	-	-	-	-
A, O	α	0.0439 (6) ⟹ 0.0088	0.0348 (5) ⟹ 0.0077	0.0273 (4) ⟹ 0.0063	0.0124 (2) ⟹ 0.0040	0.0054 (1) ⟹ 0.0021
	~~α~~	-	-	-	-	-
K, Y	α	0.0475 (7) ⟹ 0.0095	0.0385 (6) ⟹ 0.0077	0.0310 (5) ⟹ 0.0068	0.0161 (3) ⟹ 0.0040	0.0091 (2) ⟹ 0.0029
	~~α~~	-	-	-	-	-
J, T, V, X	α	0.0511 (9) ⟹ 0.0102	0.0422 (8) ⟹ 0.0084	0.0347 (7) ⟹ 0.0069	0.0199 (5) ⟹ 0.0044	0.0129 (4) ⟹ 0.0030
	~~α~~	-	-	-	-	-
L	α	0.0450 (11) ⟹ 0.0090	0.0360 (10) ⟹ 0.0072	0.0285 (9) ⟹ 0.0057	0.0136 (7) ⟹ 0.0027	0.0066 (6) ⟹ 0.0013
	~~α~~	-	-	-	-	-

Table A4-1. Demonstration (Part-1) of the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship (~~α~~, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A3-1 to A3-8.

Comparand-1 Patterns (10x10)		Comparand-2 Patterns (10x10)			
		A, O	K, Y	J, T, V, X	L
G	α	0.0439 (6) ⟹ 0.0088	0.0475 (7) ⟹ 0.0095	0.0511 (9) ⟹ 0.0102	0.0450 (11) ⟹ 0.0090
	$\cancel{\alpha}$	-	-	-	-
B, E, S	α	0.0348 (5) ⟹ 0.0077	0.0385 (6) ⟹ 0.0077	0.0422 (8) ⟹ 0.0084	0.0360 (10) ⟹ 0.0072
	$\cancel{\alpha}$	-	-	-	-
R	α	0.0273 (4) ⟹ 0.0063	0.0310 (5) ⟹ 0.0068	0.0347 (7) ⟹ 0.0069	0.0285 (9) ⟹ 0.0057
	$\cancel{\alpha}$	-	-	-	-
D, P, Q, W	α	0.0124 (2) ⟹ 0.0040	0.0161 (3) ⟹ 0.0040	0.0199 (5) ⟹ 0.0044	0.0136 (7) ⟹ 0.0027
	$\cancel{\alpha}$	-	-	-	-
C, F, H, I, M, N, U, Z	α	0.0054 (1) ⟹ 0.0021	0.0091 (2) ⟹ 0.0029	0.0129 (4) ⟹ 0.0030	0.0066 (6) ⟹ 0.0013
	$\cancel{\alpha}$	-	-	-	-
A, O	α	0	0.0038 (1) ⟹ 0.0015	0.0076 (3) ⟹ 0.0019	0.0012 (5) ⟹ 0.0003
	$\cancel{\alpha}$	-	-	-	-
K, Y	α	0.0038 (1) ⟹ 0.0015	0	0.0039 (2) ⟹ 0.0012	0.0025 (4) ⟹ 0.0006
	$\cancel{\alpha}$	-	-	-	-
J, T, V, X	α	0.0076 (3) ⟹ 0.0019	0.0039 (2) ⟹ 0.0012	0	0.0064 (2) ⟹ 0.0021
	$\cancel{\alpha}$	-	-	-	-
L	α	0.0012 (5) ⟹ 0.0003	0.0025 (4) ⟹ 0.0006	0.0064 (2) ⟹ 0.0021	0
	$\cancel{\alpha}$	-	-	-	-

Table A4-2. Demonstration (Part-2) of the diff-pc metric for the case of comparing patterns from 26 Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship ($\cancel{\alpha}$, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A3-1 to A3-8.

Input-1 patterns (2x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
A	M (x5)	0.5345	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	$1.11 \cdot 10^{-4}$	$3.925 \cdot 10^{-5}$	$1.147 \cdot 10^{-4}$	0.5349
	M (x6)	0.5345	0	$2.85 \cdot 10^{-5}$	0	0	$2.65 \cdot 10^{-5}$	0	$2.575 \cdot 10^{-5}$	$2.775 \cdot 10^{-5}$	0.5353	0.5350	0.5357	$2.6 \cdot 10^{-5}$
	Miss.	0	4	3.9998	4	4	3.9998	4	3.9998	3.9998	3.9992	3.9997	3.9991	3.9998
B	M (x5)	0	0.0026	0	$7.5 \cdot 10^{-6}$	0.0026	0	0.0028	0	0	0	0	0	0
	M (x6)	0.5349	0.0026	0.5349	0.5348	0.0026	0.5349	0.0013	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	0	4	3.9999	0	4	2.0565	4	4	4	4	4	4
C	M (x5)	$2.85 \cdot 10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4 \cdot 10^{-5}$	$5.325 \cdot 10^{-5}$	$5.95 \cdot 10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$6 \cdot 10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0
D	M (x5)	0	0.5348	$6 \cdot 10^{-6}$	0.5345	0.5348	$5.75 \cdot 10^{-6}$	0.5348	$5 \cdot 10^{-6}$	$5 \cdot 10^{-6}$	0	0	0	$5 \cdot 10^{-6}$
	M (x6)	0.5349	$7.75 \cdot 10^{-6}$	0.5349	0.5345	$7.5 \cdot 10^{-6}$	0.5349	$3 \cdot 10^{-6}$	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	3.9999	4	0	3.9999	4	4	4	4	4	4	4	4
E	M (x5)	0	0.0026	0	$8 \cdot 10^{-6}$	0.0026	0	0.0028	0	0	0	0	0	0
	M (x6)	0.5349	0.0026	0.5349	0.5348	0.0026	0.5349	0.0013	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	0	4	3.9999	0	4	2.0434	4	4	4	4	4	4
F	M (x5)	$2.625 \cdot 10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4 \cdot 10^{-5}$	$5.45 \cdot 10^{-5}$	$5.95 \cdot 10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$6 \cdot 10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0
G	M (x5)	0	0.0013	0	$3 \cdot 10^{-6}$	0.0013	0	0.5345	0	0	0	0	0	0
	M (x6)	0.5349	0.0028	0.5349	0.5348	0.0028	0.5349	0.5345	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	2.0595	4	4	2.06	4	0	4	4	4	4	4	4

Table A5-1. Experimental data of Comparation network with 2x resolution Capital English letters, A to G vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x)												
		N	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**
A	M (x5)	0.5349	0.5345	0.5349	0.5349	0.5349	0.5349	$1.142\cdot10^{-4}$	0.5349	$1.127\cdot10^{-4}$	0.5349	$1.145\cdot10^{-4}$	$3.55\cdot10^{-5}$	0.5349
	M (x6)	$2.6\cdot10^{-5}$	0.5345	0	$2.5\cdot10^{-7}$	0	0	0.5353	$2.525\cdot10^{-5}$	0.5353	0	0.5353	0.5350	$2.65\cdot10^{-5}$
	Miss.	3.9998	0	4	4	4	4	3.9991	3.9998	3.9992	4	3.9991	3.9997	3.9998
B	M (x5)	0	0	$8\cdot10^{-6}$	$7\cdot10^{-6}$	0.0024	0.5345	0	0	0	$6.25\cdot10^{-6}$	0	0	0
	M (x6)	0.5349	0.5349	0.5348	0.5348	0.0054	0.5345	0.5353	0.5349	0.5353	0.5348	0.5353	0.5350	0.5349
	Miss.	4	4	3.9999	3.9999	2.2101	0	4	4	4	4	4	4	4
C	M (x5)	0.5345	$2.675\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.375\cdot10^{-5}$	0.5345	$6.375\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.05\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$6\cdot10^{-6}$	$5\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$5.25\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0
D	M (x5)	$6\cdot10^{-6}$	0	0.5345	0.5345	0.5348	0.5348	0	$6\cdot10^{-6}$	0	0.5345	0	0	$5.75\cdot10^{-6}$
	M (x6)	0.5349	0.5349	0.5345	0.5345	$2.7\cdot10^{-5}$	$8\cdot10^{-6}$	0.5353	0.5349	0.5353	0.5345	0.5353	0.5350	0.5349
	Miss.	4	4	0	0	3.9998	3.9999	4	4	4	0	4	4	4
E	M (x5)	0	0	$7.25\cdot10^{-6}$	$8\cdot10^{-6}$	0.0024	0.0026	0	0	0	$8\cdot10^{-6}$	0	0	0
	M (x6)	0.5349	0.5349	0.5348	0.5348	0.0054	0.0026	0.5353	0.5349	0.5353	0.5348	0.5353	0.5350	0.5349
	Miss.	4	4	3.9999	3.9999	2.2075	0	4	4	4	3.9999	4	4	4
F	M (x5)	0.5345	$2.575\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$3.55\cdot10^{-4}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.275\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5\cdot10^{-6}$	$6\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.4391	0.5345	0.5353	$6\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9968	0	3.9995	4	3.9995	3.9996	0
G	M (x5)	0	0	$3\cdot10^{-6}$	$3\cdot10^{-6}$	0.0013	0.0013	0	0	0	$3\cdot10^{-6}$	0	0	0
	M (x6)	0.5349	0.5349	0.5348	0.5348	0.0057	0.0028	0.5353	0.5349	0.5353	0.5348	0.5353	0.5350	0.5349
	Miss.	4	4	4	4	3.1255	2.06	4	4	4	4	4	4	4

Table A5-2. Experimental data of Comparation network with 2x resolution Capital English letters, A to G vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
H	M (x5)	$2.6\cdot10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4\cdot10^{-5}$	$5.225\cdot10^{-5}$	$5.9\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$6\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0
I	M (x5)	$2.65\cdot10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.35\cdot10^{-5}$	$5.27\cdot10^{-5}$	$5.9\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$5\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0
J	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	$3.675\cdot10^{-4}$	0.5353
	M (x6)	$1.14\cdot10^{-4}$	0	$6.4\cdot10^{-5}$	0	0	$6.4\cdot10^{-5}$	0	$6.35\cdot10^{-5}$	$6.4\cdot10^{-5}$	0.5346	$1.315\cdot10^{-4}$	0.5357	$6.4\cdot10^{-5}$
	Miss.	3.9991	4	3.9995	4	4	3.9995	4	3.9995	3.9995	0	3.999	3.9973	3.9995
K	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	$1.32\cdot10^{-4}$	0.5345	$1.8\cdot10^{-4}$	0.5350
	M (x6)	$3.85\cdot10^{-5}$	0	$5.2\cdot10^{-5}$	0	0	$5.2\cdot10^{-5}$	0	$5.275\cdot10^{-5}$	$5.325\cdot10^{-5}$	0.5353	0.5345	0.5357	$5.175\cdot10^{-5}$
	Miss.	3.9997	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.999	0	3.9987	3.9996
L	M (x5)	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5346	0.5357
	M (x6)	$1.14\cdot10^{-4}$	0	$5.925\cdot10^{-5}$	0	0	$5.925\cdot10^{-5}$	0	$5.95\cdot10^{-5}$	$5.95\cdot10^{-5}$	$3.825\cdot10^{-4}$	$1.79\cdot10^{-4}$	0.5346	$6\cdot10^{-5}$
	Miss.	3.9991	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9971	3.9987	0	3.9996
M	M (x5)	$2.725\cdot10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4\cdot10^{-5}$	$5.45\cdot10^{-5}$	$6\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$5\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0
N	M (x5)	$2.675\cdot10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4\cdot10^{-5}$	$5.25\cdot10^{-5}$	$6.025\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$5.25\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0

Table A5-3. Experimental data of Comparation network with 2x resolution Capital English letters, H to N vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
H	M (x5)	0.5345	$2.55\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.4\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.225\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$6\cdot10^{-6}$	$5\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$5.25\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0
I	M (x5)	0.5345	$2.7\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.35\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.325\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5.25\cdot10^{-6}$	$5\cdot10^{-6}$	$7.5\cdot10^{-7}$	0	0.5353	0.5345	0.5353	$5\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0
J	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	0.5346	0.5353	0.5346	0.5353	0.5353
	M (x6)	$6.4\cdot10^{-5}$	$1.13\cdot10^{-4}$	0	0	0	0	0.5346	$6.4\cdot10^{-5}$	0.5346	0	0.5346	$1.325\cdot10^{-4}$	$6.4\cdot10^{-5}$
	Miss.	3.9995	3.9992	4	4	4	4	0	3.9995	0	4	0	3.999	3.9995
K	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	$1.27\cdot10^{-4}$	0.5350	$1.27\cdot10^{-4}$	0.5350	$1.297\cdot10^{-4}$	0.5345	0.5350
	M (x6)	$5.35\cdot10^{-5}$	$3.5\cdot10^{-5}$	0	0	0	0	0.5353	$5.425\cdot10^{-5}$	0.5353	0	0.5353	0.5345	$5.4\cdot10^{-5}$
	Miss.	3.9996	3.9997	4	4	4	4	3.9991	3.9996	3.9991	4	3.999	0	3.9996
L	M (x5)	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357	0.5357
	M (x6)	$5.925\cdot10^{-5}$	$1.147\cdot10^{-4}$	0	0	0	0	$3.82\cdot10^{-4}$	$5.925\cdot10^{-5}$	$3.862\cdot10^{-4}$	0	$3.8\cdot10^{-4}$	$1.787\cdot10^{-4}$	$6.025\cdot10^{-5}$
	Miss.	3.9996	3.9991	4	4	4	4	3.9971	3.9996	3.9971	4	3.9972	3.9987	3.9996
M	M (x5)	0.5345	$2.775\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.4\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.4\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5\cdot10^{-6}$	$6\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$5\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0
N	M (x5)	0.5345	$2.675\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.4\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.325\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5\cdot10^{-6}$	$6\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$5\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0

Table A5-4. Experimental data of Comparation network with 2x resolution Capital English letters, H to N vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
O	M (x5)	0.5345	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	$1.137\cdot10^{-4}$	$3.525\cdot10^{-5}$	$1.142\cdot10^{-4}$	0.5349
	M (x6)	0.5345	0	$2.775\cdot10^{-5}$	0	0	$2.625\cdot10^{-5}$	0	$2.65\cdot10^{-5}$	$2.8\cdot10^{-5}$	0.5353	0.5350	0.5357	$2.675\cdot10^{-5}$
	Miss.	0	4	3.9998	4	4	3.9998	4	3.9998	3.9998	3.9991	3.9997	3.9991	3.9998
P	M (x5)	0	0.5348	$5.75\cdot10^{-6}$	0.5345	0.5348	$5\cdot10^{-6}$	0.5348	$5.75\cdot10^{-6}$	$5.75\cdot10^{-6}$	0	0	0	$5.75\cdot10^{-6}$
	M (x6)	0.5349	$7\cdot10^{-6}$	0.5349	0.5345	$8\cdot10^{-6}$	0.5349	$3\cdot10^{-6}$	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	3.9999	4	0	3.9999	4	4	4	4	4	4	4	4
Q	M (x5)	0	0.5348	$5\cdot10^{-6}$	0.5345	0.5348	$5.25\cdot10^{-6}$	0.5348	$6\cdot10^{-6}$	$5.5\cdot10^{-6}$	0	0	0	$5\cdot10^{-6}$
	M (x6)	0.5349	$7\cdot10^{-6}$	0.5349	0.5345	$8\cdot10^{-6}$	0.5349	$3\cdot10^{-6}$	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	3.9999	4	0	3.9999	4	4	4	4	4	4	4	4
R	M (x5)	0	0.0054	$1\cdot10^{-6}$	$2.5\cdot10^{-5}$	0.0054	$1\cdot10^{-6}$	0.0057	$1\cdot10^{-6}$	$1\cdot10^{-6}$	0	0	0	$1\cdot10^{-6}$
	M (x6)	0.5349	0.0024	0.5349	0.5348	0.0024	0.5349	0.0013	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	2.2115	4	3.9998	2.2099	4	3.1243	4	4	4	4	4	4
S	M (x5)	0	0.0026	0	$7.75\cdot10^{-6}$	0.0026	0	0.0027	0	0	0	0	0	0
	M (x6)	0.5349	0.0026	0.5349	0.5348	0.0026	0.5349	0.0013	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	0	4	3.9999	0	4	2.0585	4	4	4	4	4	4
T	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	$3.932\cdot10^{-4}$	0.5353
	M (x6)	$1.127\cdot10^{-4}$	0	$6.4\cdot10^{-5}$	0	0	$6.4\cdot10^{-5}$	0	$6.35\cdot10^{-5}$	$6.375\cdot10^{-5}$	0.5346	$1.267\cdot10^{-4}$	0.5357	$6\cdot10^{-5}$
	Miss.	3.9992	4	3.9995	4	4	3.9995	4	3.9995	3.9995	0	3.9991	3.9971	3.9995
U	M (x5)	$2.5\cdot10^{-5}$	0.5349	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.4\cdot10^{-5}$	$5.375\cdot10^{-5}$	$5.975\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$5\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9996	0

Table A5-5. Experimental data of Comparation network with 2x resolution Capital English letters, O to U vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
O	M (x5)	0.5349	0.5345	0.5349	0.5349	0.5349	0.5349	$1.12\cdot10^{-4}$	0.5349	$1.147\cdot10^{-4}$	0.5349	$1.135\cdot10^{-4}$	$3.925\cdot10^{-5}$	0.5349
	M (x6)	$2.425\cdot10^{-5}$	0.5345	0	$5\cdot10^{-7}$	0	0	0.5353	$2.525\cdot10^{-5}$	0.5353	0	0.5353	0.5350	$2.7\cdot10^{-5}$
	Miss.	3.9998	0	4	4	4	4	3.9992	3.9998	3.9991	4	3.9992	3.9997	3.9998
P	M (x5)	$5.25\cdot10^{-6}$	$2.5\cdot10^{-7}$	0.5345	0.5345	0.5348	0.5348	0	$5\cdot10^{-6}$	0	0.5345	0	0	$5\cdot10^{-6}$
	M (x6)	0.5349	0.5349	0.5345	0.5345	$2.7\cdot10^{-5}$	$7\cdot10^{-6}$	0.5353	0.5349	0.5353	0.5345	0.5353	0.5350	0.5349
	Miss.	4	4	0	0	3.9998	3.9999	4	4	4	0	4	4	4
Q	M (x5)	$6\cdot10^{-6}$	0	0.5345	0.5345	0.5348	0.5348	0	$6\cdot10^{-6}$	0	0.5345	0	0	$5\cdot10^{-6}$
	M (x6)	0.5349	0.5349	0.5345	0.5345	$2.6\cdot10^{-5}$	$8\cdot10^{-6}$	0.5353	0.5349	0.5353	0.5345	0.5353	0.5350	0.5349
	Miss.	4	4	0	0	3.9998	3.9999	4	4	4	0	4	4	4
R	M (x5)	$1\cdot10^{-6}$	0	$2.7\cdot10^{-5}$	$2.6\cdot10^{-5}$	0.0050	0.0054	0	$1\cdot10^{-6}$	0	$2.7\cdot10^{-5}$	0	0	$1\cdot10^{-6}$
	M (x6)	0.5349	0.5349	0.5348	0.5348	0.0050	0.0024	0.5353	0.5349	0.5353	0.5348	0.5353	0.5350	0.5349
	Miss.	4	4	3.9998	3.9998	0	2.214	4	4	4	3.9998	4	4	4
S	M (x5)	0	0	$7.5\cdot10^{-6}$	$7.25\cdot10^{-6}$	0.0024	0.0026	0	0	0	$7\cdot10^{-6}$	0	0	0
	M (x6)	0.5349	0.5349	0.5348	0.5348	0.0054	0.0026	0.5353	0.5345	0.5353	0.5348	0.5353	0.5350	0.5349
	Miss.	4	4	3.9999	3.9999	2.211	0	4	4	4	3.9999	4	4	4
T	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	0.5346	0.5353	0.5346	0.5353	0.5353
	M (x6)	$6.4\cdot10^{-5}$	$1.13\cdot10^{-4}$	0	0	0	0	0.5346	$6.4\cdot10^{-5}$	0.5346	0	0.5346	$1.29\cdot10^{-4}$	$6.4\cdot10^{-5}$
	Miss.	3.9995	3.9992	4	4	4	4	0	3.9995	0	4	0	3.999	3.9995
U	M (x5)	0.5345	$2.775\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.4\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.3\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5\cdot10^{-6}$	$6\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$6\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0

Table A5-6. Experimental data of Comparation network with 2x resolution Capital English letters, O to U vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
V	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	$3.775\cdot10^{-4}$	0.5353
	M (x6)	$1.14\cdot10^{-4}$	0	$6.4\cdot10^{-5}$	0	0	$6.375\cdot10^{-5}$	0	$6.4\cdot10^{-5}$	$6.4\cdot10^{-5}$	0.5346	$1.335\cdot10^{-4}$	0.5357	$6.4\cdot10^{-5}$
	Miss.	3.9992	4	3.9995	4	4	3.9995	4	3.9995	3.9995	0	3.999	3.9972	3.9995
W	M (x5)	0	0.5348	$6\cdot10^{-6}$	0.5345	0.5348	$5\cdot10^{-6}$	0.5348	$5\cdot10^{-6}$	$6\cdot10^{-6}$	0	0	0	$5\cdot10^{-6}$
	M (x6)	0.5349	$8\cdot10^{-6}$	0.5349	0.5345	$7\cdot10^{-6}$	0.5349	$3\cdot10^{-6}$	0.5349	0.5349	0.5353	0.5350	0.5357	0.5349
	Miss.	4	3.9999	4	0	3.9999	4	4	4	4	4	4	4	4
X	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	$3.867\cdot10^{-4}$	0.5353
	M (x6)	$1.107\cdot10^{-4}$	0	$6.4\cdot10^{-5}$	0	0	$6.35\cdot10^{-5}$	0	$6.4\cdot10^{-5}$	$6.4\cdot10^{-5}$	0.5346	$1.262\cdot10^{-4}$	0.5357	$6.4\cdot10^{-5}$
	Miss.	3.9992	4	3.9995	4	4	3.9995	4	3.9995	3.9995	0	3.9991	3.9971	3.9995
Y	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	$1.292\cdot10^{-4}$	0.5345	$1.8\cdot10^{-4}$	0.5350
	M (x6)	$3.35\cdot10^{-5}$	0	$5.45\cdot10^{-5}$	0	0	$5.4\cdot10^{-5}$	0	$5.325\cdot10^{-5}$	$5.1\cdot10^{-5}$	0.5353	0.5345	0.5357	$5.25\cdot10^{-5}$
	Miss.	3.9997	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.999	0	3.9987	3.9996
Z	M (x5)	$2.675\cdot10^{-5}$	0.5345	0.5345	0.5349	0.5349	0.5345	0.5349	0.5345	0.5345	$6.375\cdot10^{-5}$	$5.3\cdot10^{-5}$	$6.05\cdot10^{-5}$	0.5345
	M (x6)	0.5349	0	0.5345	$5.25\cdot10^{-6}$	0	0.5345	0	0.5345	0.5345	0.5353	0.5350	0.5357	0.5345
	Miss.	3.9998	4	0	4	4	0	4	0	0	3.9995	3.9996	3.9995	0

Table A5-7. Experimental data of Comparation network with 2x resolution Capital English letters, V to Z vs. A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (2x)		Input-2 patterns (2x) N	O	P	Q	R	S	T	U	V	W	X	Y	Z
V	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	0.5346	0.5353	0.5346	0.5353	0.5353
	M (x6)	$6.4\cdot10^{-5}$	$1.125\cdot10^{-4}$	0	0	0	0	0.5346	$6.4\cdot10^{-5}$	0.5346	0	0.5346	$1.335\cdot10^{-4}$	$6.4\cdot10^{-5}$
	Miss.	3.9995	3.9992	4	4	4	4	0	3.9995	0	4	0	3.999	3.9995
W	M (x5)	$6\cdot10^{-6}$	0	0.5345	0.5345	0.5348	0.5348	0	$6\cdot10^{-6}$	0	0.5345	0	0	$6\cdot10^{-6}$
	M (x6)	0.5349	0.5349	0.5345	0.5345	$2.5\cdot10^{-5}$	$8\cdot10^{-6}$	0.5353	0.5349	0.5353	0.5345	0.5353	0.5350	0.5349
	Miss.	4	4	0	0	3.9998	3.9999	4	4	4	0	4	4	4
X	M (x5)	0.5353	0.5353	0.5353	0.5353	0.5353	0.5353	0.5346	0.5353	0.5346	0.5353	0.5346	0.5353	0.5353
	M (x6)	$6.4\cdot10^{-5}$	$1.117\cdot10^{-4}$	0	0	0	0	0.5346	$6.4\cdot10^{-5}$	0.5346	0	0.5346	$1.277\cdot10^{-4}$	$6.4\cdot10^{-5}$
	Miss.	3.9995	3.9992	4	4	4	4	0	3.9995	0	4	0	3.999	3.9995
Y	M (x5)	0.5350	0.5350	0.5350	0.5350	0.5350	0.5350	$1.327\cdot10^{-4}$	0.5350	$1.32\cdot10^{-4}$	0.5350	$1.325\cdot10^{-4}$	0.5345	0.5350
	M (x6)	$5.1\cdot10^{-5}$	$3.825\cdot10^{-5}$	0	0	0	0	0.5353	$5.4\cdot10^{-5}$	0.5353	0	0.5353	0.5345	$5.275\cdot10^{-5}$
	Miss.	3.9996	3.9997	4	4	4	4	3.999	3.9996	3.999	4	3.999	0	3.9996
Z	M (x5)	0.5345	$2.6\cdot10^{-5}$	0.5349	0.5349	0.5349	0.5349	$6.375\cdot10^{-5}$	0.5345	$6.4\cdot10^{-5}$	0.5349	$6.4\cdot10^{-5}$	$5.15\cdot10^{-5}$	0.5345
	M (x6)	0.5345	0.5349	$5.5\cdot10^{-6}$	$5\cdot10^{-6}$	$1\cdot10^{-6}$	0	0.5353	0.5345	0.5353	$5\cdot10^{-6}$	0.5353	0.5350	0.5345
	Miss.	0	3.9998	4	4	4	4	3.9995	0	3.9995	4	3.9995	3.9996	0

Table A5-8. Experimental data of Comparation network with 2x resolution Capital English letters, V to Z vs. N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Comparand-1 Patterns (2x)		Comparand-2 Patterns (2x)				
		G	B, E, S	R	D, P, Q, W	C, F, H, I, M, N, U, Z
G	α	0	-	-	-	-
	$\not\alpha$	-	0.1214 (4) ⟹ 0.1116	0.2165 (8) ⟹ 0.1732	0.3571 (16) ⟹ 0.2857	0.4066 (20) ⟹ 0.3253
B, E, S	α	-	0	-	-	-
	$\not\alpha$	0.1214 (4) ⟹ 0.1116	-	0.1082 (4) ⟹ 0.0995	0.2683 (12) ⟹ 0.2147	0.3245 (16) ⟹ 0.2597
R	α	-	-	0	-	-
	$\not\alpha$	0.2165 (8) ⟹ 0.1732	0.1082 (4) ⟹ 0.0995	-	0.1794 (8) ⟹ 0.1435	0.2426 (12) ⟹ 0.1941
D, P, Q, W	α	-	-	-	0	-
	$\not\alpha$	0.3571 (16) ⟹ 0.2857	0.2683 (12) ⟹ 0.2147	0.1794 (8) ⟹ 0.1435	-	0.0769 (4) ⟹ 0.0707
C, F, H, I, M, N, U, Z	α	-	-	-	-	0
	$\not\alpha$	0.4065 (20) ⟹ 0.3246	0.3245 (16) ⟹ 0.2597	0.2426 (12) ⟹ 0.1941	0.0769 (4) ⟹ 0.0707	-
A, O	α	-	-	-	-	-
	$\not\alpha$	0.4532 (24) ⟹ 0.3626	0.3777 (20) ⟹ 0.3022	0.3021 (16) ⟹ 0.2417	0.1495 (8) ⟹ 0.1196	0.0786 (4) ⟹ 0.0723
K, Y	α	-	-	-	-	-
	$\not\alpha$	0.4935 (28) ⟹ 0.3848	0.4235 (24) ⟹ 0.3388	0.3535 (20) ⟹ 0.2828	0.2121 (12) ⟹ 0.1697	0.1464 (8) ⟹ 0.1171
J, T, V, X	α	-	-	-	-	-
	$\not\alpha$	0.5542 (36) ⟹ 0.4434	0.4926 (32) ⟹ 0.3942	0.4311 (28) ⟹ 0.3449	0.3066 (20) ⟹ 0.2453	0.2488 (16) ⟹ 0.1991
L	α	-	-	-	-	-
	$\not\alpha$	0.6004 (44) ⟹ 0.4804	0.5452 (40) ⟹ 0.4362	0.4900 (36) ⟹ 0.3920	0.3784 (28) ⟹ 0.3028	0.3266 (24) ⟹ 0.2614

Table A6-1. Demonstration (Part-1) of the diff-pc metric for the case of comparing patterns from 26 2x resolution Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (5x5) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship ($\not\alpha$, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A5-1 to A5-8.

Comparand-1 Patterns (2x)		Comparand-2 Patterns (2x)			
		A, O	K, Y	J, T, V, X	L
G	α	-	-	-	-
	$\not\alpha$	0.4532 (24) ⟹ 0.3626	0.4935 (28) ⟹ 0.3948	0.5542 (36) ⟹ 0.4434	0.6004 (44) ⟹ 0.4804
B, E, S	α	-	-	-	-
	$\not\alpha$	0.3777 (20) ⟹ 0.3022	0.4235 (24) ⟹ 0.3388	0.4926 (32) ⟹ 0.3942	0.5452 (40) ⟹ 0.4362
R	α	-	-	-	-
	$\not\alpha$	0.3021 (16) ⟹ 0.2417	0.3535 (20) ⟹ 0.2828	0.4311 (28) ⟹ 0.3449	0.4900 (36) ⟹ 0.3920
D, P, Q, W	α	-	-	-	-
	$\not\alpha$	0.1495 (8) ⟹ 0.1196	0.2121 (12) ⟹ 0.1697	0.3066 (20) ⟹ 0.2453	0.3784 (28) ⟹ 0.3028
C, F, H, I, M, N, U, Z	α	-	-	-	-
	$\not\alpha$	0.0786 (4) ⟹ 0.0723	0.1464 (8) ⟹ 0.1171	0.2488 (16) ⟹ 0.1991	0.3266 (24) ⟹ 0.2614
A, O	α	0	-	-	-
	$\not\alpha$	-	0.0735 (4) ⟹ 0.0676	0.1847 (12) ⟹ 0.1478	0.2692 (20) ⟹ 0.2154
K, Y	α	-	0	-	-
	$\not\alpha$	0.0735 (4) ⟹ 0.0676	-	0.1200 (8) ⟹ 0.0960	0.2111 (16) ⟹ 0.1689
J, T, V, X	α	-	-	0	-
	$\not\alpha$	0.1847 (12) ⟹ 0.1478	0.1200 (8) ⟹ 0.0960	-	0.1035 (8) ⟹ 0.0828
L	α	-	-	-	0
	$\not\alpha$	0.2692 (20) ⟹ 0.2154	0.2111 (16) ⟹ 0.1689	0.1035 (8) ⟹ 0.0828	-

Table A6-2. Demonstration (Part-2) of the diff-pc metric for the case of comparing patterns from 26 2x resolution Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (5x5) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship ($\not\alpha$, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A5-1 to A5-8.

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Input-1 patterns (1x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
A	M (x5)	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5374	0.5375
	M (x6)	$9.95\cdot10^{-5}$	0	$5.05\cdot10^{-5}$	0	0	$5.075\cdot10^{-5}$	0	$5.15\cdot10^{-5}$	$5.025\cdot10^{-5}$	$4.722\cdot10^{-4}$	$1.642\cdot10^{-4}$	0.0018	$5.15\cdot10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9868	3.9996
B	M (x5)	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5366	0.5367
	M (x6)	$1.067\cdot10^{-4}$	0	$5.275\cdot10^{-5}$	0	0	$5.275\cdot10^{-5}$	0	$5.25\cdot10^{-5}$	$5.45\cdot10^{-5}$	$4.845\cdot10^{-4}$	$1.68\cdot10^{-4}$	0.0018	$5.375\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9987	3.9867	3.9996
C	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.055\cdot10^{-4}$	0	$5.3\cdot10^{-5}$	0	0	$5.175\cdot10^{-5}$	0	$5.075\cdot10^{-5}$	$5.25\cdot10^{-5}$	$4.75\cdot10^{-4}$	$1.652\cdot10^{-4}$	0.0018	$5.05\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
D	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$1.045\cdot10^{-4}$	0	$5.15\cdot10^{-5}$	0	0	$5.2\cdot10^{-5}$	0	$5.3\cdot10^{-5}$	$5.4\cdot10^{-5}$	$4.765\cdot10^{-4}$	$1.677\cdot10^{-4}$	0.0018	$5.225\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
E	M (x5)	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5366	0.5367
	M (x6)	$1.077\cdot10^{-4}$	0	$5.425\cdot10^{-5}$	0	0	$5.35\cdot10^{-5}$	0	$5.375\cdot10^{-5}$	$5.4\cdot10^{-5}$	$4.845\cdot10^{-4}$	$1.68\cdot10^{-4}$	0.0018	$5.275\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9987	3.9867	3.9996
F	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.032\cdot10^{-4}$	0	$5.275\cdot10^{-5}$	0	0	$5.1\cdot10^{-5}$	0	$5.05\cdot10^{-5}$	$5.05\cdot10^{-5}$	$4.772\cdot10^{-4}$	$1.68\cdot10^{-4}$	0.0018	$5.275\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9987	3.9867	3.9996
G	M (x5)	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5365	0.5366
	M (x6)	$1.057\cdot10^{-4}$	0	$5.4\cdot10^{-5}$	0	0	$5.3\cdot10^{-5}$	0	$5.425\cdot10^{-5}$	$5.5\cdot10^{-5}$	$4.86\cdot10^{-4}$	$1.687\cdot10^{-4}$	0.0018	$5.4\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9987	3.9867	3.9996

Table A7-1. Experimental data of Comparation network with 1x resolution A to G vs. 2x resolution A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x)												
		N	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**
A	**M (x5)**	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375
	M (x6)	$5.2\cdot10^{-5}$	$1.032\cdot10^{-4}$	0	0	0	0	$4.72\cdot10^{-4}$	$5.175\cdot10^{-5}$	$4.71\cdot10^{-4}$	0	$4.75\cdot10^{-4}$	$1.612\cdot10^{-4}$	$5.15\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
B	**M (x5)**	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367
	M (x6)	$5.425\cdot10^{-5}$	$1.042\cdot10^{-4}$	0	0	0	0	$4.842\cdot10^{-4}$	$5.225\cdot10^{-5}$	$4.847\cdot10^{-4}$	0	$4.84\cdot10^{-4}$	$1.68\cdot10^{-4}$	$5.425\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9987	3.9996
C	**M (x5)**	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.225\cdot10^{-5}$	$1.012\cdot10^{-4}$	0	0	0	0	$4.755\cdot10^{-4}$	$5.175\cdot10^{-5}$	$4.76\cdot10^{-4}$	0	$4.752\cdot10^{-4}$	$1.625\cdot10^{-4}$	$5.05\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
D	**M (x5)**	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$5.15\cdot10^{-5}$	$1.04\cdot10^{-4}$	0	0	0	0	$4.767\cdot10^{-4}$	$5.125\cdot10^{-5}$	$4.752\cdot10^{-4}$	0	$4.78\cdot10^{-4}$	$1.637\cdot10^{-4}$	$5.25\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9965	4	3.9964	3.9988	3.9996
E	**M (x5)**	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367
	M (x6)	$5.375\cdot10^{-5}$	$1.032\cdot10^{-4}$	0	0	0	0	$4.842\cdot10^{-4}$	$5.425\cdot10^{-5}$	$4.845\cdot10^{-4}$	0	$4.842\cdot10^{-4}$	$1.71\cdot10^{-4}$	$5.25\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9987	3.9996
F	**M (x5)**	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.2\cdot10^{-5}$	$1.022\cdot10^{-4}$	0	0	0	0	$4.742\cdot10^{-4}$	$5\cdot10^{-5}$	$4.762\cdot10^{-4}$	0	$4.725\cdot10^{-4}$	$1.622\cdot10^{-4}$	$5.2\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
G	**M (x5)**	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366	0.5366
	M (x6)	$5.45\cdot10^{-5}$	$1.042\cdot10^{-4}$	0	0	0	0	$4.86\cdot10^{-4}$	$5.375\cdot10^{-5}$	$4.85\cdot10^{-4}$	0	$4.855\cdot10^{-4}$	$1.705\cdot10^{-4}$	$5.625\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9987	3.9996

Table A7-2. Experimental data of Comparation network with 1x resolution A to G vs. 2x resolution N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x)												
		A	B	C	D	E	F	G	H	I	J	K	L	M
H	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.015 \cdot 10^{-4}$	0	$5.15 \cdot 10^{-5}$	0	0	$5.075 \cdot 10^{-5}$	0	$5.1 \cdot 10^{-5}$	$5.1 \cdot 10^{-5}$	$4.73 \cdot 10^{-4}$	$1.672 \cdot 10^{-4}$	0.0018	$5.175 \cdot 10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
I	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.02 \cdot 10^{-4}$	0	$5.075 \cdot 10^{-5}$	0	0	$5.1 \cdot 10^{-5}$	0	$5.075 \cdot 10^{-5}$	$5.175 \cdot 10^{-5}$	$4.762 \cdot 10^{-4}$	$1.647 \cdot 10^{-4}$	0.0018	$5.075 \cdot 10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
J	M (x5)	0.5381	0.5382	0.5381	0.5382	0.5382	0.5381	0.5382	0.5381	0.5381	0.5381	0.5381	0.5381	0.5381
	M (x6)	$9.875 \cdot 10^{-5}$	0	$4.825 \cdot 10^{-5}$	0	0	$4.8 \cdot 10^{-5}$	0	$4.975 \cdot 10^{-5}$	$4.9 \cdot 10^{-5}$	$4.6 \cdot 10^{-4}$	$1.605 \cdot 10^{-4}$	0.0018	$4.875 \cdot 10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9966	3.9988	3.9869	3.9996
K	M (x5)	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5376	0.5377
	M (x6)	$1.015 \cdot 10^{-4}$	0	$5.075 \cdot 10^{-5}$	0	0	$5.05 \cdot 10^{-5}$	0	$5.05 \cdot 10^{-5}$	$5.05 \cdot 10^{-5}$	$4.665 \cdot 10^{-4}$	$1.605 \cdot 10^{-4}$	0.0018	$5.125 \cdot 10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9868	3.9996
L	M (x5)	0.5387	0.5387	0.5387	0.5387	0.5387	0.5387	0.5387	0.5387	0.5387	0.5386	0.5387	0.5386	0.5387
	M (x6)	$9.65 \cdot 10^{-5}$	0	$4.75 \cdot 10^{-5}$	0	0	$4.75 \cdot 10^{-5}$	0	$4.8 \cdot 10^{-5}$	$4.8 \cdot 10^{-5}$	$4.54 \cdot 10^{-4}$	$1.56 \cdot 10^{-4}$	0.0017	$4.85 \cdot 10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9966	3.9988	3.9871	3.9996
M	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.035 \cdot 10^{-4}$	0	$5.1 \cdot 10^{-5}$	0	0	$5.175 \cdot 10^{-5}$	0	$5.075 \cdot 10^{-5}$	$5.2 \cdot 10^{-5}$	$4.757 \cdot 10^{-4}$	$1.662 \cdot 10^{-4}$	0.0018	$5.075 \cdot 10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
N	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.002 \cdot 10^{-4}$	0	$5.225 \cdot 10^{-5}$	0	0	$5.025 \cdot 10^{-5}$	0	$5.275 \cdot 10^{-5}$	$5.1 \cdot 10^{-5}$	$4.747 \cdot 10^{-4}$	$1.642 \cdot 10^{-4}$	0.0018	$5.4 \cdot 10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996

Table A7-3. Experimental data of Comparation network with 1x resolution H to N vs. 2x resolution A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
H	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.1 \cdot 10^{-5}$	$1.007 \cdot 10^{-4}$	0	0	0	0	$4.755 \cdot 10^{-4}$	$5.075 \cdot 10^{-5}$	$4.765 \cdot 10^{-4}$	0	$4.735 \cdot 10^{-4}$	$1.652 \cdot 10^{-4}$	$5.075 \cdot 10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
I	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.075 \cdot 10^{-5}$	$1.052 \cdot 10^{-4}$	0	0	0	0	$4.74 \cdot 10^{-4}$	$5.4 \cdot 10^{-5}$	$4.735 \cdot 10^{-4}$	0	$4.725 \cdot 10^{-4}$	$1.612 \cdot 10^{-4}$	$5.2 \cdot 10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
J	M (x5)	0.5381	0.5381	0.5382	0.5382	0.5382	0.5382	0.5381	0.5381	0.5381	0.5382	0.5381	0.5381	0.5381
	M (x6)	$4.95 \cdot 10^{-5}$	$1 \cdot 10^{-4}$	0	0	0	0	$4.592 \cdot 10^{-4}$	$4.875 \cdot 10^{-5}$	$4.612 \cdot 10^{-4}$	0	$4.642 \cdot 10^{-4}$	$1.602 \cdot 10^{-4}$	$4.9 \cdot 10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9966	3.9996	3.9966	4	3.9965	3.9988	3.9996
K	M (x5)	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377
	M (x6)	$4.975 \cdot 10^{-5}$	$1.027 \cdot 10^{-4}$	0	0	0	0	$4.7 \cdot 10^{-4}$	$4.975 \cdot 10^{-5}$	$4.692 \cdot 10^{-4}$	0	$4.68 \cdot 10^{-4}$	$1.605 \cdot 10^{-4}$	$4.925 \cdot 10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
L	M (x5)	0.5387	0.5387	0.5387	0.5387	0.5387	0.5387	0.5386	0.5387	0.5386	0.5387	0.5386	0.5387	0.5387
	M (x6)	$4.775 \cdot 10^{-5}$	$9.85 \cdot 10^{-5}$	0	0	0	0	$4.54 \cdot 10^{-4}$	$4.75 \cdot 10^{-5}$	$4.527 \cdot 10^{-4}$	0	$4.545 \cdot 10^{-4}$	$1.562 \cdot 10^{-4}$	$4.875 \cdot 10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9966	3.9996	3.9966	4	3.9966	3.9988	3.9996
M	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.125 \cdot 10^{-5}$	$1.022 \cdot 10^{-4}$	0	0	0	0	$4.722 \cdot 10^{-4}$	$5.35 \cdot 10^{-5}$	$4.735 \cdot 10^{-4}$	0	$4.735 \cdot 10^{-4}$	$1.642 \cdot 10^{-4}$	$5.15 \cdot 10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
N	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.275 \cdot 10^{-5}$	$1.007 \cdot 10^{-4}$	0	0	0	0	$4.737 \cdot 10^{-4}$	$5.35 \cdot 10^{-5}$	$4.73 \cdot 10^{-4}$	0	$4.737 \cdot 10^{-4}$	$1.642 \cdot 10^{-4}$	$5.15 \cdot 10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996

Table A7-4. Experimental data of Comparation network with 1x resolution H to N vs. 2x resolution N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
O	M (x5)	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5374	0.5375
	M (x6)	$1\cdot10^{-4}$	0	$5.075\cdot10^{-5}$	0	0	$5.1\cdot10^{-5}$	0	$5.125\cdot10^{-5}$	$5\cdot10^{-5}$	$4.715\cdot10^{-4}$	$1.642\cdot10^{-4}$	0.0018	$5.05\cdot10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9868	3.9996
P	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$1.045\cdot10^{-4}$	0	$5.2\cdot10^{-5}$	0	0	$5.225\cdot10^{-5}$	0	$5.2\cdot10^{-5}$	$5.2\cdot10^{-5}$	$4.787\cdot10^{-4}$	$1.632\cdot10^{-4}$	0.0018	$5.225\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9988	3.9867	3.9996
Q	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$1.04\cdot10^{-4}$	0	$5.2\cdot10^{-5}$	0	0	$5.175\cdot10^{-5}$	0	$5.125\cdot10^{-5}$	$5.2\cdot10^{-5}$	$4.782\cdot10^{-4}$	$1.645\cdot10^{-4}$	0.0018	$5.25\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9988	3.9867	3.9996
R	M (x5)	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368
	M (x6)	$1.045\cdot10^{-4}$	0	$5.4\cdot10^{-5}$	0	0	$5.375\cdot10^{-5}$	0	$5.275\cdot10^{-5}$	$5.35\cdot10^{-5}$	$4.825\cdot10^{-4}$	$1.655\cdot10^{-4}$	0.0018	$5.3\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9988	3.9866	3.9996
S	M (x5)	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5366	0.5367
	M (x6)	$1.03\cdot10^{-4}$	0	$5.3\cdot10^{-5}$	0	0	$5.475\cdot10^{-5}$	0	$5.225\cdot10^{-5}$	$5.425\cdot10^{-5}$	$4.842\cdot10^{-4}$	$1.69\cdot10^{-4}$	0.0018	$5.375\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9964	3.9987	3.9867	3.9996
T	M (x5)	0.5381	0.5382	0.5381	0.5382	0.5382	0.5381	0.5382	0.5381	0.5381	0.5381	0.5381	0.5381	0.5381
	M (x6)	$1\cdot10^{-4}$	0	$4.9\cdot10^{-5}$	0	0	$4.95\cdot10^{-5}$	0	$4.975\cdot10^{-5}$	$5.025\cdot10^{-5}$	$4.637\cdot10^{-4}$	$1.615\cdot10^{-4}$	0.0018	$4.9\cdot10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9966	3.9988	3.9869	3.9996
U	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.012\cdot10^{-4}$	0	$5.275\cdot10^{-5}$	0	0	$5.125\cdot10^{-5}$	0	$5.225\cdot10^{-5}$	$5.025\cdot10^{-5}$	$4.722\cdot10^{-4}$	$1.652\cdot10^{-4}$	0.0018	$5.1\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996

Table A7-5. Experimental data of Comparation network with 1x resolution O to U vs. 2x resolution A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
O	M (x5)	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375	0.5375
	M (x6)	$5.3\cdot10^{-5}$	$1.037\cdot10^{-4}$	0	0	0	0	$4.707\cdot10^{-4}$	$5.3\cdot10^{-5}$	$4.712\cdot10^{-4}$	0	$4.71\cdot10^{-4}$	$1.652\cdot10^{-4}$	$5.05\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
P	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$5.175\cdot10^{-5}$	$1.015\cdot10^{-4}$	0	0	0	0	$4.785\cdot10^{-4}$	$5.25\cdot10^{-5}$	$4.785\cdot10^{-4}$	0	$4.792\cdot10^{-4}$	$1.672\cdot10^{-4}$	$5.225\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9988	3.9996
Q	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$5.175\cdot10^{-5}$	$1.035\cdot10^{-4}$	0	0	0	0	$4.765\cdot10^{-4}$	$5.15\cdot10^{-5}$	$4.78\cdot10^{-4}$	0	$4.787\cdot10^{-4}$	$1.657\cdot10^{-4}$	$5.25\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9964	4	3.9964	3.9988	3.9996
R	M (x5)	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368	0.5368
	M (x6)	$5.25\cdot10^{-5}$	$1.03\cdot10^{-4}$	0	0	0	0	$4.817\cdot10^{-4}$	$5.225\cdot10^{-5}$	$4.82\cdot10^{-4}$	0	$4.817\cdot10^{-4}$	$1.665\cdot10^{-4}$	$5.25\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9988	3.9996
S	M (x5)	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367	0.5367
	M (x6)	$5.225\cdot10^{-5}$	$1.045\cdot10^{-4}$	0	0	0	0	$4.842\cdot10^{-4}$	$5.3\cdot10^{-5}$	$4.84\cdot10^{-4}$	0	$4.84\cdot10^{-4}$	$1.692\cdot10^{-4}$	$5.225\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9987	3.9996
T	M (x5)	0.5381	0.5381	0.5382	0.5382	0.5382	0.5382	0.5381	0.5381	0.5381	0.5382	0.5381	0.5381	0.5381
	M (x6)	$4.95\cdot10^{-5}$	$9.975\cdot10^{-5}$	0	0	0	0	$4.615\cdot10^{-4}$	$4.875\cdot10^{-5}$	$4.632\cdot10^{-4}$	0	$4.59\cdot10^{-4}$	$1.607\cdot10^{-4}$	$4.85\cdot10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9966	3.9996	3.9966	4	3.9966	3.9988	3.9996
U	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.3\cdot10^{-5}$	$1.035\cdot10^{-4}$	0	0	0	0	$4.732\cdot10^{-4}$	$5.175\cdot10^{-5}$	$4.73\cdot10^{-4}$	0	$4.725\cdot10^{-4}$	$1.625\cdot10^{-4}$	$5.225\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996

Table A7-6. Experimental data of Comparation network with 1x resolution O to U vs. 2x resolution N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x) A	B	C	D	E	F	G	H	I	J	K	L	M
V	M (x5)	0.5381	0.5382	0.5381	0.5382	0.5382	0.5381	0.5382	0.5381	0.5381	0.5381	0.5381	0.5381	0.5381
	M (x6)	$9.875\cdot10^{-5}$	0	$5.025\cdot10^{-5}$	0	0	$4.925\cdot10^{-5}$	0	$5\cdot10^{-5}$	$5\cdot10^{-5}$	$4.657\cdot10^{-4}$	$1.587\cdot10^{-4}$	0.0018	$4.825\cdot10^{-5}$
	Miss.	3.9993	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9869	3.9996
W	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$1.035\cdot10^{-4}$	0	$5.15\cdot10^{-5}$	0	0	$5.3\cdot10^{-5}$	0	$5.25\cdot10^{-5}$	$5.175\cdot10^{-5}$	$4.767\cdot10^{-4}$	$1.657\cdot10^{-4}$	0.0018	$5.25\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996
X	M (x5)	0.5381	0.5382	0.5381	0.5382	0.5382	0.5381	0.5382	0.5381	0.5381	0.5381	0.5381	0.5381	0.5381
	M (x6)	$1.025\cdot10^{-4}$	0	$4.875\cdot10^{-5}$	0	0	$4.975\cdot10^{-5}$	0	$4.875\cdot10^{-5}$	$4.9\cdot10^{-5}$	$4.597\cdot10^{-4}$	$1.615\cdot10^{-4}$	0.0018	$4.95\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9966	3.9988	3.9869	3.9996
Y	M (x5)	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5376	0.5377
	M (x6)	$1.022\cdot10^{-4}$	0	$4.95\cdot10^{-5}$	0	0	$4.925\cdot10^{-5}$	0	$4.975\cdot10^{-5}$	$5.175\cdot10^{-5}$	$4.685\cdot10^{-4}$	$1.622\cdot10^{-4}$	0.0018	$5.075\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9868	3.9996
Z	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5372	0.5373
	M (x6)	$1.007\cdot10^{-4}$	0	$5.3\cdot10^{-5}$	0	0	$5.125\cdot10^{-5}$	0	$5.225\cdot10^{-5}$	$5.125\cdot10^{-5}$	$4.762\cdot10^{-4}$	$1.617\cdot10^{-4}$	0.0018	$5.075\cdot10^{-5}$
	Miss.	3.9992	4	3.9996	4	4	3.9996	4	3.9996	3.9996	3.9965	3.9988	3.9867	3.9996

Table A7-7. Experimental data of Comparation network with 1x resolution V to Z vs. 2x resolution A to M. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Input-1 patterns (1x)		Input-2 patterns (2x)												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
V	M (x5)	0.5381	0.5381	0.5382	0.5382	0.5382	0.5382	0.5381	0.5381	0.5381	0.5382	0.5381	0.5381	0.5381
	M (x6)	$4.95\cdot10^{-5}$	$1.002\cdot10^{-4}$	0	0	0	0	$4.64\cdot10^{-4}$	$4.85\cdot10^{-5}$	$4.597\cdot10^{-4}$	0	$4.637\cdot10^{-4}$	$1.582\cdot10^{-4}$	$4.85\cdot10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9966	3.9996	3.9966	4	3.9966	3.9988	3.9996
W	M (x5)	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371	0.5371
	M (x6)	$5.175\cdot10^{-5}$	$1.05\cdot10^{-4}$	0	0	0	0	$4.782\cdot10^{-4}$	$5.125\cdot10^{-5}$	$4.77\cdot10^{-4}$	0	$4.79\cdot10^{-4}$	$1.657\cdot10^{-4}$	$5.2\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9964	3.9996	3.9964	4	3.9964	3.9988	3.9996
X	M (x5)	0.5381	0.5381	0.5382	0.5382	0.5382	0.5382	0.5381	0.5381	0.5381	0.5382	0.5381	0.5381	0.5381
	M (x6)	$4.95\cdot10^{-5}$	$1.007\cdot10^{-4}$	0	0	0	0	$4.595\cdot10^{-4}$	$5.1\cdot10^{-5}$	$4.6\cdot10^{-4}$	0	$4.61\cdot10^{-4}$	$1.61\cdot10^{-4}$	$5\cdot10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9966	3.9996	3.9966	4	3.9966	3.9988	3.9996
Y	M (x5)	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377	0.5377
	M (x6)	$5.175\cdot10^{-5}$	$1.005\cdot10^{-4}$	0	0	0	0	$4.685\cdot10^{-4}$	$4.9\cdot10^{-5}$	$4.665\cdot10^{-4}$	0	$4.67\cdot10^{-4}$	$1.62\cdot10^{-4}$	$5.075\cdot10^{-5}$
	Miss.	3.9996	3.9993	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996
Z	M (x5)	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373	0.5373
	M (x6)	$5.275\cdot10^{-5}$	$1.02\cdot10^{-4}$	0	0	0	0	$4.75\cdot10^{-4}$	$5.05\cdot10^{-5}$	$4.742\cdot10^{-4}$	0	$4.74\cdot10^{-4}$	$1.665\cdot10^{-4}$	$5.175\cdot10^{-5}$
	Miss.	3.9996	3.9992	4	4	4	4	3.9965	3.9996	3.9965	4	3.9965	3.9988	3.9996

Table A7-8. Experimental data of Comparation network with 1x resolution V to Z vs. 2x resolution N to Z. Each box has three entries, such that two are steady state (final iteration of simulation, 6000) of the average (median) node of respective motor-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 10x10.

Comparand-1 Patterns (1x)		Comparand-2 Patterns (2x)				
		G	**B, E, S**	**R**	**D, P, Q, W**	**C, F, H, I, M, N, U, Z**
G	α	-	-	-	-	-
	~~α~~	0.6422 (54) ⟹ 0.5138	0.5928 (50) ⟹ 0.4742	0.5433 (46) ⟹ 0.4347	0.4434 (38) ⟹ 0.3547	0.3970 (34) ⟹ 0.3176
B, E, S	α	-	-	-	-	-
	~~α~~	0.6455 (55) ⟹ 0.5164	0.5966 (51) ⟹ 0.4773	0.5476 (47) ⟹ 0.4381	0.4486 (39) ⟹ 0.3589	0.4027 (35) ⟹ 0.3221
R	α	-	-	-	-	-
	~~α~~	0.6483 (56) ⟹ 0.5186	0.5997 (52) ⟹ 0.4798	0.5511 (48) ⟹ 0.4409	0.4529 (40) ⟹ 0.3623	0.4073 (36) ⟹ 0.3259
D, P, Q, W	α	-	-	-	-	-
	~~α~~	0.6536 (58) ⟹ 0.5229	0.6057 (54) ⟹ 0.4846	0.5579 (50) ⟹ 0.4463	0.4611 (42) ⟹ 0.3689	0.4162 (38) ⟹ 0.3330
C, F, H, I, M, N, U, Z	α	-	-	-	-	-
	~~α~~	0.6561 (59) ⟹ 0.5248	0.6085 (55) ⟹ 0.4868	0.5610 (51) ⟹ 0.4488	0.4650 (43) ⟹ 0.3720	0.4204 (39) ⟹ 0.3363
A, O	α	-	-	-	-	-
	~~α~~	0.6579 (60) ⟹ 0.5263	0.6106 (56) ⟹ 0.4885	0.5634 (52) ⟹ 0.4507	0.4678 (44) ⟹ 0.3743	0.4235 (40) ⟹ 0.3388
K, Y	α	-	-	-	-	-
	~~α~~	0.6592 (61) ⟹ 0.5273	0.6121 (57) ⟹ 0.4897	0.5650 (53) ⟹ 0.4520	0.4598 (45) ⟹ 0.3759	0.4257 (41) ⟹ 0.3405
J, T, V, X	α	-	-	-	-	-
	~~α~~	0.6605 (63) ⟹ 0.5284	0.6136 (59) ⟹ 0.4909	0.5667 (55) ⟹ 0.4533	0.4719 (47) ⟹ 0.3775	0.4279 (43) ⟹ 0.3423
L	α	-	-	-	-	-
	~~α~~	0.6583 (65) ⟹ 0.5266	0.6111 (61) ⟹ 0.4889	0.5639 (57) ⟹ 0.4511	0.4685 (49) ⟹ 0.3748	0.4242 (45) ⟹ 0.3394

Table A8-1. Demonstration (Part-1) of the diff-pc metric for the case of comparing patterns 1x resolution vs. 2x resolution Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (5x5) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4 and … For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship (~~α~~, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A7-1 to A7-8.

Comparand-1 Patterns (1x)		Comparand-2 Patterns (2x): A, O	K, Y	J, T, V, X	L
G	α	-	-	-	-
	~~α~~	0.3456 (30) ⟹ 0.2765	0.2936 (26) ⟹ 0.2349	0.1972 (18) ⟹ 0.1578	0.1045 (10) ⟹ 0.0836
B, E, S	α	-	-	-	-
	~~α~~	0.3517 (31) ⟹ 0.2813	0.3002 (27) ⟹ 0.2401	0.2047 (19) ⟹ 0.1638	0.1129 (11) ⟹ 0.0903
R	α	-	-	-	-
	~~α~~	0.3567 (32) ⟹ 0.2854	0.3056 (28) ⟹ 0.2445	0.2109 (20) ⟹ 0.1687	0.1197 (12) ⟹ 0.0958
D, P, Q, W	α	-	-	-	-
	~~α~~	0.3664 (34) ⟹ 0.2931	0.3161 (30) ⟹ 0.2528	0.2228 (22) ⟹ 0.1782	0.1330 (14) ⟹ 0.1064
C, F, H, I, M, N, U, Z	α	-	-	-	-
	~~α~~	0.3709 (35) ⟹ 0.2967	0.3209 (31) ⟹ 0.2567	0.2283 (23) ⟹ 0.1827	0.1391 (15) ⟹ 0.1113
A, O	α	-	-	-	-
	~~α~~	0.3743 (36) ⟹ 0.2994	0.3246 (32) ⟹ 0.2596	0.2325 (24) ⟹ 0.1860	0.1438 (16) ⟹ 0.1150
K, Y	α	-	-	-	-
	~~α~~	0.3766 (37) ⟹ 0.3013	0.3271 (33) ⟹ 0.2617	0.2353 (25) ⟹ 0.1883	0.1470 (17) ⟹ 0.1176
J, T, V, X	α	-	-	-	-
	~~α~~	0.3790 (39) ⟹ 0.3032	0.3297 (35) ⟹ 0.2638	0.2383 (27) ⟹ 0.1906	0.1503 (19) ⟹ 0.1202
L	α	-	-	-	-
	~~α~~	0.3750 (41) ⟹ 0.3000	0.3254 (37) ⟹ 0.2603	0.2334 (29) ⟹ 0.1867	0.1448 (21) ⟹ 0.1158

Table A8-2. Demonstration (Part-2) of the diff-pc metric for the case of comparing patterns 1x resolution vs. 2x resolution Capital English letters of retinal map size, 10x10. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. But unlike the previous case (5x5) the pixels have increased 4x, thus (px) → 4•ppx. The ppx values are: (1) → 4•0.4 = 1.6, (2) → 4•0.32 = 1.6, (3) → 4•0.25 = 1, (4) → 4•0.23 = 0.92, (5) → 4•0.22 = 0.88, (6 to 10) → 4•0.8 = 3.2, (11 to 20) → 4•0.8•2 = 6.4 and … For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship (~~α~~, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on tables A7-1 to A7-8.

Input-1 patterns (5x5)		Input-2 patterns (5x5)									
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**M (x5)**	0.5347	0.0059	0.5347	0.0063	0.0062	0.5347	0.5347	0.0057	0.5347	0.5347
	M (x6)	0.5347	0.5370	0.5348	0.5366	0.5366	0.5347	0.5347	0.5374	0.5346	0.5348
	Miss.	0	3.9562	0.0007554	3.9532	3.9537	0.0003441	0.0003441	3.9573	0.0002693	0.0007554
1	**M (x5)**	0.5370	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5349	0.5370	0.5349
	M (x6)	0.0059	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9561	0	0.0011216	0.0006131	0.0006131	0.0015404	0.0015404	0.0007476	3.9785	0.0011216
2	**M (x5)**	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5363	0.5348
	M (x6)	0.5347	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0030	0.5348
	Miss.	0.0007554	0.0011216	0	0.000501	0.000501	0.0004188	0.0004188	0.0018765	3.9779	0
3	**M (x5)**	0.5366	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0063	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9528	0.0006131	0.000501	0	0	0.0009198	0.0009198	0.0013607	3.9781	0.000501
4	**M (x5)**	0.5366	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0062	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9539	0.0006131	0.000501	0	0	0.0009198	0.0009198	0.0013607	3.9781	0.000501
5	**M (x5)**	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.0211	0.5360	0.5347
	M (x6)	0.5347	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5373	0.0032	0.5348
	Miss.	0.0003441	0.0015404	0.0004188	0.0009198	0.0009198	0	0	3.8432	3.9758	0.0004188
6	**M (x5)**	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.0214	0.5360	0.5347
	M (x6)	0.5347	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5373	0.0032	0.5348
	Miss.	0.0003441	0.0015404	0.0004188	0.0009198	0.0009198	0	0	3.8409	3.9759	0.0004188
7	**M (x5)**	0.5374	0.5350	0.5350	0.5350	0.5350	0.5373	0.5373	0.5350	0.5374	0.5350
	M (x6)	0.0057	0.5349	0.5348	0.5348	0.5348	0.0207	0.0207	0.5350	0.0028	0.5348
	Miss.	3.9573	0.0007476	0.0018765	0.0013607	0.0013607	3.8455	3.8462	0	3.9788	0.0018765
8	**M (x5)**	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0033	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9781	3.9781	3.9759	3.9753	3.9789	0	3.9779
9	**M (x5)**	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5363	0.5348
	M (x6)	0.5347	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0030	0.5348
	Miss.	0.0007554	0.0011216	0	0.000501	0.000501	0.0004188	0.0004188	0.0018765	3.9779	0

Table A9. Experimental data of Comparation network with Numerals, 0 to 9 vs. 0 to 9. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Comparand-1 Patterns (5x5)		Comparand-2 Patterns (5x5)						
		8	**0**	**5, 6**	**2, 9**	**3, 4**	**1**	**7**
8	α	0	0.0725 (1) ⟹ 0.0290	-	-	-	-	-
	$\not\alpha$	-	-	0.1318 (2) ⟹ 0.0421	0.1829 (3) ⟹ 0.0457	0.2268 (4) ⟹ 0.0521	0.2628 (5) ⟹ 0.0578	0.2924 (6) ⟹ 0.0585
0	α	0.0725 (1) ⟹ 0.0290	0	0.0639 (1) ⟹ 0.0255	0.1190 (2) ⟹ 0.0380	-	-	-
	$\not\alpha$	-	-	-	-	0.1664 (3) ⟹ 0.0416	0.2052 (4) ⟹ 0.0471	0.2370 (5) ⟹ 0.0521
5, 6	α	-	0.0639 (1) ⟹ 0.0255	0	0.0588 (1) ⟹ 0.0235	0.1094 (2) ⟹ 0.0350	0.1508 (3) ⟹ 0.0377	-
	$\not\alpha$	0.1318 (2) ⟹ 0.0421	-	-	-	-	-	0.1849 (5) ⟹ 0.0425
2, 9	α	-	0.1190 (2) ⟹ 0.0380	0.0588 (1) ⟹ 0.0235	0	0.0538 (1) ⟹ 0.0215	0.0978 (2) ⟹ 0.0313	0.1340 (3) ⟹ 0.0335
	$\not\alpha$	0.1829 (3) ⟹ 0.0457	-	-	-	-	-	-
3, 4	α	-	-	0.1094 (2) ⟹ 0.0350	0.0538 (1) ⟹ 0.0215	0	0.0465 (1) ⟹ 0.0186	0.0847 (2) ⟹ 0.0271
	$\not\alpha$	0.2268 (4) ⟹ 0.0521	0.1664 (3) ⟹ 0.0416	-	-	-	-	-
1	α	-	-	0.1508 (3) ⟹ 0.0377	0.0978 (2) ⟹ 0.0313	0.0465 (1) ⟹ 0.0186	0	0.0400 (1) ⟹ 0.0160
	$\not\alpha$	0.2628 (5) ⟹ 0.0578	0.2052 (4) ⟹ 0.0471	-	-	-	-	-
7	α	-	-	-	0.1340 (3) ⟹ 0.0335	0.0847 (2) ⟹ 0.0271	0.0400 (1) ⟹ 0.0160	0
	$\not\alpha$	0.2924 (6) ⟹ 0.0584	0.2370 (5) ⟹ 0.0521	0.1849 (4) ⟹ 0.0425	-	-	-	-

Table A10. Demonstration of the diff-pc metric for the case of comparing patterns from Arabic Numerals, 0 to 9 of retinal map size, 5x5. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship ($\not\alpha$, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome is based on table A9.

Input-1 patterns (5x5)		Input-2 patterns (5x5)									
		0	1	2	3	4	5	6	7	8	9
A	M (x5)	0.5347	0.0059	0.5347	0.0063	0.0062	0.5347	0.5347	0.0057	0.5347	0.5347
	M (x6)	0.5347	0.5370	0.5348	0.5366	0.5366	0.5347	0.5347	0.5374	0.5346	0.5348
	Miss.	0	3.956	0.0007554	3.9533	3.9539	0.0003441	0.0003441	3.9573	0.0002693	0.0007554
B	M (x5)	$3.94\cdot10^{-4}$	$3.45\cdot10^{-4}$	$3.59\cdot10^{-4}$	$3.537\cdot10^{-4}$	$3.555\cdot10^{-4}$	$3.735\cdot10^{-4}$	$3.7\cdot10^{-4}$	$3.4\cdot10^{-4}$	$4.092\cdot10^{-4}$	$3.607\cdot10^{-4}$
	M (x6)	0.5358	0.5371	0.5364	0.5367	0.5367	0.5361	0.5361	0.5375	0.5356	0.5364
	Miss.	3.9971	3.9974	3.9973	3.9974	3.9974	3.9972	3.9972	3.9975	3.9969	3.9973
C	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9782	3.9781	3.9759	3.9764	3.9789	0	3.9779
D	M (x5)	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0015	0.5346	0.0016
	M (x6)	0.5358	0.5370	0.5363	0.5367	0.5367	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	3.9882	3.9883	3.9878	3.988	3.988	3.9878	3.9878	3.9886	0.0002244	3.9878
E	M (x5)	$3.89\cdot10^{-4}$	$3.495\cdot10^{-4}$	$3.645\cdot10^{-4}$	$3.57\cdot10^{-4}$	$3.562\cdot10^{-4}$	$3.747\cdot10^{-4}$	$3.845\cdot10^{-4}$	$3.557\cdot10^{-4}$	$4.092\cdot10^{-4}$	$3.715\cdot10^{-4}$
	M (x6)	0.5358	0.5371	0.5364	0.5367	0.5367	0.5361	0.5361	0.5375	0.5356	0.5364
	Miss.	3.9971	3.9974	3.9973	3.9973	3.9973	3.9972	3.9971	3.9974	3.9969	3.9972
F	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9781	3.9782	3.9764	3.9762	3.9789	0	3.9779
G	M (x5)	$2.46\cdot10^{-4}$	$2.315\cdot10^{-4}$	$2.35\cdot10^{-4}$	$2.232\cdot10^{-4}$	$2.272\cdot10^{-4}$	$2.355\cdot10^{-4}$	$2.482\cdot10^{-4}$	$2.205\cdot10^{-4}$	$2.57\cdot10^{-4}$	$2.295\cdot10^{-4}$
	M (x6)	0.5358	0.5371	0.5364	0.5367	0.5367	0.5361	0.5361	0.5375	0.5356	0.5364
	Miss.	3.9982	3.9983	3.9982	3.9983	3.9983	3.9982	3.9981	3.9984	3.9981	3.9983
H	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9781	3.9781	3.9763	3.9762	3.9789	0	3.9779
I	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9784	3.9779	3.9781	3.9781	3.9765	3.9763	3.9789	0	3.9779
J	M (x5)	0.5366	0.5348	0.5348	0.5348	0.5348	0.4406	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0063	0.5349	0.5348	0.5348	0.5348	0.4397	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9529	0.0006131	0.000501	0	0	0.0079168	0.0009198	0.0013607	3.9781	0.000501

Table A11-1. Experimental data of Comparation network with Capital English letters, A to J vs. Numerals, 0 to 9. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Input-1 patterns (5x5)		Input-2 patterns (5x5)									
		0	1	2	3	4	5	6	7	8	9
K	M (x5)	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.5347	0.0197	0.5360	0.5347
	M (x6)	0.5347	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5373	0.0032	0.5348
	Miss.	0.0003441	0.0015404	0.0004188	0.0009198	0.0009198	0	0	3.8534	3.9761	0.0004188
L	M (x5)	0.5374	0.5350	0.5350	0.5350	0.5350	0.5373	0.5373	0.5350	0.5374	0.5350
	M (x6)	0.0057	0.5349	0.5348	0.5348	0.5348	0.0218	0.0214	0.5350	0.0028	0.5348
	Miss.	3.9574	0.0007476	0.0018765	0.0013607	0.0013607	3.8375	3.8408	0	3.9788	0.0018765
M	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9784	3.9779	3.9781	3.9781	3.9761	3.9762	3.9789	0	3.9779
N	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0033	0.0034	0.0261	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.4430	0.5346	0.5363
	Miss.	0.0002693	3.9784	3.9779	3.9781	3.9781	3.9756	3.9749	3.764	0	3.9779
O	M (x5)	0.5347	0.0059	0.5347	0.0063	0.0063	0.5347	0.5347	0.0057	0.5347	0.5347
	M (x6)	0.5347	0.5370	0.5348	0.5366	0.5366	0.5347	0.5347	0.5374	0.5346	0.5348
	Miss.	0	3.9561	0.0007554	3.953	3.9531	0.0003441	0.0003441	3.9573	0.0002693	0.0007554
P	M (x5)	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0015	0.5346	0.0016
	M (x6)	0.5358	0.5370	0.5363	0.5367	0.5367	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	3.9882	3.9883	3.9878	3.988	3.988	3.9878	3.9878	3.9885	0.0002244	3.9878
Q	M (x5)	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0015	0.5346	0.0016
	M (x6)	0.5358	0.5370	0.5363	0.5367	0.5367	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	3.9882	3.9883	3.9878	3.988	3.988	3.9879	3.9879	3.9885	0.0002244	3.9878
R	M (x5)	$6.267\cdot10^{-4}$	$5.537\cdot10^{-4}$	$5.887\cdot10^{-4}$	$5.625\cdot10^{-4}$	$5.62\cdot10^{-4}$	$6.042\cdot10^{-4}$	$6.032\cdot10^{-4}$	$5.422\cdot10^{-4}$	$6.397\cdot10^{-4}$	$5.787\cdot10^{-4}$
	M (x6)	0.5358	0.5371	0.5364	0.5367	0.5367	0.5361	0.5361	0.5375	0.5356	0.5364
	Miss.	3.9953	3.9959	3.9956	3.9958	3.9958	3.9955	3.9955	3.996	3.9952	3.9957
S	M (x5)	$3.935\cdot10^{-4}$	$3.447\cdot10^{-4}$	$3.665\cdot10^{-4}$	$3.537\cdot10^{-4}$	$3.602\cdot10^{-4}$	$3.727\cdot10^{-4}$	$3.775\cdot10^{-4}$	$3.425\cdot10^{-4}$	$4.075\cdot10^{-4}$	$3.595\cdot10^{-4}$
	M (x6)	0.5358	0.5371	0.5364	0.5367	0.5367	0.5361	0.5361	0.5375	0.5356	0.5364
	Miss.	3.9971	3.9974	3.9973	3.9974	3.9973	3.9972	3.9972	3.9975	3.997	3.9973
T	M (x5)	0.5366	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0063	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.953	0.0006131	0.000501	0	0	0.0009198	0.0009198	0.0013607	3.9781	0.000501

Table A11-2. Experimental data of Comparation network with Capital English letters, K to T vs. Numerals, 0 to 9. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

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Input-1 patterns (5x5)		Input-2 patterns (5x5) 0	1	2	3	4	5	6	7	8	9
U	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0034	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9781	3.9781	3.9762	3.9743	3.9788	0	3.9779
V	M (x5)	0.5366	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0063	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9528	0.0006131	0.000501	0	0	0.0009198	0.0009198	0.0013607	3.9781	0.000501
W	M (x5)	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0016	0.0015	0.5346	0.0016
	M (x6)	0.5358	0.5370	0.5363	0.5367	0.5367	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	3.9882	3.9882	3.9878	3.988	3.988	3.9879	3.9879	3.9885	0.0002244	3.9878
X	M (x5)	0.5366	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5348	0.5366	0.5348
	M (x6)	0.0062	0.5349	0.5348	0.5348	0.5348	0.5347	0.5347	0.5350	0.0029	0.5348
	Miss.	3.9535	0.0006131	0.000501	0	0	0.0009198	0.0009198	0.0013607	3.9781	0.000501
Y	M (x5)	0.5347	0.4397	0.5347	0.5347	0.5347	0.5347	0.5347	0.0243	0.5360	0.5347
	M (x6)	0.5347	0.4411	0.5348	0.5348	0.5348	0.5347	0.5347	0.5373	0.0032	0.5348
	Miss.	0.0003441	0.012334	0.0004188	0.0009198	0.0009198	0	0	3.8191	3.9764	0.0004188
Z	M (x5)	0.5346	0.0029	0.0030	0.0029	0.0029	0.0032	0.0032	0.0028	0.5346	0.0030
	M (x6)	0.5347	0.5370	0.5363	0.5366	0.5366	0.5360	0.5360	0.5374	0.5346	0.5363
	Miss.	0.0002693	3.9785	3.9779	3.9781	3.9781	3.9761	3.9762	3.9789	0	3.9779

Table A11-3. Experimental data of Comparation network with Capital English letters, U to Z vs. Numerals, 0 to 9. Each box has three entries, such that two are steady state (final iteration of simulation, 4000) of the average (median) node of respective M-field and bottom entry the mismatch value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. The retinal-map size is 5x5.

Comparand-1 Patterns (5x5)		Comparand-2 Patterns (5x5)						
		8	**0**	**5, 6**	**2, 9**	**3, 4**	**1**	**7**
G	α	-	-	-	-	-	-	-
	~~α~~	0.4027 (5) ⟹ 0.0885	0.4460 (6) ⟹ 0.0892	0.4814 (7) ⟹ 0.0962	0.5119 (8) ⟹ 0.1023	0.5382 (9) ⟹ 0.1076	0.5597 (10) ⟹ 0.1119	0.5773 (11) ⟹ 0.1154
B, E, S	α	-	-	-	-	-	-	-
	~~α~~	0.3223 (4) ⟹ 0.0741	0.3715 (5) ⟹ 0.0817	0.4117 (6) ⟹ 0.0823	0.4463 (7) ⟹ 0.0892	0.4760 (8) ⟹ 0.0952	0.5004 (9) ⟹ 0.1000	0.5205 (10) ⟹ 0.1041
R	α	-	-	-	-	-	-	-
	~~α~~	0.2380 (3) ⟹ 0.0595	0.2983 (4) ⟹ 0.0674	0.3385 (5) ⟹ 0.0744	0.3774 (6) ⟹ 0.0754	0.4109 (7) ⟹ 0.0821	0.4383 (8) ⟹ 0.0876	0.4608 (9) ⟹ 0.0921
D, P, Q, W	α	0.0769 (1) ⟹ 0.0307	-	-	-	-	-	-
	~~α~~	-	0.1439 (2) ⟹ 0.0460	0.1987 (3) ⟹ 0.0496	0.2457 (4) ⟹ 0.0565	0.2864 (5) ⟹ 0.0630	0.3195 (6) ⟹ 0.0639	0.3468 (7) ⟹ 0.0693
C, F, H, I, M, N, U, Z	α	0	0.0725 (1) ⟹ 0.0290	-	-	-	-	-
	~~α~~	-	-	0.1319 (2) ⟹ 0.0422	0.1829 (3) ⟹ 0.0457	0.2269 (4) ⟹ 0.0521	0.2628 (5) ⟹ 0.0578	0.2924 (6) ⟹ 0.0584
A, O	α	0.0725 (1) ⟹ 0.0290	0	0.0640 (1) ⟹ 0.0256	0.1190 (2) ⟹ 0.0380	-	-	-
	~~α~~	-	-	-	-	0.1664 (3) ⟹ 0.0416	0.2052 (4) ⟹ 0.0471	0.2371 (5) ⟹ 0.0521
K, Y	α	-	0.0640 (1) ⟹ 0.0256	0	0.0588 (1) ⟹ 0.0235	0.1094 (2) ⟹ 0.0350	0.1508 (3) ⟹ 0.0377	-
	~~α~~	0.1319 (2) ⟹ 0.0422	-	-	-	-	-	0.1849 (4) ⟹ 0.0425
J, T, V, X	α	-	-	0.1094 (2) ⟹ 0.0350	0.0538 (1) ⟹ 0.0215	0	0.0465 (1) ⟹ 0.0186	0.0848 (2) ⟹ 0.0271
	~~α~~	0.2269 (4) ⟹ 0.0521	0.1664 (3) ⟹ 0.0416	-	-	-	-	-
L	α	-	-	-	0.1340 (3) ⟹ 0.0335	0.0848 (2) ⟹ 0.0271	0.0400 (1) ⟹ 0.0160	0
	~~α~~	0.2924 (6) ⟹ 0.0584	0.2371 (5) ⟹ 0.0521	0.1849 (4) ⟹ 0.0425	-	-	-	-

Table A12. Demonstration of the diff-pc metric for the case of comparing Capital English against Arabic Numerals of retinal map size, 5x5. Every patterns has a corresponding cumulative pixel value, CPV. If two patterns have different CPV's, U and L such that U > L. Then difference-factor, diff-fact = (U – L) / U and difference-percentage, diff-pc = diff-fact • ppx. Every unique difference of number of non-zero pixels, px has an empirically determined parameter, ppx. Thus (px) → ppx. The ppx values are: (1) → 0.4, (2) → 0.32, (3) → 0.25, (4) → 0.23, (5) → 0.22, (6 to 10) → 0.8, (11 to 20) → 0.8•2 = 1.6, (21 to 30) → 0.8•3 = 2.4, (31 to 40) → 0.8•4 = 3.2, (41 to 50) → 0.8•5 = 4, (51 to 60) → 0.8•6 = 4.8 and so on… For each pattern-combo, value (diff-fact • ppx ⟹ diff-pc) depending upon the outcome, relationship (α, upper row; diff-pc < 4%) or non-relationship (~~α~~, lower row; diff-pc > 4%) is entered and "-" is entered for the non-outcome. The outcome are based on tables A11-1 to A11-3.

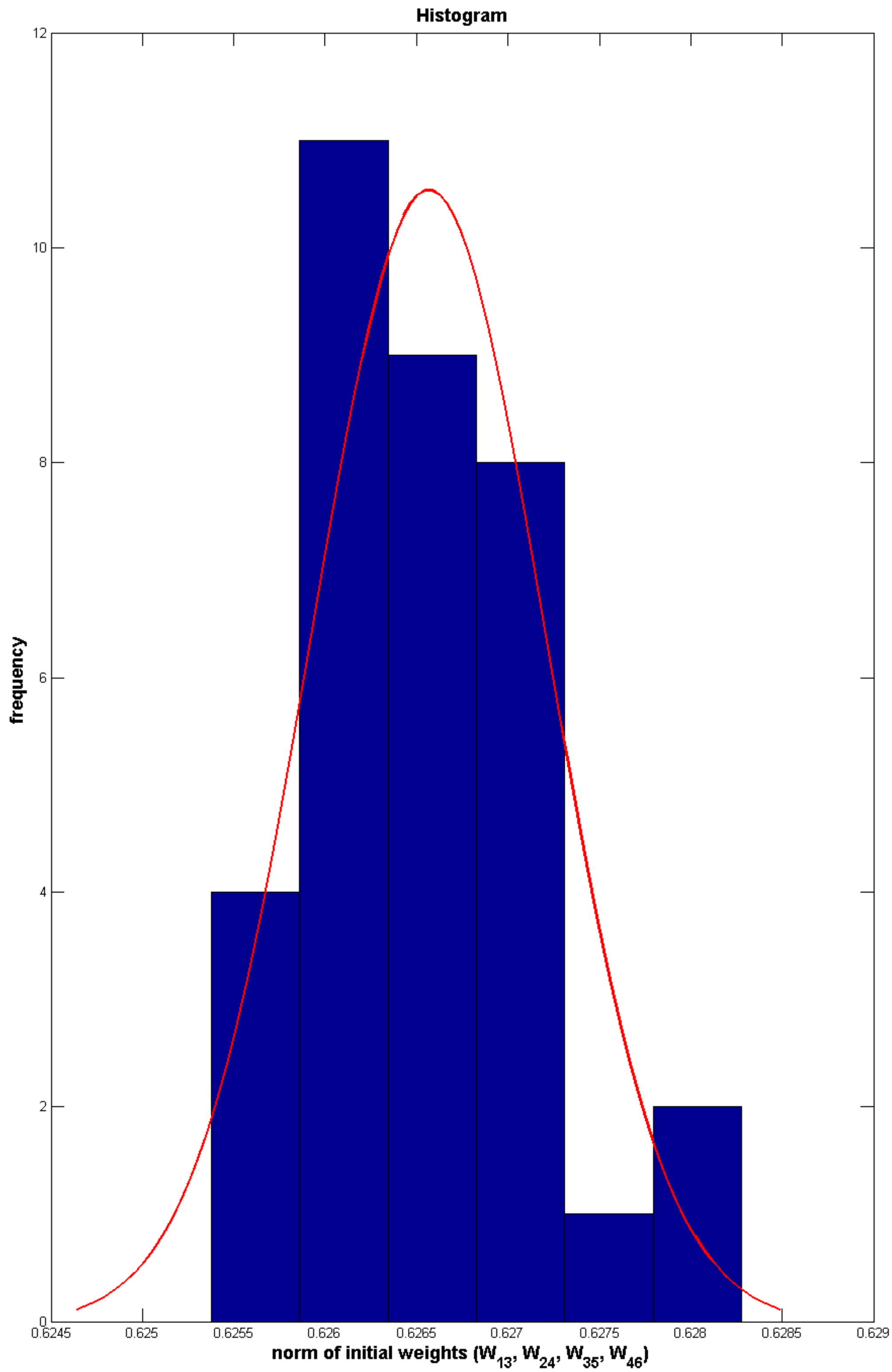

Figure A2. Histogram of norm of initial weights for paired t-test with sample size, 35. The superimposed normal (red) curve demonstrates randomly independent sample. Frequencies are for the infinity-norm of the vector composed of infinity-norm of the initial W_{13}, W_{24}, W_{35} and W_{46} matrices.

Input-1 patterns		Input-2 patterns												
		A	B	C	D	E	F	G	H	I	J	K	L	M
A	$\bar{x}_1$	0.5347	0.5358	0.5347	0.5358	0.5358	0.5347	0.5358	0.5347	0.5347	0.0080	0.5347	0.0062	0.5347
	$\bar{x}_2$	0.5347	$5.183\cdot10^{-4}$	0.5346	0.0025	$5.187\cdot10^{-4}$	0.5346	$3.267\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5347	0.5374	0.5346
	C.I	[0, 0]	[0.5353, 0.5353]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[0.5333, 0.5333]	[0.5353, 0.5353]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[0.5355, 0.5355]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[-0.5286, -0.5285]	[$-4.6\cdot10^{-5}$, $-4.6\cdot10^{-5}$]	[-0.5312, -0.5312]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]
	p-value	-	$1.45\cdot10^{-168}$	0	$5.59\cdot10^{-137}$	$1.11\cdot10^{-165}$	0	$6.02\cdot10^{-168}$	0	0	$1.13\cdot10^{-117}$	0	$1.16\cdot10^{-140}$	0
B	$\bar{x}_1$	$5.207\cdot10^{-4}$	0.5346	$5.750\cdot10^{-4}$	$6.710\cdot10^{-4}$	0.5346	$5.756\cdot10^{-4}$	0.5349	$5.740\cdot10^{-4}$	$5.756\cdot10^{-4}$	$4.396\cdot10^{-4}$	$4.828\cdot10^{-4}$	$4.137\cdot10^{-4}$	$5.746\cdot10^{-4}$
	$\bar{x}_2$	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	0.0029	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	C.I	[-0.5353, -0.5353]	[0, 0]	[-0.5350, -0.5350]	[-0.5347, -0.5347]	[0, 0]	[-0.5350, -0.5350]	[0.5320, 0.5321]	[-0.5350, -0.5350]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5371, -0.5371]	[-0.5350, -0.5350]
	p-value	$7.64\cdot10^{-164}$	-	$1.73\cdot10^{-173}$	$3.97\cdot10^{-170}$	-	$1.08\cdot10^{-166}$	$9.34\cdot10^{-130}$	$2.47\cdot10^{-168}$	$6.47\cdot10^{-168}$	$1.69\cdot10^{-166}$	$8.49\cdot10^{-167}$	$2.56\cdot10^{-169}$	$3.47\cdot10^{-169}$
C	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0055	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.753\cdot10^{-4}$	0.5346	0.5346	$5.754\cdot10^{-4}$	0.5346	$3.543\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[$3.5\cdot10^{-5}$, $3.5\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5306, -0.5305]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$1.75\cdot10^{-171}$	-	0	$1.36\cdot10^{-172}$	-	$6.43\cdot10^{-169}$	-	-	$1.04\cdot10^{-161}$	$3.51\cdot10^{-117}$	$1.19\cdot10^{-153}$	-
D	$\bar{x}_1$	0.0025	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0019	0.0021	0.0017	0.5346
	$\bar{x}_2$	0.5358	$6.710\cdot10^{-4}$	0.5346	0.5346	$6.697\cdot10^{-4}$	0.5346	$4.03\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	C.I	[-0.5333, -0.5333]	[0.5347, 0.5347]	[$-3\cdot10^{-5}$, $-3\cdot10^{-5}$]	[0, 0]	[0.5347, 0.5347]	[$-3\cdot10^{-5}$, $-3\cdot10^{-5}$]	[0.5350, 0.5350]	[$-3\cdot10^{-5}$, $-3\cdot10^{-5}$]	[$-3\cdot10^{-5}$, $-3\cdot10^{-5}$]	[-0.5348, -0.5348]	[-0.5339, -0.5339]	[-0.5357, -0.5357]	[$-3\cdot10^{-5}$, $-3\cdot10^{-5}$]
	p-value	$2.60\cdot10^{-146}$	$2.47\cdot10^{-172}$	0	-	$2.16\cdot10^{-170}$	0	$5.69\cdot10^{-170}$	0	0	$5.98\cdot10^{-162}$	$3.16\cdot10^{-174}$	$8.05\cdot10^{-160}$	0
E	$\bar{x}_1$	$5.186\cdot10^{-4}$	0.5346	$5.760\cdot10^{-4}$	$6.710\cdot10^{-4}$	0.5346	$5.757\cdot10^{-4}$	0.5349	$5.758\cdot10^{-4}$	$5.755\cdot10^{-4}$	$4.406\cdot10^{-4}$	$4.827\cdot10^{-4}$	$4.144\cdot10^{-4}$	$5.750\cdot10^{-4}$
	$\bar{x}_2$	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	0.0028	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	C.I	[-0.5353, -0.5353]	[0, 0]	[-0.5350, -0.5350]	[-0.5347, -0.5347]	[0, 0]	[-0.5350, -0.5350]	[0.5321, 0.5321]	[-0.5350, -0.5350]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5371, -0.5371]	[-0.5350, -0.5350]
	p-value	$4.81\cdot10^{-166}$	-	$1.39\cdot10^{-168}$	$3.32\cdot10^{-171}$	-	$3.22\cdot10^{-167}$	$9.11\cdot10^{-130}$	$3.70\cdot10^{-168}$	$8.43\cdot10^{-169}$	$1.13\cdot10^{-165}$	$4.56\cdot10^{-168}$	$6.35\cdot10^{-168}$	$1.24\cdot10^{-167}$

Table A13-1. Statistical t-test results for Comparation network with Capital English letters, A to E vs. A to M. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

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Input-1 patterns		Input-2 patterns N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	$\bar{x}_1$	0.5347	0.5347	0.5358	0.5358	0.5358	0.5358	0.0080	0.5347	0.0080	0.5358	0.0080	0.5347	0.5347
	$\bar{x}_2$	0.5346	0.5347	0.0025	0.0025	$8.349\cdot10^{-4}$	$5.187\cdot10^{-4}$	0.5366	0.5346	0.5366	0.0025	0.5366	0.5347	0.5346
	C.I	$[3.6\cdot10^{-5}, 3.6\cdot10^{-5}]$	[0, 0]	[0.5333, 0.5333]	[0.5333, 0.5333]	[0.5350, 0.5350]	[0.5353, 0.5353]	[-0.5286, -0.5285]	$[3.6\cdot10^{-5}, 3.6\cdot10^{-5}]$	[-0.5286, -0.5285]	[0.5333, 0.5333]	[-0.5286, -0.5285]	$[-4.6\cdot10^{-5}, -4.6\cdot10^{-5}]$	$[3.6\cdot10^{-5}, 3.6\cdot10^{-5}]$
	p-value	0	-	$1.69\cdot10^{-141}$	$6.51\cdot10^{-140}$	$8.40\cdot10^{-168}$	$6.98\cdot10^{-166}$	$1.68\cdot10^{-121}$	0	$1.61\cdot10^{-114}$	$4.13\cdot10^{-139}$	$4.0\cdot10^{-117}$	0	0
B	$\bar{x}_1$	$5.753\cdot10^{-4}$	$5.194\cdot10^{-4}$	$6.694\cdot10^{-4}$	$6.696\cdot10^{-4}$	0.0023	0.5346	$4.403\cdot10^{-4}$	$5.753\cdot10^{-4}$	$4.399\cdot10^{-4}$	$6.702\cdot10^{-4}$	$4.406\cdot10^{-4}$	$4.829\cdot10^{-4}$	$5.749\cdot10^{-4}$
	$\bar{x}_2$	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	C.I	[-0.5350, -0.5350]	[-0.5353, -0.5353]	[-0.5347, -0.5347]	[-0.5347, -0.5347]	[-0.5328, -0.5328]	[0, 0]	[-0.5363, -0.5363]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5347, -0.5347]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5350, -0.5350]
	p-value	$1.19\cdot10^{-167}$	$3.79\cdot10^{-166}$	$1.64\cdot10^{-171}$	$1.75\cdot10^{-172}$	$5.31\cdot10^{-127}$	-	$7.49\cdot10^{-166}$	$1.20\cdot10^{-166}$	$1.63\cdot10^{-163}$	$1.33\cdot10^{-171}$	$2.48\cdot10^{-162}$	$3.54\cdot10^{-165}$	$5.13\cdot10^{-169}$
C	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0054	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.263\cdot10^{-4}$	$5.772\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	$[-3.6\cdot10^{-5}, -3.6\cdot10^{-5}]$	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5333, -0.5332]	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	[-0.5332, -0.5332]	[-0.5307, -0.5305]	[0, 0]
	p-value	-	0	0	0	$5.22\cdot10^{-176}$	$3.89\cdot10^{-167}$	$3.01\cdot10^{-159}$	-	$1.68\cdot10^{-163}$	0	$2.57\cdot10^{-161}$	$5.95\cdot10^{-115}$	-
D	$\bar{x}_1$	0.5346	0.0025	0.5346	0.5346	0.5354	0.5354	0.0019	0.5346	0.0019	0.5346	0.0019	0.0021	0.5346
	$\bar{x}_2$	0.5346	0.5358	0.5346	0.5346	0.0011	$6.716\cdot10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	C.I	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5333, -0.5333]	[0, 0]	[0, 0]	[0.5343, 0.5343]	[0.5347, 0.5347]	[-0.5348, -0.5348]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5348, -0.5348]	[0, 0]	[-0.5348, -0.5348]	[-0.5339, -0.5339]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$
	p-value	0	$1.21\cdot10^{-141}$	-	-	$8.29\cdot10^{-168}$	$6.64\cdot10^{-174}$	$1.81\cdot10^{-165}$	0	$3.86\cdot10^{-162}$	-	$1.90\cdot10^{-164}$	$1.38\cdot10^{-173}$	0
E	$\bar{x}_1$	$5.752\cdot10^{-4}$	$5.194\cdot10^{-4}$	$6.699\cdot10^{-4}$	$6.697\cdot10^{-4}$	0.0023	0.5346	$4.407\cdot10^{-4}$	$5.736\cdot10^{-4}$	$4.390\cdot10^{-4}$	$6.688\cdot10^{-4}$	$4.418\cdot10^{-4}$	$4.833\cdot10^{-4}$	$5.772\cdot10^{-4}$
	$\bar{x}_2$	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	C.I	[-0.5350, -0.5350]	[-0.5353, -0.5353]	[-0.5347, -0.5347]	[-0.5347, -0.5347]	[-0.5328, -0.5328]	[0, 0]	[-0.5363, -0.5363]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5347, -0.5347]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5350, -0.5350]
	p-value	$5.69\cdot10^{-167}$	$1.20\cdot10^{-166}$	$4.58\cdot10^{-172}$	$1.01\cdot10^{-173}$	$2.21\cdot10^{-130}$	-	$4.80\cdot10^{-164}$	$5.87\cdot10^{-171}$	$2.77\cdot10^{-170}$	$4.24\cdot10^{-173}$	$2.45\cdot10^{-164}$	$4.40\cdot10^{-165}$	$4.78\cdot10^{-168}$

Table A13-2. Statistical t-test results for Comparation network with Capital English letters, A to E vs. N to Z. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

Input-1 patterns		Input-2 patterns A	B	C	D	E	F	G	H	I	J	K	L	M
F	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0055	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.751 \cdot 10^{-4}$	0.5346	0.5346	$5.750 \cdot 10^{-4}$	0.5346	$3.570 \cdot 10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	$[-3.6 \cdot 10^{-5}, -3.6 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	$[3.5 \cdot 10^{-5}, 3.5 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5306, -0.5304]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$2.58 \cdot 10^{-173}$	-	0	$5.68 \cdot 10^{-168}$	-	$6.19 \cdot 10^{-166}$	-	-	$3.07 \cdot 10^{-159}$	$2.27 \cdot 10^{-109}$	$3.21 \cdot 10^{-158}$	-
G	$\bar{x}_1$	$3.258 \cdot 10^{-4}$	0.0029	$3.551 \cdot 10^{-4}$	$4.02 \cdot 10^{-4}$	0.0029	$3.533 \cdot 10^{-4}$	0.5345	$3.532 \cdot 10^{-4}$	$3.548 \cdot 10^{-4}$	$2.838 \cdot 10^{-4}$	$3.061 \cdot 10^{-4}$	$2.688 \cdot 10^{-4}$	$3.532 \cdot 10^{-4}$
	$\bar{x}_2$	0.5358	0.5349	0.5356	0.5354	0.5349	0.5356	0.5345	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	C.I	[-0.5355, -0.5355]	[-0.5321, -0.5320]	[-0.5352, -0.5352]	[-0.5350, -0.5350]	[-0.5321, -0.5320]	[-0.5352, -0.5352]	[0, 0]	[-0.5352, -0.5352]	[-0.5352, -0.5352]	[-0.5364, -0.5364]	[-0.5358, -0.5358]	[-0.5372, -0.5372]	[-0.5352, -0.5352]
	p-value	$1.08 \cdot 10^{-168}$	$5.53 \cdot 10^{-131}$	$1.60 \cdot 10^{-169}$	$3.72 \cdot 10^{-172}$	$7.57 \cdot 10^{-130}$	$7.05 \cdot 10^{-171}$	-	$8.47 \cdot 10^{-173}$	$8.55 \cdot 10^{-170}$	$6 \cdot 10^{-169}$	$3.03 \cdot 10^{-169}$	$1.06 \cdot 10^{-168}$	$2.17 \cdot 10^{-168}$
H	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0057	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.739 \cdot 10^{-4}$	0.5346	0.5346	$5.765 \cdot 10^{-4}$	0.5346	$3.557 \cdot 10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	$[-3.6 \cdot 10^{-5}, -3.6 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	$[3.5 \cdot 10^{-5}, 3.5 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5305, -0.5302]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$6.45 \cdot 10^{-168}$	-	0	$6.10 \cdot 10^{-166}$	-	$1.08 \cdot 10^{-167}$	-	-	$1.62 \cdot 10^{-156}$	$4.79 \cdot 10^{-105}$	$2.30 \cdot 10^{-152}$	-
I	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0055	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.757 \cdot 10^{-4}$	0.5346	0.5346	$5.763 \cdot 10^{-4}$	0.5346	$3.543 \cdot 10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	$[-3.6 \cdot 10^{-5}, -3.6 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	$[3.5 \cdot 10^{-5}, 3.5 \cdot 10^{-5}]$	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5307, -0.5303]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$2.89 \cdot 10^{-169}$	-	0	$4.64 \cdot 10^{-169}$	-	$6.53 \cdot 10^{-170}$	-	-	$1.33 \cdot 10^{-160}$	$2.38 \cdot 10^{-105}$	$2.44 \cdot 10^{-151}$	-
J	$\bar{x}_1$	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0080	$4.4 \cdot 10^{-4}$	0.0034	0.0019	$4.424 \cdot 10^{-4}$	0.0034	$2.839 \cdot 10^{-4}$	0.0034	0.0034	0.5348	0.5347	0.5350	0.0034
	C.I	[0.5286, 0.5287]	[0.5363, 0.5363]	[0.5332, 0.5333]	[0.5348, 0.5348]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5364, 0.5364]	[0.5332, 0.5332]	[0.5332, 0.5333]	[0, 0]	$[1.2 \cdot 10^{-4}, 1.2 \cdot 10^{-4}]$	$[-1.8 \cdot 10^{-4}, -1.8 \cdot 10^{-4}]$	[0.5332, 0.5332]
	p-value	$1.57 \cdot 10^{-120}$	$5.69 \cdot 10^{-165}$	$8.35 \cdot 10^{-160}$	$9.83 \cdot 10^{-165}$	$3.52 \cdot 10^{-164}$	$6.07 \cdot 10^{-162}$	$2.16 \cdot 10^{-168}$	$1.62 \cdot 10^{-160}$	$1.32 \cdot 10^{-160}$	-	0	0	$6.38 \cdot 10^{-156}$

Table A13-3. Statistical t-test results for Comparation network with Capital English letters, F to J vs. A to M. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

Input-1 patterns		Input-2 patterns N	O	P	Q	R	S	T	U	V	W	X	Y	Z
F	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0053	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.277\cdot10^{-4}$	$5.761\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[-0.5332, -0.5332]	[-0.5307, -0.5306]	[0, 0]
	p-value	-	0	0	0	$5.72\cdot10^{-176}$	$8.12\cdot10^{-172}$	$9.81\cdot10^{-159}$	-	$2.28\cdot10^{-156}$	0	$1.31\cdot10^{-163}$	$9.74\cdot10^{-118}$	-
G	$\bar{x}_1$	$3.534\cdot10^{-4}$	$3.271\cdot10^{-4}$	$4.018\cdot10^{-4}$	$4.015\cdot10^{-4}$	$7.720\cdot10^{-4}$	0.0029	$2.848\cdot10^{-4}$	$3.544\cdot10^{-4}$	$2.844\cdot10^{-4}$	$4\cdot10^{-4}$	$2.852\cdot10^{-4}$	$3.067\cdot10^{-4}$	$3.557\cdot10^{-4}$
	$\bar{x}_2$	0.5356	0.5358	0.5354	0.5354	0.5351	0.5349	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	C.I	[-0.5352, -0.5352]	[-0.5355, -0.5355]	[-0.5350, -0.5350]	[-0.5350, -0.5350]	[-0.5343, -0.5343]	[-0.5321, -0.5321]	[-0.5364, -0.5364]	[-0.5352, -0.5352]	[-0.5364, -0.5364]	[-0.5350, -0.5350]	[-0.5364, -0.5364]	[-0.5358, -0.5358]	[-0.5352, -0.5352]
	p-value	$1.78\cdot10^{-169}$	$9.80\cdot10^{-167}$	$3.59\cdot10^{-170}$	$5.52\cdot10^{-169}$	$1.78\cdot10^{-159}$	$8.15\cdot10^{-129}$	$1.25\cdot10^{-166}$	$6.46\cdot10^{-170}$	$4.11\cdot10^{-171}$	$3.96\cdot10^{-173}$	$1.46\cdot10^{-166}$	$5.70\cdot10^{-171}$	$1.25\cdot10^{-169}$
H	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0056	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.264\cdot10^{-4}$	$5.752\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[-0.5332, -0.5332]	[-0.5306, -0.5303]	[0, 0]
	p-value	-	0	0	0	$5.49\cdot10^{-177}$	$3.09\cdot10^{-170}$	$3.08\cdot10^{-156}$	-	$8.74\cdot10^{-158}$	0	$1.79\cdot10^{-156}$	$5.81\cdot10^{-106}$	-
I	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0055	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.286\cdot10^{-4}$	$5.760\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[-0.5332, -0.5332]	[-0.5307, -0.5304]	[0, 0]
	p-value	-	0	0	0	$1.58\cdot10^{-174}$	$1.72\cdot10^{-169}$	$7.87\cdot10^{-160}$	-	$7.08\cdot10^{-160}$	0	$6.64\cdot10^{-160}$	$2.25\cdot10^{-107}$	-
J	$\bar{x}_1$	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0034	0.0079	0.0019	0.0019	$6.879\cdot10^{-4}$	$4.413\cdot10^{-4}$	0.5348	0.0034	0.5348	0.0019	0.5348	0.5347	0.0034
	C.I	[0.5332, 0.5332]	[0.5286, 0.5287]	[0.5348, 0.5348]	[0.5348, 0.5348]	[0.5360, 0.5360]	[0.5363, 0.5363]	[0, 0]	[0.5332, 0.5332]	[0, 0]	[0.5348, 0.5348]	[0, 0]	[$1.2\cdot10^{-4}$, $1.2\cdot10^{-4}$]	[0.5332, 0.5333]
	p-value	$5.09\cdot10^{-158}$	$1.15\cdot10^{-121}$	$6.61\cdot10^{-166}$	$2.43\cdot10^{-160}$	$1.43\cdot10^{-161}$	$8.25\cdot10^{-164}$	-	$1.44\cdot10^{-156}$	-	$3.37\cdot10^{-162}$	-	0	$1.84\cdot10^{-162}$

Table A13-4. Statistical t-test results for Comparation network with Capital English letters, F to J vs. N to Z. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

Input-1 patterns		Input-2 patterns												
		A	B	C	D	E	F	G	H	I	J	K	L	M
K	$\bar{x}_1$	0.5347	0.5361	0.5360	0.5360	0.5361	0.5360	0.5361	0.5360	0.5360	0.5347	0.5347	0.0210	0.5360
	$\bar{x}_2$	0.5347	$4.839\cdot10^{-4}$	0.0055	0.0021	$4.817\cdot10^{-4}$	0.0055	$3.085\cdot10^{-4}$	0.0055	0.0054	0.5348	0.5347	0.5373	0.0057
	C.I	[$4.6\cdot10^{-5}$, $4.6\cdot10^{-5}$]	[0.5356, 0.5356]	[0.5305, 0.5307]	[0.5339, 0.5339]	[0.5356, 0.5356]	[0.5305, 0.5307]	[0.5358, 0.5358]	[0.5304, 0.5307]	[0.5306, 0.5307]	[$-1.2\cdot10^{-4}$, $-1.2\cdot10^{-4}$]	[0, 0]	[-0.5167, -0.5160]	[0.5302, 0.5305]
	p-value	0	$3.83\cdot10^{-163}$	$2.54\cdot10^{-115}$	$1.22\cdot10^{-172}$	$1.48\cdot10^{-165}$	$2.01\cdot10^{-110}$	$9.99\cdot10^{-168}$	$6.51\cdot10^{-110}$	$3.09\cdot10^{-113}$	0	-	$5.18\cdot10^{-94}$	$2.47\cdot10^{-104}$
L	$\bar{x}_1$	0.5374	0.5375	0.5374	0.5374	0.5375	0.5374	0.5375	0.5374	0.5374	0.5350	0.5373	0.5350	0.5374
	$\bar{x}_2$	0.0062	$4.167\cdot10^{-4}$	0.0031	0.0017	$4.163\cdot10^{-4}$	0.0031	$2.716\cdot10^{-4}$	0.0031	0.0031	0.5348	0.0210	0.5350	0.0031
	C.I	[0.5312, 0.5312]	[0.5371, 0.5371]	[0.5343, 0.5343]	[0.5357, 0.5357]	[0.5371, 0.5371]	[0.5343, 0.5343]	[0.5372, 0.5372]	[0.5343, 0.5343]	[0.5343, 0.5343]	[$1.8\cdot10^{-4}$, $1.8\cdot10^{-4}$]	[0.5159, 0.5166]	[0, 0]	[0.5343, 0.5343]
	p-value	$9.68\cdot10^{-143}$	$1.08\cdot10^{-163}$	$7.37\cdot10^{-154}$	$3.35\cdot10^{-157}$	$1.19\cdot10^{-162}$	$1.09\cdot10^{-153}$	$1.65\cdot10^{-165}$	$4.27\cdot10^{-150}$	$2.27\cdot10^{-153}$	0	$3.31\cdot10^{-92}$	-	$3.95\cdot10^{-151}$
M	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0056	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.753\cdot10^{-4}$	0.5346	0.5346	$5.748\cdot10^{-4}$	0.5346	$3.543\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[$3.5\cdot10^{-5}$, $3.5\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5305, -0.5303]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$2.78\cdot10^{-169}$	-	0	$4.63\cdot10^{-170}$	-	$5.21\cdot10^{-170}$	-	-	$6.21\cdot10^{-156}$	$4.29\cdot10^{-107}$	$6.07\cdot10^{-151}$	-
N	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0056	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.754\cdot10^{-4}$	0.5346	0.5346	$5.746\cdot10^{-4}$	0.5346	$3.541\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[$3.5\cdot10^{-5}$, $3.5\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5305, -0.5303]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$7.7\cdot10^{-168}$	-	0	$7.27\cdot10^{-168}$	-	$1.83\cdot10^{-168}$	-	-	$6.07\cdot10^{-157}$	$1.35\cdot10^{-109}$	$5.47\cdot10^{-151}$	-
O	$\bar{x}_1$	0.5347	0.5358	0.5347	0.5358	0.5358	0.5347	0.5358	0.5347	0.5347	0.0079	0.5347	0.0062	0.5347
	$\bar{x}_2$	0.5347	$5.199\cdot10^{-4}$	0.5346	0.0025	$5.217\cdot10^{-4}$	0.5346	$3.265\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5347	0.5374	0.5346
	C.I	[0, 0]	[0.5353, 0.5353]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[0.5333, 0.5333]	[0.5353, 0.5353]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[0.5355, 0.5355]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[$3.6\cdot10^{-5}$, $3.6\cdot10^{-5}$]	[-0.5288, -0.5287]	[$-4.6\cdot10^{-5}$, $-4.6\cdot10^{-5}$]	[-0.5312, -0.5312]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]
	p-value	-	$2.83\cdot10^{-166}$	0	$2.15\cdot10^{-138}$	$4.01\cdot10^{-164}$	0	$3.29\cdot10^{-169}$	0	0	$3.49\cdot10^{-122}$	0	$3.48\cdot10^{-147}$	0

Table A13-5. Statistical t-test results for Comparation network with Capital English letters, K to O vs. A to M. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

Input-1 patterns		Input-2 patterns												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
K	$\bar{x}_1$	0.5360	0.5347	0.5360	0.5360	0.5361	0.5361	0.5347	0.5360	0.5347	0.5360	0.5347	0.5347	0.5360
	$\bar{x}_2$	0.0059	0.5347	0.0021	0.0021	$7.68 \cdot 10^{-4}$	$4.815 \cdot 10^{-4}$	0.5348	0.0059	0.5348	0.0021	0.5348	0.5347	0.0054
	C.I	[0.5300, 0.5303]	[$4.6 \cdot 10^{-5}$, $4.6 \cdot 10^{-5}$]	[0.5339, 0.5339]	[0.5339, 0.5339]	[0.5353, 0.5353]	[0.5356, 0.5356]	[$-1.2 \cdot 10^{-4}$, $-1.2 \cdot 10^{-4}$]	[0.5300, 0.5303]	[$-1.2 \cdot 10^{-4}$, $-1.2 \cdot 10^{-4}$]	[0.5339, 0.5339]	[$-1.2 \cdot 10^{-4}$, $-1.2 \cdot 10^{-4}$]	[0, 0]	[0.5305, 0.5307]
	p-value	$8.92 \cdot 10^{-105}$	0	$4.72 \cdot 10^{-174}$	$1.94 \cdot 10^{-171}$	$1.77 \cdot 10^{-163}$	$2.99 \cdot 10^{-165}$	0	$3.74 \cdot 10^{-104}$	0	$4.54 \cdot 10^{-173}$	0	-	$8.2 \cdot 10^{-116}$
L	$\bar{x}_1$	0.5374	0.5374	0.5374	0.5374	0.5375	0.5375	0.5350	0.5374	0.5350	0.5374	0.5350	0.5373	0.5374
	$\bar{x}_2$	0.0031	0.0062	0.0017	0.0017	$6.43 \cdot 10^{-4}$	$4.16 \cdot 10^{-4}$	0.5348	0.0031	0.5348	0.0017	0.5348	0.0211	0.0031
	C.I	[0.5343, 0.5343]	[0.5312, 0.5312]	[0.5357, 0.5357]	[0.5357, 0.5357]	[0.5368, 0.5368]	[0.5371, 0.5371]	[$1.8 \cdot 10^{-4}$, $1.8 \cdot 10^{-4}$]	[0.5343, 0.5343]	[$1.8 \cdot 10^{-4}$, $1.8 \cdot 10^{-4}$]	[0.5357, 0.5357]	[$1.8 \cdot 10^{-4}$, $1.8 \cdot 10^{-4}$]	[0.5158, 0.5166]	[0.5343, 0.5343]
	p-value	$6.76 \cdot 10^{-152}$	$4.61 \cdot 10^{-148}$	$6.37 \cdot 10^{-161}$	$1.43 \cdot 10^{-154}$	$1.36 \cdot 10^{-159}$	$4.37 \cdot 10^{-162}$	0	$5.39 \cdot 10^{-153}$	0	$1.84 \cdot 10^{-155}$	0	$2.20 \cdot 10^{-91}$	$2.45 \cdot 10^{-153}$
M	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0057	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.265 \cdot 10^{-4}$	$5.755 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6 \cdot 10^{-5}$, $-3.6 \cdot 10^{-5}$]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[-0.5332, -0.5332]	[-0.5305, -0.5301]	[0, 0]
	p-value	-	0	0	0	$3.02 \cdot 10^{-176}$	$5.39 \cdot 10^{-170}$	$4.09 \cdot 10^{-157}$	-	$1.36 \cdot 10^{-156}$	0	$3.38 \cdot 10^{-155}$	$7.67 \cdot 10^{-106}$	-
N	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0057	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.265 \cdot 10^{-4}$	$5.742 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6 \cdot 10^{-5}$, $-3.6 \cdot 10^{-5}$]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	[$3 \cdot 10^{-5}$, $3 \cdot 10^{-5}$]	[-0.5332, -0.5332]	[-0.5305, -0.5301]	[0, 0]
	p-value	-	0	0	0	$5.11 \cdot 10^{-176}$	$8.37 \cdot 10^{-170}$	$2.86 \cdot 10^{-159}$	-	$1.93 \cdot 10^{-158}$	0	$3.63 \cdot 10^{-157}$	$2.57 \cdot 10^{-103}$	-
O	$\bar{x}_1$	0.5347	0.5347	0.5358	0.5358	0.5358	0.5358	0.0079	0.5347	0.0079	0.5358	0.0079	0.5347	0.5347
	$\bar{x}_2$	0.5346	0.5347	0.0025	0.0025	$8.342 \cdot 10^{-4}$	$5.223 \cdot 10^{-4}$	0.5366	0.5346	0.5366	0.0025	0.5366	0.5347	0.5346
	C.I	[$3.6 \cdot 10^{-5}$, $3.6 \cdot 10^{-5}$]	[0, 0]	[0.5333, 0.5333]	[0.5333, 0.5333]	[0.5350, 0.5350]	[0.5353, 0.5353]	[-0.5287, -0.5286]	[$3.6 \cdot 10^{-5}$, $3.6 \cdot 10^{-5}$]	[-0.5288, -0.5286]	[0.5333, 0.5333]	[-0.5287, -0.5286]	[$-4.6 \cdot 10^{-5}$, $-4.6 \cdot 10^{-5}$]	[$3.6 \cdot 10^{-5}$, $3.6 \cdot 10^{-5}$]
	p-value	0	-	$4.13 \cdot 10^{-142}$	$1.91 \cdot 10^{-141}$	$8.98 \cdot 10^{-167}$	$7.72 \cdot 10^{-165}$	$3.74 \cdot 10^{-124}$	0	$5.77 \cdot 10^{-119}$	$2.07 \cdot 10^{-137}$	$7.18 \cdot 10^{-123}$	0	0

Table A13-6. Statistical t-test results for Comparation network with Capital English letters, K to O vs. N to Z. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

Input-1 patterns		Input-2 patterns A	B	C	D	E	F	G	H	I	J	K	L	M
P	$\bar{x}_1$	0.0025	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0019	0.0021	0.0017	0.5346
	$\bar{x}_2$	0.5358	$6.724\cdot10^{-4}$	0.5346	0.5346	$6.705\cdot10^{-4}$	0.5346	$4.03\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	C.I	[-0.5333, -0.5333]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0, 0]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0.5350, 0.5350]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5348, -0.5348]	[-0.5339, -0.5339]	[-0.5357, -0.5357]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$
	p-value	$5.16\cdot10^{-146}$	$3.59\cdot10^{-169}$	0	-	$3.14\cdot10^{-172}$	0	$9.47\cdot10^{-170}$	0	0	$3.51\cdot10^{-164}$	$2.99\cdot10^{-174}$	$1.60\cdot10^{-157}$	0
Q	$\bar{x}_1$	0.0025	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0019	0.0021	0.0017	0.5346
	$\bar{x}_2$	0.5358	$6.718\cdot10^{-4}$	0.5346	0.5346	$6.695\cdot10^{-4}$	0.5346	$4.01\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	C.I	[-0.5333, -0.5333]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0, 0]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0.5350, 0.5350]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5348, -0.5348]	[-0.5339, -0.5339]	[-0.5357, -0.5357]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$
	p-value	$7.13\cdot10^{-138}$	$2.84\cdot10^{-168}$	0	-	$1.27\cdot10^{-172}$	0	$1.42\cdot10^{-167}$	0	0	$7.47\cdot10^{-159}$	$1.96\cdot10^{-173}$	$1.45\cdot10^{-157}$	0
R	$\bar{x}_1$	$8.344\cdot10^{-4}$	0.5351	$9.27\cdot10^{-4}$	0.0011	0.5351	$9.276\cdot10^{-4}$	0.5351	$9.259\cdot10^{-4}$	$9.281\cdot10^{-4}$	$6.859\cdot10^{-4}$	$7.683\cdot10^{-4}$	$6.412\cdot10^{-4}$	$9.261\cdot10^{-4}$
	$\bar{x}_2$	0.5358	0.0023	0.5356	0.5354	0.0023	0.5356	$7.752\cdot10^{-4}$	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	C.I	[-0.5350, -0.5350]	[0.5327, 0.5328]	[-0.5346, -0.5346]	[-0.5343, -0.5343]	[0.5328, 0.5328]	[-0.5346, -0.5346]	[0.5343, 0.5343]	[-0.5347, -0.5346]	[-0.5346, -0.5346]	[-0.5360, -0.5360]	[-0.5353, -0.5353]	[-0.5368, -0.5368]	[-0.5347, -0.5346]
	p-value	$1\cdot10^{-169}$	$3.53\cdot10^{-127}$	$2.14\cdot10^{-181}$	$4.59\cdot10^{-168}$	$3.71\cdot10^{-132}$	$5.59\cdot10^{-176}$	$1.09\cdot10^{-163}$	$1.19\cdot10^{-174}$	$5.36\cdot10^{-176}$	$1.36\cdot10^{-166}$	$1.78\cdot10^{-166}$	$1.04\cdot10^{-162}$	$2.38\cdot10^{-174}$
S	$\bar{x}_1$	$5.180\cdot10^{-4}$	0.5346	$5.767\cdot10^{-4}$	$6.694\cdot10^{-4}$	0.5346	$5.750\cdot10^{-4}$	0.5349	$5.758\cdot10^{-4}$	$5.763\cdot10^{-4}$	$4.390\cdot10^{-4}$	$4.838\cdot10^{-4}$	$4.137\cdot10^{-4}$	$5.737\cdot10^{-4}$
	$\bar{x}_2$	0.5358	0.5346	0.5356	0.5354	0.5346	0.5356	0.0029	0.5356	0.5356	0.5367	0.5361	0.5375	0.5356
	C.I	[-0.5353, -0.5353]	[0, 0]	[-0.5350, -0.5350]	[-0.5347, -0.5347]	[0, 0]	[-0.5350, -0.5350]	[0.5320, 0.5321]	[-0.5350, -0.5350]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5371, -0.5371]	[-0.5350, -0.5350]
	p-value	$5.96\cdot10^{-172}$	-	$8.74\cdot10^{-168}$	$4.17\cdot10^{-174}$	-	$2.01\cdot10^{-170}$	$3.52\cdot10^{-127}$	$9.16\cdot10^{-166}$	$3.79\cdot10^{-172}$	$6.53\cdot10^{-167}$	$1.87\cdot10^{-162}$	$2.59\cdot10^{-166}$	$4.1\cdot10^{-174}$
T	$\bar{x}_1$	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0080	$4.406\cdot10^{-4}$	0.0034	0.0019	$4.405\cdot10^{-4}$	0.0034	$2.829\cdot10^{-4}$	0.0034	0.0034	0.5348	0.5347	0.5350	0.0034
	C.I	[0.5286, 0.5287]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5348, 0.5348]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5364, 0.5364]	[0.5332, 0.5332]	[0.5332, 0.5332]	[0, 0]	$[1.2\cdot10^{-4}, 1.2\cdot10^{-4}]$	$[-1.8\cdot10^{-4}, -1.8\cdot10^{-4}]$	[0.5332, 0.5332]
	p-value	$5.46\cdot10^{-116}$	$2.01\cdot10^{-165}$	$2.16\cdot10^{-162}$	$1.02\cdot10^{-162}$	$3.44\cdot10^{-164}$	$1.11\cdot10^{-160}$	$2.06\cdot10^{-170}$	$8.29\cdot10^{-156}$	$6.55\cdot10^{-160}$	-	0	0	$3.87\cdot10^{-159}$

Table A13-7. Statistical t-test results for Comparation network with Capital English letters, P to T vs. A to M. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

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Input-1 patterns		Input-2 patterns												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
P	$\bar{x}_1$	0.5346	0.0025	0.5346	0.5346	0.5354	0.5354	0.0019	0.5346	0.0019	0.5346	0.0019	0.0021	0.5346
	$\bar{x}_2$	0.5346	0.5358	0.5346	0.5346	0.0011	$6.721 \cdot 10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	C.I	$[-3 \cdot 10^{-5}, -3 \cdot 10^{-5}]$	[-0.5333, -0.5333]	[0, 0]	[0, 0]	[0.5343, 0.5343]	[0.5347, 0.5347]	[-0.5348, -0.5348]	$[-3 \cdot 10^{-5}, -3 \cdot 10^{-5}]$	[-0.5348, -0.5348]	[0, 0]	[-0.5348, -0.5348]	[-0.5339, -0.5339]	$[3 \cdot 10^{-5}, 3 \cdot 10^{-5}]$
	p-value	0	$6.81 \cdot 10^{-143}$	-	-	$2.75 \cdot 10^{-170}$	$1.7 \cdot 10^{-172}$	$2.39 \cdot 10^{-163}$	0	$1.47 \cdot 10^{-160}$	-	$4.63 \cdot 10^{-163}$	$1.51 \cdot 10^{-171}$	0
Q	$\bar{x}_1$	0.5346	0.0025	0.5346	0.5346	0.5354	0.5354	0.0019	0.5346	0.0019	0.5346	0.0019	0.0021	0.5346
	$\bar{x}_2$	0.5346	0.5358	0.5346	0.5346	0.0011	$6.688 \cdot 10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	C.I	$[-3 \cdot 10^{-5}, -3 \cdot 10^{-5}]$	[-0.5333, -0.5333]	[0, 0]	[0, 0]	[0.5343, 0.5343]	[0.5347, 0.5347]	[-0.5348, -0.5348]	$[-3 \cdot 10^{-5}, -3 \cdot 10^{-5}]$	[-0.5348, -0.5348]	[0, 0]	[-0.5348, -0.5348]	[-0.5339, -0.5339]	$[-3 \cdot 10^{-5}, -3 \cdot 10^{-5}]$
	p-value	0	$4.54 \cdot 10^{-144}$	-	-	$1.12 \cdot 10^{-167}$	$9.83 \cdot 10^{-176}$	$6.82 \cdot 10^{-163}$	0	$1.83 \cdot 10^{-157}$	-	$3.95 \cdot 10^{-159}$	$7.26 \cdot 10^{-174}$	0
R	$\bar{x}_1$	$9.269 \cdot 10^{-4}$	$8.347 \cdot 10^{-4}$	0.0011	0.0011	0.5346	0.5351	$6.855 \cdot 10^{-4}$	$9.262 \cdot 10^{-4}$	$6.896 \cdot 10^{-4}$	0.0011	$6.855 \cdot 10^{-4}$	$7.669 \cdot 10^{-4}$	$9.282 \cdot 10^{-4}$
	$\bar{x}_2$	0.5356	0.5358	0.5354	0.5354	0.5346	0.0023	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	C.I	[-0.5346, -0.5346]	[-0.5350, -0.5350]	[-0.5343, -0.5343]	[-0.5343, -0.5343]	[0, 0]	[0.5328, 0.5328]	[-0.5360, -0.5360]	[-0.5347, -0.5346]	[-0.5360, -0.5360]	[-0.5343, -0.5343]	[-0.5360, -0.5360]	[-0.5353, -0.5353]	[-0.5346, -0.5346]
	p-value	$1.25 \cdot 10^{-171}$	$3.44 \cdot 10^{-169}$	$3.42 \cdot 10^{-165}$	$1.51 \cdot 10^{-165}$	-	$1.7 \cdot 10^{-131}$	$4.16 \cdot 10^{-163}$	$1.18 \cdot 10^{-175}$	$8.37 \cdot 10^{-161}$	$2.41 \cdot 10^{-170}$	$1.01 \cdot 10^{-164}$	$3.86 \cdot 10^{-167}$	$2.87 \cdot 10^{-176}$
S	$\bar{x}_1$	$5.740 \cdot 10^{-4}$	$5.204 \cdot 10^{-4}$	$6.702 \cdot 10^{-4}$	$6.712 \cdot 10^{-4}$	0.0023	0.5346	$4.409 \cdot 10^{-4}$	$5.761 \cdot 10^{-4}$	$4.390 \cdot 10^{-4}$	$6.701 \cdot 10^{-4}$	$4.406 \cdot 10^{-4}$	$4.832 \cdot 10^{-4}$	$5.758 \cdot 10^{-4}$
	$\bar{x}_2$	0.5356	0.5358	0.5354	0.5354	0.5351	0.5346	0.5367	0.5356	0.5367	0.5354	0.5367	0.5361	0.5356
	C.I	[-0.5350, -0.5350]	[-0.5353, -0.5353]	[-0.5347, -0.5347]	[-0.5347, -0.5347]	[-0.5328, -0.5327]	[0, 0]	[-0.5363, -0.5363]	[-0.5350, -0.5350]	[-0.5363, -0.5363]	[-0.5347, -0.5347]	[-0.5363, -0.5363]	[-0.5356, -0.5356]	[-0.5350, -0.5350]
	p-value	$1.28 \cdot 10^{-170}$	$1.9 \cdot 10^{-164}$	$9.67 \cdot 10^{-174}$	$1.77 \cdot 10^{-167}$	$3.24 \cdot 10^{-126}$	-	$6.03 \cdot 10^{-163}$	$5.37 \cdot 10^{-166}$	$3.02 \cdot 10^{-167}$	$7.59 \cdot 10^{-172}$	$1.44 \cdot 10^{-164}$	$1.79 \cdot 10^{-164}$	$1.31 \cdot 10^{-166}$
T	$\bar{x}_1$	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0034	0.0079	0.0019	0.0019	$6.857 \cdot 10^{-4}$	$4.413 \cdot 10^{-4}$	0.5348	0.0034	0.5348	0.0019	0.5348	0.5347	0.0034
	C.I	[0.5332, 0.5332]	[0.5286, 0.5287]	[0.5348, 0.5348]	[0.5348, 0.5348]	[0.5360, 0.5360]	[0.5363, 0.5363]	[0, 0]	[0.5332, 0.5332]	[0, 0]	[0.5348, 0.5348]	[0, 0]	$[1.2 \cdot 10^{-4}, 1.2 \cdot 10^{-4}]$	[0.5332, 0.5332]
	p-value	$1.27 \cdot 10^{-159}$	$2.12 \cdot 10^{-123}$	$1.79 \cdot 10^{-162}$	$1.02 \cdot 10^{-159}$	$2.19 \cdot 10^{-163}$	$1.46 \cdot 10^{-164}$	-	$3.63 \cdot 10^{-157}$	-	$3.42 \cdot 10^{-159}$	-	0	$3.11 \cdot 10^{-163}$

Table A13-8. Statistical t-test results for Comparation network with Capital English letters, P to T vs. N to Z. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

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Input-1 patterns		Input-2 patterns												
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**
U	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0056	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.740\cdot10^{-4}$	0.5346	0.5346	$5.742\cdot10^{-4}$	0.5346	$3.542\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	$[-3.6\cdot10^{-5}, -3.6\cdot10^{-5}]$	[0.5350, 0.5350]	[0, 0]	$[3.5\cdot10^{-5}, 3.5\cdot10^{-5}]$	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5306, -0.5302]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$6.34\cdot10^{-172}$	-	0	$5.01\cdot10^{-167}$	-	$1.02\cdot10^{-167}$	-	-	$4.87\cdot10^{-156}$	$1.01\cdot10^{-104}$	$1.7\cdot10^{-149}$	-
V	$\bar{x}_1$	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0079	$4.396\cdot10^{-4}$	0.0034	0.0019	$4.416\cdot10^{-4}$	0.0034	$2.839\cdot10^{-4}$	0.0034	0.0034	0.5348	0.5347	0.5350	0.0034
	C.I	[0.5286, 0.5287]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5348, 0.5348]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5364, 0.5364]	[0.5332, 0.5332]	[0.5332, 0.5333]	[0, 0]	$[1.2\cdot10^{-4}, 1.2\cdot10^{-4}]$	$[-1.8\cdot10^{-4}, -1.8\cdot10^{-4}]$	[0.5332, 0.5332]
	p-value	$4.43\cdot10^{-120}$	$4.91\cdot10^{-165}$	$1.54\cdot10^{-160}$	$1.18\cdot10^{-163}$	$3.68\cdot10^{-162}$	$1.86\cdot10^{-156}$	$8.8\cdot10^{-170}$	$3.82\cdot10^{-156}$	$4.87\cdot10^{-162}$	-	0	0	$2.8\cdot10^{-159}$
W	$\bar{x}_1$	0.0025	0.5354	0.5346	0.5346	0.5354	0.5346	0.5354	0.5346	0.5346	0.0019	0.0021	0.0017	0.5346
	$\bar{x}_2$	0.5358	$6.697\cdot10^{-4}$	0.5346	0.5346	$6.703\cdot10^{-4}$	0.5346	$4\cdot10^{-4}$	0.5346	0.5346	0.5367	0.5360	0.5374	0.5346
	C.I	[-0.5333, -0.5333]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0, 0]	[0.5347, 0.5347]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[0.5350, 0.5350]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5348, -0.5348]	[-0.5339, -0.5339]	[-0.5357, -0.5357]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$
	p-value	$2.59\cdot10^{-140}$	$1.03\cdot10^{-171}$	0	-	$3.16\cdot10^{-172}$	0	$2.99\cdot10^{-170}$	0	0	$8.38\cdot10^{-162}$	$1.91\cdot10^{-172}$	$3.59\cdot10^{-155}$	0
X	$\bar{x}_1$	0.5366	0.5367	0.5366	0.5367	0.5367	0.5366	0.5367	0.5366	0.5366	0.5348	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0079	$4.412\cdot10^{-4}$	0.0034	0.0019	$4.388\cdot10^{-4}$	0.0034	$2.844\cdot10^{-4}$	0.0034	0.0034	0.5348	0.5347	0.5350	0.0034
	C.I	[0.5286, 0.5288]	[0.5363, 0.5363]	[0.5332, 0.5332]	[0.5348, 0.5348]	[0.5363, 0.5363]	[0.5332, 0.5333]	[0.5364, 0.5364]	[0.5332, 0.5332]	[0.5332, 0.5332]	[0, 0]	$[1.2\cdot10^{-4}, 1.2\cdot10^{-4}]$	$[-1.8\cdot10^{-4}, -1.8\cdot10^{-4}]$	[0.5332, 0.5332]
	p-value	$3.71\cdot10^{-120}$	$8.33\cdot10^{-165}$	$4.49\cdot10^{-159}$	$2.52\cdot10^{-163}$	$4.56\cdot10^{-168}$	$1.31\cdot10^{-161}$	$1.25\cdot10^{-165}$	$3.21\cdot10^{-155}$	$1.56\cdot10^{-161}$	-	0	0	$2.34\cdot10^{-156}$
Y	$\bar{x}_1$	0.5347	0.5361	0.5360	0.5360	0.5361	0.5360	0.5361	0.5360	0.5360	0.5347	0.5347	0.0213	0.5360
	$\bar{x}_2$	0.5347	$4.823\cdot10^{-4}$	0.0054	0.0021	$4.812\cdot10^{-4}$	0.0055	$3.098\cdot10^{-4}$	0.0057	0.0055	0.5348	0.5347	0.5373	0.0056
	C.I	$[4.6\cdot10^{-5}, 4.6\cdot10^{-5}]$	[0.5356, 0.5356]	[0.5305, 0.5307]	[0.5339, 0.5339]	[0.5356, 0.5356]	[0.5304, 0.5306]	[0.5358, 0.5358]	[0.5302, 0.5304]	[0.5304, 0.5306]	$[-1.2\cdot10^{-4}, -1.2\cdot10^{-4}]$	[0, 0]	[-0.5165, -0.5156]	[0.5303, 0.5305]
	p-value	0	$1.51\cdot10^{-166}$	$2.06\cdot10^{-112}$	$1.56\cdot10^{-174}$	$6.09\cdot10^{-166}$	$2.21\cdot10^{-108}$	$1.59\cdot10^{-165}$	$1.32\cdot10^{-107}$	$3.43\cdot10^{-110}$	0	-	$9.59\cdot10^{-90}$	$2.07\cdot10^{-108}$

Table A13-9. Statistical t-test results for Comparation network with Capital English letters, U to Y vs. A to M. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

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Input-1 patterns		Input-2 patterns N	O	P	Q	R	S	T	U	V	W	X	Y	Z
U	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0056	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.278\cdot10^{-4}$	$5.736\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	$[-3.6\cdot10^{-5}, -3.6\cdot10^{-5}]$	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5332, -0.5332]	$[3\cdot10^{-5}, 3\cdot10^{-5}]$	[-0.5332, -0.5332]	[-0.5306, -0.5303]	[0, 0]
	p-value	-	0	0	0	$6.64\cdot10^{-175}$	$3.96\cdot10^{-169}$	$8.88\cdot10^{-158}$	-	$1.45\cdot10^{-157}$	0	$1.9\cdot10^{-156}$	$3\cdot10^{-108}$	-
V	$\bar{x}_1$	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0034	0.0079	0.0019	0.0019	$6.858\cdot10^{-4}$	$4.412\cdot10^{-4}$	0.5348	0.0034	0.5348	0.0019	0.5348	0.5347	0.0034
	C.I	[0.5332, 0.5332]	[0.5286, 0.5287]	[0.5348, 0.5348]	[0.5348, 0.5348]	[0.5360, 0.5360]	[0.5363, 0.5363]	[0, 0]	[0.5332, 0.5332]	[0, 0]	[0.5348, 0.5348]	[0, 0]	$[1.2\cdot10^{-4}, 1.2\cdot10^{-4}]$	[0.5332, 0.5333]
	p-value	$1.42\cdot10^{-157}$	$5.45\cdot10^{-119}$	$7.01\cdot10^{-161}$	$1.07\cdot10^{-159}$	$3.59\cdot10^{-164}$	$1.1\cdot10^{-165}$	-	$5.33\cdot10^{-158}$	-	$4.78\cdot10^{-160}$	-	0	$5.89\cdot10^{-164}$
W	$\bar{x}_1$	0.5346	0.0025	0.5346	0.5346	0.5354	0.5354	0.0019	0.5346	0.0019	0.5346	0.0019	0.0021	0.5346
	$\bar{x}_2$	0.5346	0.5358	0.5346	0.5346	0.0011	$6.708\cdot10^{-4}$	0.5367	0.5346	0.5367	0.5346	0.5367	0.5360	0.5346
	C.I	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5333, -0.5333]	[0, 0]	[0, 0]	[0.5343, 0.5343]	[0.5347, 0.5347]	[-0.5348, -0.5348]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$	[-0.5348, -0.5348]	[0, 0]	[-0.5348, -0.5348]	[-0.5339, -0.5339]	$[-3\cdot10^{-5}, -3\cdot10^{-5}]$
	p-value	0	$2.69\cdot10^{-137}$	-	-	$2.9\cdot10^{-168}$	$1.47\cdot10^{-170}$	$1.58\cdot10^{-159}$	0	$2.05\cdot10^{-167}$	-	$1.76\cdot10^{-159}$	$4.65\cdot10^{-171}$	0
X	$\bar{x}_1$	0.5366	0.5366	0.5367	0.5367	0.5367	0.5367	0.5348	0.5366	0.5348	0.5367	0.5348	0.5348	0.5366
	$\bar{x}_2$	0.0034	0.0079	0.0019	0.0019	$6.897\cdot10^{-4}$	$4.379\cdot10^{-4}$	0.5348	0.0034	0.5348	0.0019	0.5348	0.5347	0.0034
	C.I	[0.5332, 0.5332]	[0.5286, 0.5287]	[0.5348, 0.5348]	[0.5348, 0.5348]	[0.5360, 0.5360]	[0.5363, 0.5363]	[0, 0]	[0.5332, 0.5332]	[0, 0]	[0.5348, 0.5348]	[0, 0]	$[1.2\cdot10^{-4}, 1.2\cdot10^{-4}]$	[0.5332, 0.5332]
	p-value	$1.37\cdot10^{-157}$	$3.48\cdot10^{-120}$	$4.77\cdot10^{-162}$	$9.03\cdot10^{-160}$	$4.93\cdot10^{-162}$	$1.9\cdot10^{-169}$	-	$2.22\cdot10^{-154}$	-	$5.82\cdot10^{-158}$	-	0	$4.62\cdot10^{-159}$
Y	$\bar{x}_1$	0.5360	0.5347	0.5360	0.5360	0.5361	0.5361	0.5347	0.5360	0.5347	0.5360	0.5347	0.5347	0.5360
	$\bar{x}_2$	0.0057	0.5347	0.0021	0.0021	$7.682\cdot10^{-4}$	$4.809\cdot10^{-4}$	0.5348	0.0056	0.5348	0.0021	0.5348	0.5347	0.0054
	C.I	[0.5302, 0.5305]	$[4.6\cdot10^{-5}, 4.6\cdot10^{-5}]$	[0.5339, 0.5339]	[0.5339, 0.5339]	[0.5353, 0.5353]	[0.5356, 0.5356]	$[-1.2\cdot10^{-4}, -1.2\cdot10^{-4}]$	[0.5303, 0.5305]	$[-1.2\cdot10^{-4}, -1.2\cdot10^{-4}]$	[0.5339, 0.5339]	$[-1.2\cdot10^{-4}, -1.2\cdot10^{-4}]$	[0, 0]	[0.5305, 0.5307]
	p-value	$9.2\cdot10^{-104}$	0	$1.49\cdot10^{-173}$	$3.22\cdot10^{-171}$	$2.84\cdot10^{-164}$	$1.27\cdot10^{-169}$	0	$9.29\cdot10^{-109}$	0	$4.38\cdot10^{-172}$	0	-	$6.22\cdot10^{-110}$

Table A13-10. Statistical t-test results for Comparation network with Capital English letters, U to Y vs. N to Z. Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

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Input-1 patterns		Input-2 patterns												
		A	B	C	D	E	F	G	H	I	J	K	L	M
Z	$\bar{x}_1$	0.5346	0.5356	0.5346	0.5346	0.5356	0.5346	0.5356	0.5346	0.5346	0.0034	0.0055	0.0031	0.5346
	$\bar{x}_2$	0.5347	$5.753\cdot10^{-4}$	0.5346	0.5346	$5.759\cdot10^{-4}$	0.5346	$3.551\cdot10^{-4}$	0.5346	0.5346	0.5366	0.5360	0.5374	0.5346
	C.I	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[$3.5\cdot10^{-5}$, $3.5\cdot10^{-5}$]	[0.5350, 0.5350]	[0, 0]	[0.5352, 0.5352]	[0, 0]	[0, 0]	[-0.5332, -0.5332]	[-0.5307, -0.5304]	[-0.5343, -0.5343]	[0, 0]
	p-value	0	$9.4\cdot10^{-172}$	-	0	$3.51\cdot10^{-168}$	-	$2.53\cdot10^{-166}$	-	-	$6.15\cdot10^{-162}$	$2.83\cdot10^{-107}$	$1.8\cdot10^{-154}$	-

Input-1 patterns		Input-2 patterns												
		N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Z	$\bar{x}_1$	0.5346	0.5346	0.5346	0.5346	0.5356	0.5356	0.0034	0.5346	0.0034	0.5346	0.0034	0.0054	0.5346
	$\bar{x}_2$	0.5346	0.5347	0.5346	0.5346	$9.277\cdot10^{-4}$	$5.749\cdot10^{-4}$	0.5366	0.5346	0.5366	0.5346	0.5366	0.5360	0.5346
	C.I	[0, 0]	[$-3.6\cdot10^{-5}$, $-3.6\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[0.5346, 0.5346]	[0.5350, 0.5350]	[-0.5332, -0.5332]	[0, 0]	[-0.5333, -0.5332]	[$3\cdot10^{-5}$, $3\cdot10^{-5}$]	[-0.5332, -0.5332]	[-0.5307, -0.5305]	[0, 0]
	p-value	-	0	0	0	$9.59\cdot10^{-176}$	$2.41\cdot10^{-169}$	$6.08\cdot10^{-163}$	-	$2.53\cdot10^{-162}$	0	$1.37\cdot10^{-162}$	$2.49\cdot10^{-114}$	-

Table A13-11. Statistical t-test results for Comparation network with Capital English letters, Z vs. A to M (top) and Z vs. N to Z (bottom). Each box has four entries: mean of the average (median) activity of all nodes in respective M-field at final iteration (3000) over n-samples (n=35), 95% confidence interval (CI) and p-value. Input-1 & 2 patterns correspond to M(x5)-field & M(x6)-field respectively. Note that p-value is not computed for cases with CI = [0, 0]. The pattern-set is the same as in tables A1 and A2 with retinal-map size 5x5.

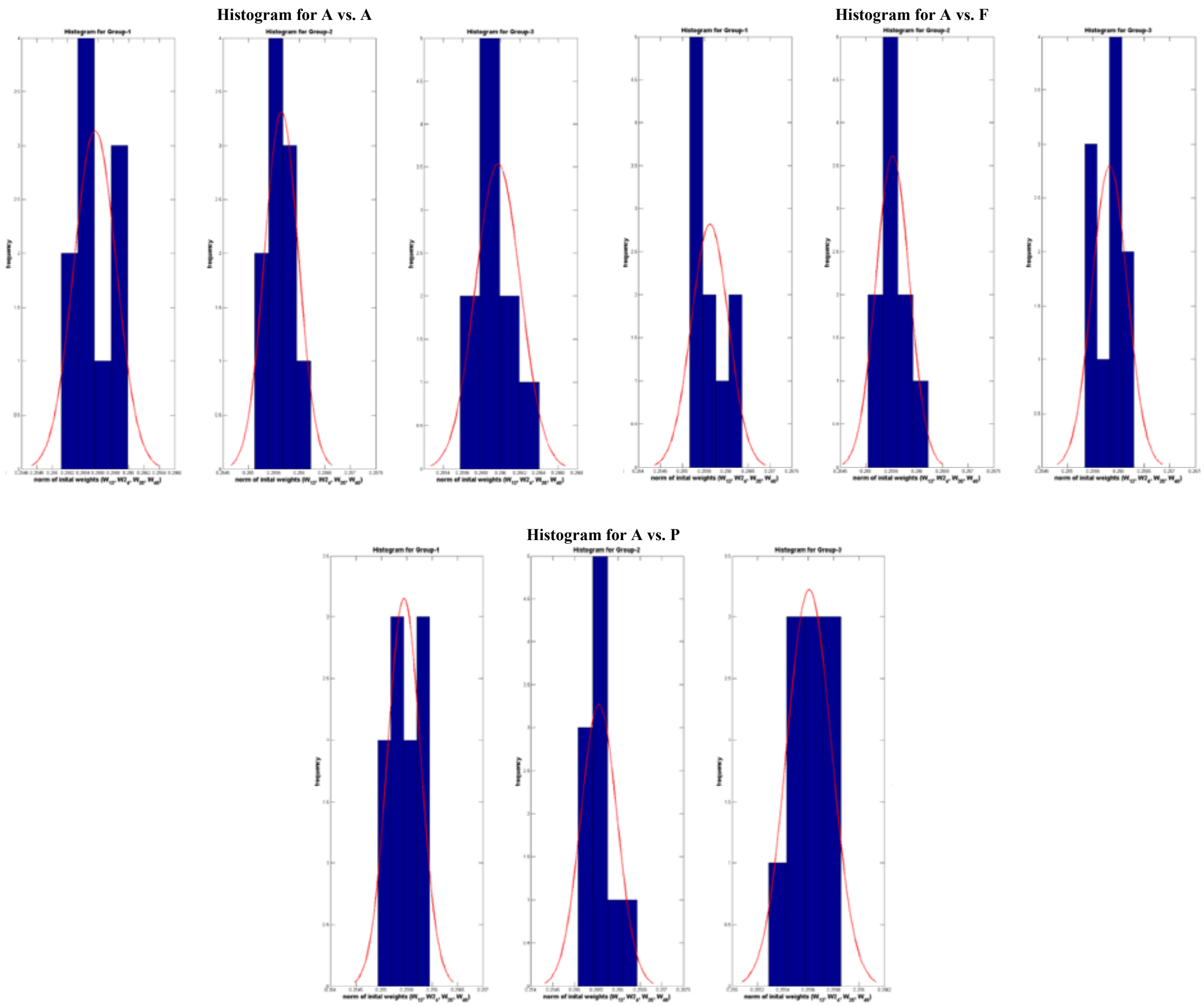


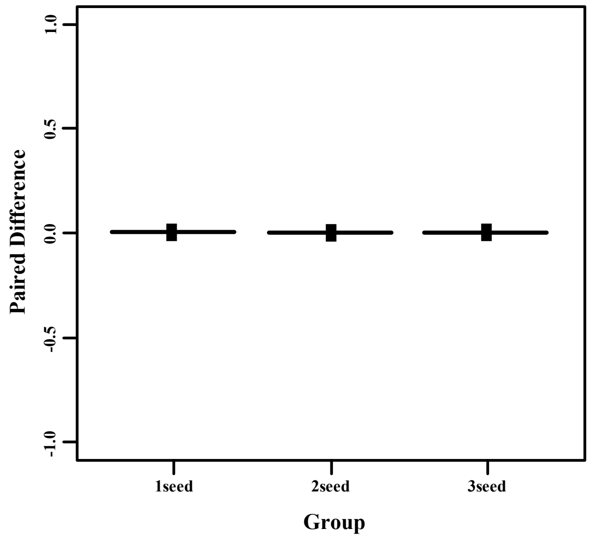
Figure A3-1. Histogram of norm of initial weights for ANOVA f-test with total sample size, N = 30. For the ANOVA f-test we consider, k = 3 groups. The groups are defined with respect to the seed (= 1, 2, 3) of the random number generator. Each group has sample size, $n_k = 10$. Thus, $N = n_1 + n_2 + n_3 = 30$.

For a given pattern-combo, there are three histograms. Each histogram demonstrates independent random samples (within respective group).

The superimposed normal (red) curve demonstrates randomly independent sample. Frequencies are for the infinity-norm of the vector composed of infinity-norm of the initial W_{13}, W_{24}, W_{35} and W_{46} matrices.

A vs. A

Box-Plot of paired difference for the three groups



ANOVA Table

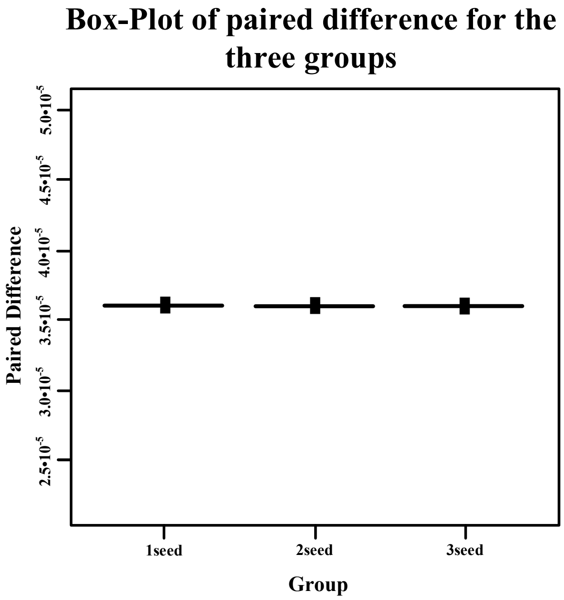
Source	df	Sum Sq.	Mean Sq.	F	P
Groups	2	0	0	-	-
Error	27	0	0		
Total	29	0			

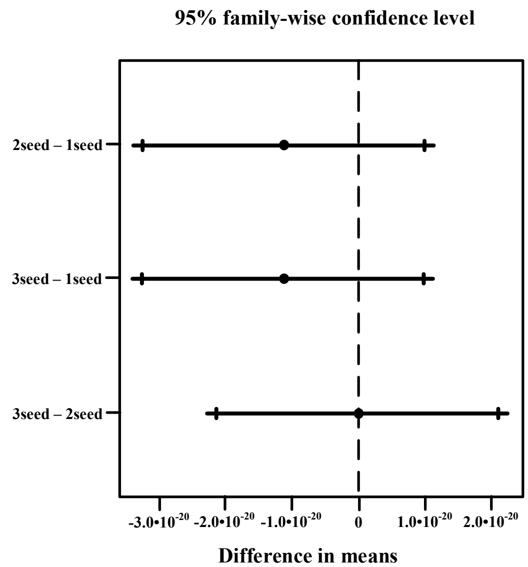
Figure A3-2. Comparison of paired-difference (pattern-combo, A vs. A) for three (k) groups. The patterns have retinal-map size 5x5. For the ANOVA f-test the groups are defined with respect to the seed (= 1, 2, 3) of the random number generator. Each group has sample size, $n_k = 10$. Thus, $N = n_1 + n_2 + n_3 = 30$.

Paired-difference is the difference of the means of M5 and M6-field activities at final iteration (2000) over n_k samples for respective k-group. The ■ within the box indicates sample mean.

Notice that the sample means are all = 0. Thus sum of squares for the groups = 0 and hence mean square for groups also = 0.

A vs. F





ANOVA Table

Source	df	Sum Sq.	Mean Sq.	F	P
Groups	2	0	0	-	-
Error	27	0	0		
Total	29	0			

Figure A3-3. Comparison of paired-difference (pattern-combo, A vs. F) for three (k) groups. The patterns have retinal-map size 5x5. For the ANOVA f-test the groups are defined with respect to the seed (= 1, 2, 3) of the random number generator. Each group has sample size, $n_k = 10$. Thus, $N = n_1 + n_2 + n_3 = 30$.

Paired-difference is the difference of the means of M5 and M6-field activities at final iteration (2000) over n_k samples for respective k-group. The ■ within the box indicates sample mean.

Notice that the sample means are all equal to $\approx 3.6 \cdot 10^{-5}$. Thus sum of squares for the groups = 0 and hence mean square for groups also = 0. Since the sample means are ≠ 0, confidence intervals can be computed.

The 95% simultaneous confidence intervals (Tukey's procedures) indicate that all the three intervals cover 0.

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