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Computing Action Potentials by Phase Interference in Realistic Neural Networks

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Abstract

A mathematical deconstruction of either the action potential and of the more recently described action potential pulse reveals that the action potential is not binary but is a compound digital phase ternary object with an analogue third phase. This mathematical object is described and predicted by textbook descriptions of the action potential. It has been recorded electrophysiologically and has the following phases

- The first phase is the resting potential
- The second is the digit comprising the potential above the resting potential (electrophysiologically recorded as the spike)
- The third phase is the refractory period, which is time dependent and is itself an analogue variable.

Critical examination of this mathematical arrangement produces a computational object the Computational Action Potential Pulse (CAPP). This structure moves along the axon at defined speed according to the transmission dynamics of the membrane at that location and contains a digital ternary-phase with an analogue refractory 3^{rd} phase (+1,0,-1t).

Examination of the CAPP reveals an inherent ability to compute in a realistic artificial Brain Neural Network (BNN) by action of the analogue time component of the third phase, which is effectively able to reroute action potentials along different pathways through the neural matrix; i.e. the refractory period is capable of interference at axon bifurcations and the axon hillock of cell bodies to produce effective deflection of action potentials along different axonal pathways in the neural network or to cause mutual occlusion.

Computation by phase has not previously been described. This type of computation is ineffective except in a brain neural network where almost all connection dynamics may be considered plastic over time and the network is small-world. Computation by CAPP is distinct from gating because gated computation must have a time-pause whereas phase computation occurs at the same rate as unobstructed transmission. In addition, the CAPP has native error redaction providing almost error free transmission.

Keywords: *Computation by Phase; Neural Network; Brain Coding; Association; Computational Action Potential; Pulse; Computation, Neocortex; Ternary; Phase; Error; Noise Signal Ratio*

Abbreviations

AI: Artificial Intelligence; AP: Action Potential; APPulse: [1] – Compound Oscillating Action Potential Pulse formed from the entropy of the Action Potential [2] and the lipid accompanying pulse; Neural Network: a neural network contains neurons with the same transmission dynamics as a biological neuron; Artificial Neural Network: distinct from Neural Network and is the type of NN used in AI; CAPP: Computational Action Potential derived from the AP [2] or APPulse [1]; Φ: the Greek letter "phi" meaning "phase" in this context

Definitions

Liquid Network: A liquid network is a complete physical neural network whose plastic connections change over time or due to stimulation. In this network memory is not fixed to structure but to the distinct pathways where each pathway represents a memory abstract. The complete memory abstracts in the network form a self-organising memory map SOM. As the pathways change the abstracts are free to redistribute in the network and a re-associate with other abstracts. No memory is fixed to any physical item whether neuron synapse or other.

Depth in a neural network: This is a function of the number of layers of the neural network evaluated during computation: note the biological brain neural network is unrestricted giving depth as the maximum number of potential pathways traversed by neurons. In the biological brain this amounts to larger than the number of neurons as pathways concatenate.

Aim

To elucidate the computational properties of the action potential by selective deconstruction into elements of activity in a neural network.

Introduction

When considering biological processes that might support Sentience and Perception some prerequisites are important: timing, error, efficiency [3], both natural and artificial neural networks [4-13] and a conduction system to associate memories and processes [14,15]. In this paper, we solely consider conduction by action potentials and their ability to act as compound phase-ternary objects for an artificial neural network. The basic mechanisms of the action potential are covered elsewhere and both the Hodgkin Huxley [1] and APPulse [2] may be used in this model. It should be noted that the APPulse has a time component, which explains the speed at which an action potential travels and why at each bifurcation, action potentials will inevitably collide over the network by giving a predicted speed for the action potential at each finite point on an axon. Where there is a refractory period present out of phase with the action potential, this collision will redact the action potential.

Studies of the action potential [1,2] show that timing is critical for action potential propagation with impulses travelling at under 1m/s and closer to 1 mm/s in the finer fibres of nervous systems [9]. Memory at the earliest moment in the neonate must be processed as the somatosensory information is passed onto the neural network [6,14]. This means that processing may be achieved in a very small neural network and that information must be available to be processed efficiently by that network in order for it to become promptly available [9,14,15].

This paper is primarily concerned with modelling computation in a full whole brain neural network in vertebrates and possibly in advanced invertebrates such as cephalopod molluscs [16] and decapod crustacea [15]. Thought processes in the vertebrates are known to occur very quickly. Simple shape recognition and learning has been timed to be less than 200ms removing motor input and output suggests the passage of less than 10 neurons in neural network depth making continuous forward flow of information the only method [17-20]. Error in small dendrites where noise is of the same order of magnitude as the action potential also needs to be taken into account [20,21]. In any neural network error is additive through the layers and any computation model would have to have a system to redact this. The human brain is a structure of about 86 billion neurons [22,24] and has evolutionary consistency with other primates [23,24]. From timing studies [25,26] and cognitive studies the brain appears to associate and process different sets of information concurrently with little loss of timing [18,19] and importantly no loss through error that would preclude the many degrees of association necessary within the system [20,21].

Current trends in both Neuroscience and Artificial Intelligence have concentrated resources into examining ‘synaptic gated’ theories of memory retention and processing abilities [28,29]. This relies upon assumptions that the action potential can only carry binary information and that interaction leading to memory processing takes place only at synapses. This has led to a mathematicians proposing models of “Artificial Intelligence” based not upon the properties of the neuron but upon current trends in Information Technology. However, any model of nerve conduction that claims inspiration from nature must include appropriate physiologically observed parameters.

Here we investigate how the mathematics of the action potential affects the processing of information within a biological neural network using a mathematical model. Although a full treatment of computational methods is beyond the scope of this paper they may be found elsewhere [30-34].

Methods

An examination was undertaken into the historical significance of research into computation within the human brain [23-30]. Networks and mathematical models were compared [8,31-35]. Speed of transmission and computational methods were considered, as was the action potential itself. Computational bases were reflected upon and compared with the physiological action potential. Models of computation were contemplated taking into account the shortcomings of current artificial nodal neural network models [30] and the absence of appropriate software, or mathematics and no timer/clock to synchronise processing. Error in biological systems is high and signal to noise ratios are often indistinguishable in small neurons in many vertebrate studies indicating that there is error redaction. Other methods of computation were investigated including Balanced Ternary computation [36-40] and added to the discussion.

The action potential was deconstructed to examine it for computational properties. From balanced ternary studies, the mathematics of balanced phase ternary became apparent and the similarities compared to the action potential. A compound ternary object was discovered and further investigation showed that the action potential is a compound balanced ternary phase object with an analogue refractory phase as described in the results. Following this discovery, the computational properties were examined in terms of simple collisions of action potentials. Examples were created of possible interactions between action potentials [41-43] in the light of the above discoveries. Relevant working is shown indicating that at each stage the action potential and collisions among coalescing action potentials corresponds fully to physiological observations of efficiency, error, cognitive timing and brain function. In addition, at all times results were checked to ensure a structured model that adhered to a minimum of error and maximum memory which could compute and memorise synchronously in a neural network or a liquid neural network of the type observed in the brain, particularly in the cerebral cortex.

Results

A deconstruction of the action potential limits the spectrum of possibilities for computation to a number of bases; 2,3 were considered but the lack of an accurate timing mechanism and the accuracy of memory argued against base computation and in favour of phase computation. This resulted in only one candidate: a Compound Digital Balanced Ternary Phase action potential containing an analogue refractory 3rd phase. Specifically, the analogue refractory 3rd phase acts to provide interference nullification of colliding action potentials, changing or nulling phase, and is inherently capable of deflecting successive action potentials along discrete paths in a neural network.

Speed of the Action Potential and distance travelled

The speed of the action potential and the distance travelled [17,18] across the membrane surface defines the likelihood of the refractory period of one action potential colliding and interfering with another where axons come together at branches and on the axon hillock. The computational information that can be stored by the action potential does not follow the functional phases of the neurophysiological action potential but follows the binary computational action potential [2].

The Computational Action Potential Pulse (*CAPP*)

Here we describe the discrete deconstructed elements of the physiological action potential pulse [2] as described for stimulation that might be applied to computation and processing of memory; the areas of the action potential are discussed in relation to accurate timing and connectivity over the length of an axon.

Signal to Noise, Accuracy and Precision – variability of transmission

In the action potential digit, there is a low signal to noise ratio [20,21]. We know from cognition that the brain is both accurate and precise but this is the opposite of what is expected from the variability and random noise experienced by researchers [20]. Typically, in recording from biological systems there is considerable noise that historically was attributed to experimental techniques but it has become clear that these are natural and can be ascribed to normal biological processes within the axon [20]. Artificial networks are predominantly geared towards producing next-generation computation effectively using scaled down artificial neural networks [40] where noise is of little relevance. However, in contemporary biological models this presents a problem in a neural network of only limited depth where noise creates additive error in synaptically gated systems and makes any processing ineffective [20,21]. When considering a larger network, superficial timing and error makes this mechanism untenable.

Consecutive Time

There is no 'clock' in the brain that can accurately predict a standard for conventional processing. A 'clock' is essential when considering processing by conventional computing. In contrast the brain uses adaptive timing recording and processing memories concurrently according to the provoking parallel somatosensory information from many different stimuli. When considering input into a biological neural network it is important to accept that somatosensory information arrives into it continuously. There is no evidence that separate challenges or processes are separated like a film-strip and action is by continuous flow. It is therefore safe to assume that the most efficient method of assimilation of this information into the brain neural network is likewise concurrent with perceived time. Perceived time is the time perceived for each somatosensory object to be assimilated into the associative network – for example while the neural network is engaged upon associating inputs it is occupied and perceives little time passing. The continuous flow of events into the neural network produces concatenated perceived time, which in total makes up a string of consecutively timed events. In practice, somatosensory information must continuously enter the neural network and be assimilated concurrently with processing. Each consecutive set of parallel inputs is computed sequentially into the neural network by association.

Synaptic computation inhibition and 'weighting'

Transmission of Action Potentials at the synapse is facilitated by neurotransmitters triggered by rising intracellular calcium concentration in the nerve terminals due to depolarisation caused by the rising phase of the action potential. At this point the computational dynamics of the presynaptic action potential cease and the computational dynamics of a new action potential is created post-synapse. At the synapse, individual action potentials are effectively binary. An incoming spike may or may not produce an outgoing and there is no possibility to deflect only to nullify action potentials when other pathways are active. Single or successive releases of neurotransmitter into the synaptic space will instigate transmission according to the specific dynamics of the synapse and the presence of external neuroactive substances. Synaptic transmission is essentially unidirectional digital binary with an input spike often leading to an output. Blocking synapses individually performs redirection. This is distinct from computation from the biological action potential where interference across a wide surface membrane may in the pyramidal neurons have the effect of blocking multiple pathways independently.

Computation across the neuron from Synapse to Synapse

Synapse free Computational interference

Evidence for a functional method of computation across the neuron from synapse to synapse has been available in the methods and results of many studies in neuroscience historically back to and including Huxley Hodgkin quantitative description of the action potential [2]. To understand how this computation takes place it is necessary to deconstruct the action potential and consider the early work of pioneers in both computing and neuroscience retrospectively. Taking the whole neuron as the functional element of computation the nodes of the neural network are the branches of the dendritic trees and the action potential is the facilitator of computation during collisions [41-43]. The start of the CAPP occurs when threshold is exceeded. Thus, variability is minimised, as any further digit depolarisation is unnecessary; the variable refractory digit/refractory period timing is from the timing from threshold to the time when another threshold is reached to trigger another action potential.

The threshold is a momentary space of time when enough ion gates open to create an exponential positive feedback opening of ion gates and hyperpolarisation. Although in physiological terms this is portrayed as a gradual increase caused by the ionic field of the main digit, in computational terms it is the absolute time - taking into account error in the form of variability - before threshold goes to full hyperpolarisation and after the initial rising phase where exponential depolarisation is uncertain. For a 99% certainty, this figure where the rising potential wavers between threshold and digit can be calculated from the probability of full depolarisation over a specific time period, for example if it is approximately < 20 μs this would correspond to a distance of < 20 μm at $1ms^{-1}$ as a maximum figure. This marks the beginning of the CAPP and may commence at some physical distance from the beginning of the physiological threshold.

There also is another computational unit: the refractory period – specifically its end. The refractory period is defined by the absolute dynamics of the membrane (ion channels, gates, leakage, soliton effect [1] etc.) contributing to the speed of repolarisation of the membrane at any point; for the purposes of computation, it may be physically located anywhere that branching or interference may take place. Thus, the refractory period is fixed by its position in the axon. It is a variable within each membrane AP combination giving a distinct value for each axon of given composition over given positions on an axon. Although the refractory period changes from position to position down neurites at each specific point the variable is a constant determined by local membrane dynamics. Thus, the threshold voltage is dependent upon the specific qualities of the axon at the position of interference as is time (t) of the refractory period.

The CAPP is therefore in three distinct parts per discrete portion of membrane: resting, digit and refractory. If the speed along an axon is 1 m/s for a 10 μm unmyelinated axon then a 1ms spike will travel along the membrane a distance of 1 mm [25]. The distance the threshold travels is considerably less and is the functional mechanism for the spike. The refractory variable is dependent not upon the spike timing but on the threshold trigger to repolarisation time; although there is variation this is minimised by having this time period match the absolute positioning on the axon. For each dendrite-soma-axon pathway the refractory period is variable, and different from other pathways but is itself relatively constant.

Ternary notation

Ternary notation has long been considered for computation [31,45] due to its advantages over binary notation [36,40]. Phase-ternary, which is a time-dependent object has the same mathematical advantages. Balanced Ternary (-1,0,+1) reduces the number of digits in a line of code needed to represent a memory. Euler's number (≃2.7) provides the most efficient base for representing arbitrary characters [31] and ternary (3) and phase ternary φ3t are the closest integers to e (2.718…) and therefore, base 3 is more efficient than base 2 when used to build digital systems. The mathematics is similar for phase-base ternary as for ternary; characters representing processing code and memory in a conventional computer may also be represented by concentrations of action potentials in a representative neural network. Base 3 minimizes complexity and increases efficiency in a computational process.

Binary logic can be summarized as AND OR and NOT where every expression can only evaluate to 0 or 1, there are no other possibilities. In balanced ternary, each digit has one of 3 values: −1, 0, or +1; these values may also be simplified to −, 0, +, respectively. Ternary logic is also easily configurable and amounts to three states: YES, NO, NULL. Note that 0 is not reduced to -1, only +1 is negated to 0. In balanced-phase-ternary timing is important because the refractory period is analogue so the logic becomes: YES, NO, NULL (time). This logic has a fundamental advantage when considering computation within a large unlimited depth neural network as it readily permits deep networks randomly formed to form a unique functioning 'like operator' able in single stages of discriminating abstract objects from one another. This logic changes the directions of deflection of action potentials as they arrive at branches. This logic is also much closer to human logic rather than binary providing an effective decision functioning of Yes, No, Don't know; rather than a binary yes, no. This reduces logic steps in processing and increasing efficiency.

In respect of the CAPP computation advantages become apparent when considered in conjunction specifically with a representative brain neural network as described as a model for this paper. Historically a relative slow moving pulse structure was thought to travel too slowly to compute within observed time and the model action potential used for computation used fixed latency and gating. On examination of the neural network and by using a loose model where no connection is fixed for any length of time, all connections are random and liquid and the depth is theoretically unlimited. Advantages of efficiency, accuracy error and computation become visible on understanding of how the action potential is directed into concurrent parallel pathways within the brain neural network. The neural network may be any size or depth and plasticity enhances its operation. As the action potential travels along the axon the tailing refractory period acts as a nullifier to erase colliding action potentials if the action potential phase threshold +1 collides with the refractory period -1t of another where t is the refractory time. This effectively shifts the phase eradicating some action potentials from the collision and directing them along distinct pathways and generating multiple separate spikes as can happen in multiple spiking neurons [44]. The deflection of action potentials along pathways is distinct according to the absolute qualities of the neurite at the point of collisions, the refractory period and the exact phase of the colliding action potentials.

The Ternary Phases φ

1. Phase φ1: The resting potential is the potential difference caused by the ionic difference across the membrane as exists at equilibrium. This may be different between cells and may, where channel gradients change along the axon, also be unstable over length. This phase is of indeterminate length and maintains its potential integrity under normal resting conditions.

2. Phase φ2: The rising phase of the action potential. Specifically, the timed momentary threshold able to instigate the action potential pulse. This is the result of the exponential flow of ions depolarising the membrane by exponential opening of ion channels. As described above this is a variable figure but approximates to < 20 μm along a fast axon < 2 μm for a slow. For computation to take place a factor of 10 greater or 100 lower would not affect the inevitability of interference. In the soma of some large neurones with calcium dependent spikes (for example in the pyramidal neuron [45]) this figure is reduced by the inclusion of Ca^{2+} channels that cause Ca^{2+} entry during the recovery phase. This has the action of reducing both the rising phase and importantly shortening the refractory phase allowing possibly for some interesting AP dynamics due to the shape of the Soma.

3. Phase φ3t. The refractory phase. This is the phase when no new action potentials may be created and as described includes the falling phase of the neurophysiological action potential. This is the third computational phase. This phase is dependent upon the distinct qualities of the axon at the exact position where interference is to take place and which will change the length of φ3 by time t. Time t is critical to the behavioural interference of action potentials when they collide as time t prevents a new threshold and subsequent action potential being formed.

There is less than a 20 μm distance at 1 m/s computationally separating the resting from the refractory phase: for example, a 5 ms variable refractory period causes a 5mm refractory period at 1 ms 0.5 mm at 0.1 ms. The length of neurites from a single neuron vary from almost zero to many cm making collision at branches inevitable. Unlike these large neurons, those in neural networks contain small diameter neurons where collisions are more likely to interact and the refractory periods cancel if out of phase, thus making interference inevitable. A typical length of the membrane covered by the refractory distance along the membrane in the neocortex might be of the order of 300-500μm. Many axons are much smaller with correspondingly shorter refractory distances where the length of refractory period will ensure that collisions result in interference; in addition, ion protein channels and other mechanisms may reduce the refractory period to near 0 by the action of fast repolarisation. Single dendrite-soma-axon pathways in the brain vary from a few μm to a few mm – and some may be spikeless [46]; in addition, consecutive pathways within the neural network form further pathways allowing an almost unlimited variation of refractory distance making interference inevitable. This interference leads to phase cancellation and phase change.

The Threshold: In the CAPP, the digit is replaced by only that part forming the threshold. Importantly, for computation to occur within the neuron branch or soma only the threshold of the Action Potential needs to be reached – not the whole digit – any depolarisation before this is irrelevant as it does not lead to an Action Potential and any depolarisation after is irrelevant as it is incapable of affecting the digit and is computationally part of the refractory period. Physiologically, the digit-phase may have a relevance to triggering vesicle release [48], but this latency will per pathway remain constant. Any interruption during the momentary threshold spike of a few microseconds will halt the AP permitting the refractory period of any colliding AP to interfere with accuracy. The refractory period (t) is of indeterminate length and changes from neuron to neuron being one of the distinct dynamics that facilitates computation. It is the start of threshold/digit and the changing value of t that is of importance in computation as it gives a phase-change length of the order of the time taken to open just a few ion gates or during an extended refractory period ≥ 10 ms depending upon the pathway.

Collisions and Computation

Studies have shown that collisions of action potentials may result in their occlusion [41-45]. According to action potential theory [1,2] the refractory period depends upon the distinct qualities of the axon. This is shown for the CAPP described in Figure 1.

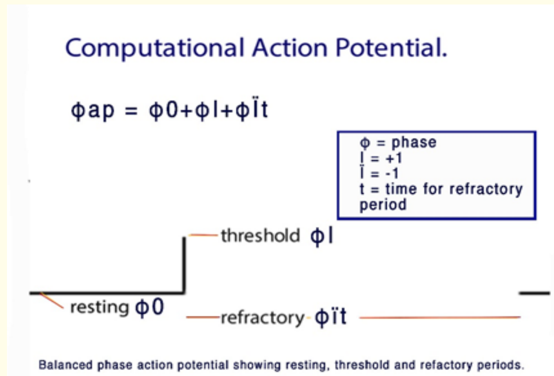

Figure 1: *Representation of the CAPP, showing the digital resting phase, digital threshold and the analogue refractory phase. In this view, the resting potential serves as the ternary 0 of a ternary action potential. Any rise above threshold is the digit or +1 and the refractory period acts as phase -1 refracting any digit+1 during collision to 0. The refractory period is analogue and is a result of the specific dynamic of the membrane at that point where the action potential exists.*

An example of how action potentials collide is shown in Figure 2. Action potentials firing in-phase map together, whilst those with +1 and -1t overlapping cancel to 0. In addition, because the third phase 3φt is time dependent any refractory period cutting into a phase 2φ will create a double action potential with changes in phase.

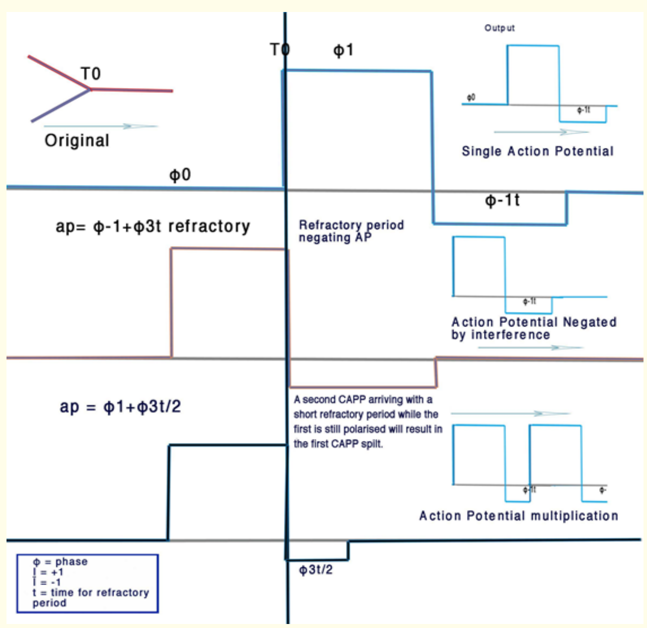

Figure 2: *Computation phase ternary interactions - Collisions from CAPP s may result in nullification of CAPP (second row) or division (last row) into two CAPPs depending upon phase and the dynamics of the membrane at the point of collision. Multiple collisions form patterns navigating pathways through the network. These patterns form a memory liquid memory structure that changes continuously with added inputs.*

Timing. Accuracy is defined in terms of the phase changes as action potentials deflect into different branches of a neurite

When considering accuracy, it is important to consider which part of the signal might be responsible for timing. In contemporary models this is assumed to be the spike, but as a detailed examination of the CAPP above demonstrates only exceeding the threshold is essential to a digital system. After the threshold digit depolarisation is timed until the refractory period. Computation occurs from interference between the digit of one CAPP and the refractory period of another CAPP at positions where CAPPs combine over the surface of the membrane. For computation to occur by interference there must be time variants or discrete latencies able to be detected with minimal error between one AP pulse and the next and within the action potential as it travels. The two important functions of the action potential therefore are the threshold and the length of the refractory period t.

Error Restriction in the Brain Neural Network – balanced phase negation of noise

Excitatory synaptic transmission defines the start of ternary-phase computation because each neuron is separate computationally. During the transmission of action potentials, the error in variability in transmission between two synapses over a set period of time is less than 1% [21], because the computation takes place between defined synapses. As discussed later, the neural network is proposed to contain many distinct but an almost infinite number of variable pathways formed from the up to 10,000 connections between neurons formed from the up-to 10,000 connections between neurons – based on the cerebral cortex; parallel pathways within the network will also restrict error further.

Noise Signal to noise ratio

The parallel processing of axons leading to the same neuron reduces variability likewise in the CAPP neural network where connections are randomly formed and neurons are connected by more than one pathway and may reduce signal to noise ratio (Figure 3). In a concatenated balanced phase system with many interfering CAPPs, noise is automatically negated at each parallel point of processing by interference. This occurs where a pulse train travels along adjacent parallel pathways whether through one or more neurons. This is a mathematical certainty where two CAPPs collide from parallel pathways to a common node. This error negation is particular to phase ternary and depends upon the logic of interference where two spikes are compared from different sources and tested automatically for a match. Error in this system is negated at the point of balanced phase computation. Any attempted measurement of the spikes shown at any point will also show noise, however at each successive point/points down a chain of neurons the active spike pulses are well defined and available without error. It is assumed that parallel processing takes place within the system, as there is no restriction on this taking place.

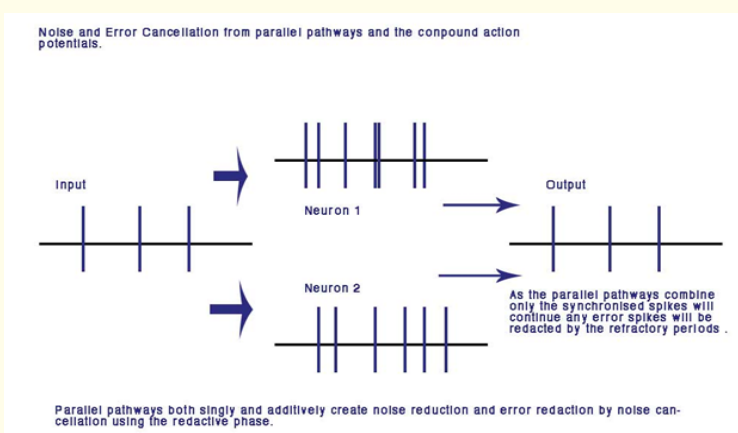

Figure 3: *Error redaction by phase ternary. In parallel connections, any out of phase errors and spontaneous spikes are automatically redacted by the refractory periods of neighbouring spikes: using the CAPP any phase shift or spontaneous spike will be reduced to the resting potential by the colliding neighbour CAPP.*

The solution proposed by synapse plasticity Balanced Phase sequentially negates error natively between two or more neurons over many parallel pathways.

Discussion

Timing in the brain is of absolute importance when considering processing of information. The brain is a highly efficient organ capable of multiple parallel computing in a many dimensioned associative database in the neural network and of concurrent memory retrieval and storage. As the network forms at a very early stage of life it is able to associate and store somatosensory information in real time and store information associatively from 0 memory or knowledge learning as diverse information is associated into the network by the patterns of pathways and by time forming a liquid connective network of all memory. Mathematical models of the brain neural network using fixed latency binary and gating of the synapses do not compute or act in the same manner as the brain. Here we assume that the brain is highly plastic; neither the connections, the neurons, nor any part of the neural network has to be a fixed structure and the plasticity inherent and observed by numerous authors [47] is essential for processing of information. The model proposed here is infinitely scalable from 1 branching neuron to infinite numbers of neurons and associates memory within the first connections.

The evidence we have presented indicates that the analogue refractory period almost certainly has a profound effect on the distribution of action potentials in the neural network as well as providing a third phase capable of enhancing the computational properties of the action potential from binary to ternary phase. It is not of concern to the overall speed of thought, that the action potential is a time dependent object because in a neural network only the first few layers take significant time. If each neuron is connected to 10,000 others and some of these connections may be distant then a small world network exists capable of associating 10,000 memory elements incrementally. 10,000 associations from one neuron becomes at least 10^{10} associations after 1 move but 10^{20} after 2 and 10^{40} after 3. This produces rapidity through the system capable of beating any conventional computer for this type of action where the associations need to be of great depth as after only a few moves every association has been compared. This new type of computation uses abstracts and the complex structure of the network over time so that recognition is available using only a few processing steps by minimising the number of connections required for processing. In contrast a conventional computer uses many steps and would require error and noise redaction to enhance the speed of associations.

More detailed associations are formed because of the small world nature of the network and are accessed concurrently; an almost infinite number of associations (though 'lossy' over time when associations may become overwritten) are therefore possible in the minimum of time. Because memory is held within a 'liquid network' where plasticity changes the connections and connectivity [47] and may be re-associated when plasticity information is updated, memory may be duplicated but nevertheless associated as such. Using the computational phase action potential is the only plausible way in which error and noise can be effectively redacted from the system allowing a fully operationally infinite depth network capable of associations of 10,000 or more per node. The action potential at physiological speeds inevitably will form collisions. Backpropagation and antidromic inhibition/assistance if added to the system may provide further computational dimensions.

Conclusions

Unusually for biological systems and importantly, the CAPP and the brain neural network forms a mathematically accurate computational algorithm based on existing evidence. It is by far the most likely candidate to facilitate computation in a neural network using action potentials overcoming all the discrepancies in other models and functions to associate memory by compound phase ternary logic by deflection.

The CAPP and the brain neural network model predict that the action potential is a compound digital phase-ternary structure with time-analogue refractory phase. At physiological speeds collisions between action potential are inevitable and those interactions will result in cancellation or change of phase. The actions of multiple action potentials in parallel both in and out of synchronisation within a structurally intact brain neural network will cause action potentials and action potential trains to deflect according to the CAPP. Deflection along pathways in the network occurs similarly for similar stimuli and naturally aligns with specific pathways. The nodes of attraction define each pathway. Each node of attraction is similarly connected to other nodes by association.

In this neural network memory is processed into associations in consecutive time. Memory is not fixed to neurons but to pathways and as the pathways change then the memory moves in the network and will cause re-association momentarily liquefying the memory patterns within the network.

Note that all memory must be learned and programming must be by association.

This model of Brain neural network creates an error free environment in which the compound digital ternary action potential forms memory by deflection. CAPP computation is fully conducive to the network dynamics and the physiology of the brain neural network. It explains the depth of memory and the speed of processing and its unique error redaction makes CAPP efficient and effective. Deflection from branches and the soma of neurons is mathematically inevitable from the collisions between CAPPs by nature of the refractive analogue phase.

There are no better candidates for memory processing and retention in the brain than ternary phase CAPP diffusion and computation. This method of processing uniquely explains the efficiency, computation speed, logic, error redaction and size of memory as well as providing insight into the formation of perception and sentience through the plastic connections and the liquid network.

Conflict of Interests

No conflicts of interest.

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Volume 5 Issue 3 March 2017