Review

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Posted Date: 25 October 2023

doi: 10.20944/preprints202310.1594.v1

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Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 October 2023 doi:10.20944/preprints202310.1594.v1

Review

Neurocomputational Mechanisms Underlying Perception and Sentience in the Neocortex

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Abstract: The basis for computation in the brain is the quantum threshold of the 'soliton' accompanying the ion changes of the action potential and the refractory membrane at convergences. We provide a logical explanation from the action potential to a neuronal model of the coding and computation of the retina and have explained how the visual cortex operates by quantum phase processing. In the small world network parallel frequencies collide into definable patterns of distinct objects. Elsewhere we have shown how many sensory cells are mean sampled to a single neuron and that convergences of neurons are common. We have also demonstrated, using the threshold and refractory period of a quantum phase pulse, that action potentials diffract across a neural network due to the annulment of parallel collisions in phase ternary computation (PTC). Thus, PTC applied to neuron convergences results in collective mean sampled frequency and is the only mathematical solution within the constraints of brain neural networks (BNN). In the retina and other sensory areas, we discuss how this information is coded and then understood in terms of network abstracts within the lateral geniculate nucleus (LGN) and visual cortex. First by defined neural patterning within a neural network, and then in terms of contextual networks, we demonstrate that the output of frequencies from the visual cortex contain information amounting to abstract representations of objects in increasing detail. We show that nerve tracts from the LGN provide time synchronisation to the neocortex (defined as the location of the combination of connections of the visual cortex, motor cortex, auditory cortex, etc). The full image is therefore combined in the neocortex with other sensory modalities so that it receives information about the object from the eye, and all abstracts that make up the object. Spatial patterns in the visual cortex are formed from individual patterns illuminating the retina and memory is encoded by reverberatory loops of computational actions potentials (CAPs). We demonstrate that a similar process of PTC may take place in the cochlea and associated ganglia, as well as ascending information from the spinal cord, and that this function should be considered universal where convergences of neurons occur.

Keywords: nerve impulse; physiological action potential; soliton; action potential pulse; computational action potential; reverberatory circuits; perception; sentience

Definitions: QPAP: quantum phase action potential. Object: any object capable of being recognised by the cortex and may be an abstract of a larger entity. Abstract: any recognisable form that can make up an object. Event: a timeline of objects, sensations, and their interactions. Small world random neural network: randomly formed network where latencies between nodes are random and every node is connected within 3 degrees of separation.

INTRODUCTION

According to Ahissar and Assa (1) "perception of external objects is a closed loop dynamical process encompassing loops that integrate the organism and its environment" and thus provide a probable basis for understanding perception and sentience. Furthermore, neocortical functions are dependent on bidirectional thalamic communications via cortico-thalamic-cortical (CTC) loops interlinked to one another by cortico-cortical (CC) circuits forming extended chains of loops for communication within the cortex (2). These findings are based on the painstakingly researched physiological connections of neurons within the brains of experimental mammals such as mice, where many neurons communicate by action potentials and synaptic terminals, either chemical or electrical, although some neurons are spikeless, devoid of action potentials. However, action potentials themselves are known to have three independent functions: communication, modulation, and computation (3) and are the primary elements underlying sentience (4). Furthermore, an individual action potential is an ensemble of three inseparable concurrent states as shown in Figure 1(3).

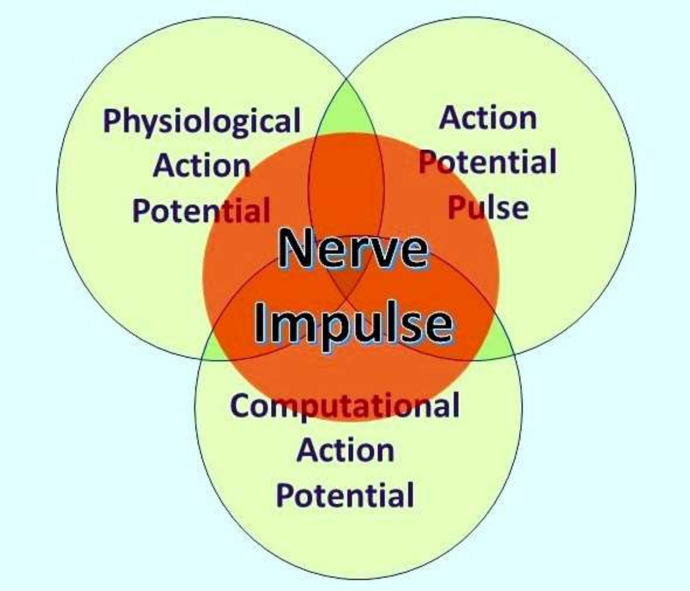


Figure 1. – The nerve impulse is an ensemble of three inseparable, concurrent states of the action potential. What an observer will perceive depends on their investigational perspective. The physiological action potential is the orthodox action potential described in detail by Hodgkin and Huxley (1952). The action potential pulse is the mechanical pressure wave for which substantial evidence has been presented elsewhere (Winlow and Johnson, 2022) and the computational action potential, first described by Johnson and Winlow (2017). .

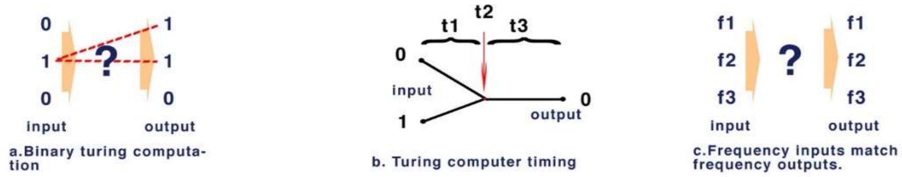
Here we concentrate on computational action potentials (CAPs) generated from sensory inputs and how they compute from sensory areas. We discuss artificial intelligence (AI) and its value as analogy for brain computation. Computational models of the action potential usually describe it as a binary event, but we have provided evidence that it is quantum ternary event (5), whose temporal fixed point is the threshold (6,7,8), rather than the rather plastic action potential peak used in other models. In AI, diffraction of pathways through a network is predetermined by programming each step, we demonstrate that brain neural network CAPs annul on phase asymmetry leading to distinct network patterning and frequency outputs. We also provide evidence that reverberatory loops of CAPs, each containing 1 trit of information (5, 8) can provide immediate active memory for every connection in the network, synchronised by phase and thus providing circuit memory. The decoding of the visual cortex is explained by first explaining how CAPs affect the patterning of distinct pathways in response to stimulation. A logical examination of the connectome of the visual cortex neurons in response to quantum phase ternary CAPs demonstrates that timing separates the image from the eye into abstracts which the neocortex can recognise as objects.

Using the same technique, we show that there is a logical explanation for the actions of the cortex (defined as the convergence of all sensory abstracts). The cortex takes sensory information in the form of abstracts containing all sensory information. It therefore contains all the live action; sight, touch, feel, taste, hearing, smell, proprioception, etc and combines them as action sequences. The cortex therefore may be compared with playing a video with sensation and thus records live memory. We postulate that the prefrontal neocortex (which we define in terms of connectivity) takes these events and contextualises them by importance. Thus, the prefrontal neocortex can compare events in the past to the present and can categorise them by context. The brain is therefore able to both compare events by time and by the objects/abstracts within. Further examination of the brain connectome using the knowledge of how the brain neural network function should eventually reveal its full function.

The cortex is a random neural network, formed during development, from random positioning of neurons and synapses with differing latencies of CAPs. The neocortex contains many events indexed primarily by time where impactful (repetition and change of context) events become learned. In the frontal lobes of the neocortex we believe that present perceptions from other cortical areas are then stored contextually by event and the abstracts within. Therefore, through contextual abstracts we may view connected past events and imagine future ones. Human thought is a process of comparing the present with past abstractions of what we know of the past and predicting the future from what we know.

1. Does the brain work by Turing computation?

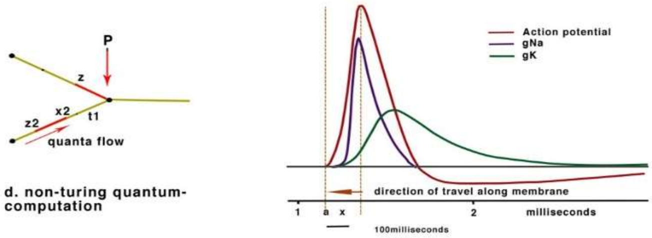
Computational theories for the brain rely on analogies with conventional Turing computation. A fundamental of Turing computing is the requirement for set-processing (an abstract machine that manipulates symbols on a strip of tape according to a sequential table of rules), usually facilitated by a central timer. However, there is no form of timer in the human brain with the precision to compute action potentials at the rate necessary in the reaction time available (5). Sensory receptors (muscle spindles, rods, cones, etc) all modulate action potential (CAP) frequency in response to sensation, similarly precise activation of muscle is by varying frequencies of stimulation: these frequencies are often connected by convergence onto interneurons coding many neuronal outputs into one. The human brain is therefore not a Turing machine. However, both the brain and Turing machines comply to basic computation rules. At its simplest computation is the resolving of unique inputs with appropriate outputs (Figure 2a).



a.Binary turing computation

b. Turing computer timing

c.Frequency inputs match frequency outputs.



d. non-turing quantum-computation

Figure 2. Basic computation rules. (a). Inputs must match outputs. (b). Turing computers use timing. (c). In neural networks frequency inputs must match respective outputs. (d). The Quantum threshold of the action potential (red) propagate to the convergence (P). As the quantum threshold passes the membrane at point P the membrane becomes refractory blocking further CAP. The second CAP therefore is destroyed leading to a reduction of CAP according to phase. The action potential showing the threshold area (orange vertical dotted lines) forms the beginning of the quantal soliton with rising and falling currents across the membrane.

2. The Computational Action Potential (CAP)

Conventional Turing computers process inputs sequentially according to the timing of a gate directing output and its programming figure 2b. The division of time is absolute between operations. The brain however computes frequencies rather than time (Figure. 2c). To confirm the computational functions of the human brain it is necessary to fulfil the requirements of computation and explain how this takes place within the limitations of a living neural network and measured behavioural properties of neurons and their connections.

Conventional computing and then more recently artificial intelligence (AI) evolved because binary chips became commercially available providing a platform that had not existed previously. The gated mechanism of a transistor is fundamentally different from that of a neuron, the first acting at nearly light speed and neurons at a leisurely 1m/s. Conventional computing and AI assumes that the action potential is binary, and that computation is facilitated through the synapses. We disagree and have previously argued that such a mechanism would be too slow, unstable and error prone (4). It is therefore necessary to review the platform of the nervous system from the complexity and positioning of the brain areas down to the fundamental unit of the action potential and to form a hypothesis from the evidence of demonstrated neuron behaviour.

In a conventional computer and in AI gating of current is performed by a program defining 0 or 1 (figure 2b). In Johnson and Winlow (7,8) we described how action potential colliding at convergences can result in similar patterns across a neural network. This form of computation had not been previously described and yet forms an intrinsic property of a neuron. Thus, an action potential can be better described as a quantum pulse with a threshold and peak. As an action potential propagates across a membrane a refractory period occurs where the pulse has travelled blocking subsequent CAPs. The mathematics are of quantum processing and depend upon the phase of the colliding CAPs (figure 2d). In Johnson and Winlow (6) we demonstrated that the spike of an action potential is not sufficiently precise to use in computation, but that the threshold had appropriate precision. This supports our view that the CAP is an electromechanical pulse APPulse (4, 5, 6, 9) where a pressure pulse (soliton (10-14)) is the marker for computation rather than the spike. The accuracy, precision and speed of the CAP is therefore defined by the quantum threshold (figure 2e). The threshold is the moment of propagation and is at the point the CAP moves across the membrane. The CAP is therefore comprised of a binary signal with a phase element (5, 8). It is the phase shift when collisions occur that changes the frequency of the outputs (figure 2e). This is very important when considering frequency computation as the soliton is precise to microseconds. In addition, in (7, 9) we explain how parallel information in a quantum phase system automatically redacts error – this is especially important when considering noise within the nervous system - and forms concurrent circuit (loop) memory.

3. Sensory inputs to the CNS

Complex nervous systems have substantial neuronal redundancy and multiple feedback systems to multiple specialised command lines driving central pattern generators (CPGs) (14). Computation of sensory inputs, leading eventually to motor outputs, is most likely by parallel distributed processing achieved from complex interacting networks in which the CPGs are also embedded. There are innumerable sensory inputs into the mammalian CNS many of which have been physiologically described, but which need to be understood in computational terms as we have set out in Figure 3, in relation to retinal processing. Figure 3 a, b, c and d are deconstructed illustrations of the basic connectivity of a converging neural network and the observed results (8). The refractory period of the action potential is dependent on the ability of the membrane to recover. Frequency of action potentials are limited in neurons with most in the range of 0-60 Hz. Observations of frequencies of input in all converging systems of neurons demonstrate that frequencies of inputs are proportional to outputs (figure 3c) as we commented on in our paper on the neural transactions of the retina (8). The resolution of this mechanism mathematically within the constraints of a neuron is the key to understanding its coding. In Johnson & Winlow (8) we suggested that only possible mechanism for this universal effect was interference when the refractory period of the membrane after an initial action potential blocked all others over the same surface for a set period (figure 3c). After elucidating the mechanism, we then applied this code to the retina. The retina in common with many other sensory neural networks (auditory, taste, skin) has similar connectivity of converging activity where regular neural networks from adjacent receptive fields, each supplying a nerve overlap (figure 3d). In each case the initial CAP frequencies are determined by sensory cells (for example: rods and cones). CAPs then converge with interneurons (for example retinal bipolar cells (RBC). An additive effect of the increasing number of convergences (5 cones to 1 RBC, or 20 rods to 1 RBC) has not been observed. Experimentally the result of convergence of firing neurons is the mean of the inputs figure 3 a,b,c,d. In a,b,c, and d, all the CAPs are in phase and so the result is collective mean sampling of the input frequencies. Thus, in the retina the resulting frequency of the bipolar cell is a mean firing frequency of all its connected light receptors. Therefore, each bipolar cell frequency is the mean representative of a receptive field. Where fields overlap adjacent receptive fields program the light variations and gradients from the bisections (figure 3 a. b c, d). Thus, the bipolar cells effectively code 5-20 photosensitive rods or cones into one bipolar cell. The frequency of CAPs leaving each bipolar cell represents the amount of light activating its respective receptive field. Bipolar cells with adjacent, overlapping fields contain information of light gradients across both fields. Gradient information between three of more overlapping photocells contains all the information necessary by cross indexing, to precisely detect variations of light across the whole retina. By using gradients, the information from the 5-20 cones is the same as if each cone had its own bipolar cells and optic nerve neuron. Horizontal cells add information from other bipolar cells in adjacent overlapping gradients coding detail and similarity into the existing frequency. Coding to the ganglion cells follows the same mechanism.

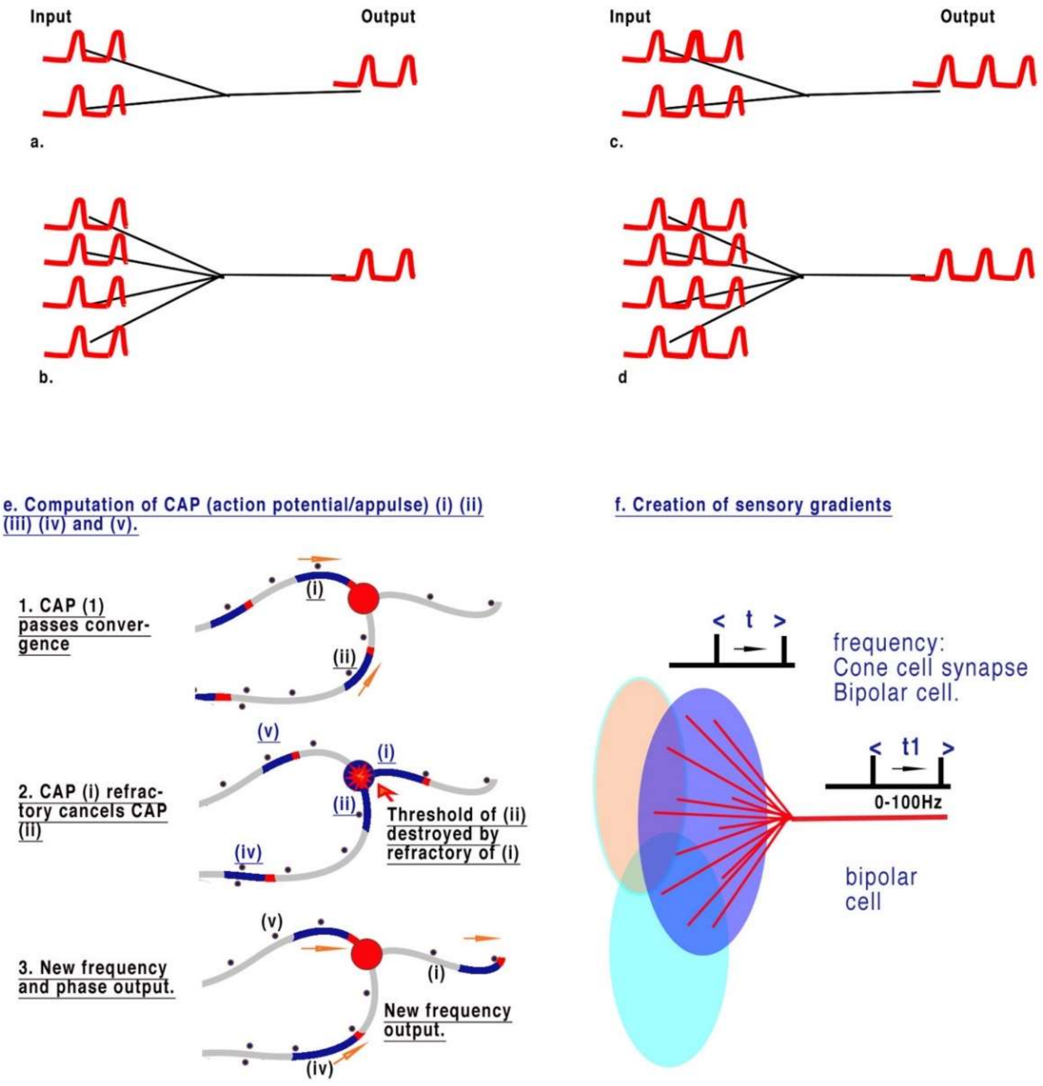


Figure 3. The sensory coding of neurons. Figure 3a to d is a deconstructed illustration of the basic connectivity of a converging neural network. The refractory period of the action potential is dependent on the ability of the membrane to recover. Frequency of action potential are therefore limited in neurons with most in the range of 0-60 Hz. Observations of frequencies of input in all converging systems of neurons demonstrate that frequencies of inputs are proportional to outputs figure 3a, b, show 2 and 4 synapses converging respectively. Each of the pairs of CAPs arrive in phase and thus neither add nor subtract, c and d show an increased frequency always with the result of collective mean sampling. e. Shows detail of CAP cancellation at the convergence. F creation of coded sensory gradients in the retina bipolar cells.

4. The Visual Cortex: what does it do?

Coded parallel independent frequencies of CAPs travel along corresponding optic nerve neurons. Before the Visual Cortex, CAPs are processed by the lateral geniculate nucleus (LGN) which has fast connections to the prefrontal cortex. The LGN can be described within the context of the visual cortex and its function of synchronisation. The LGN connects to layer 4 of the primary visual cortex (16) figure 5 b. The appearance of the visual cortex is of neurons of many types grouped into layers with many synapses to many areas. The sensory neural networks of the retina like the other sensory networks are regular neural networks permitting coding of the CAP frequencies as mentioned. The visual cortex is a layered but otherwise randomly formed network where both

doi:10.20944/preprints202310.1594.v1

positioning of synapses and neurons are spaced so that latencies of CAPs are randomly defined. There is also plasticity in both neurons, their connections and synapses changing CAP latencies over time (16, 17), which is important with the context of the neural network as it permits memory circuits (figure 4 d and figure 5a) to be fluid within the network. Plasticity is therefore a functional benefit to the network permitting potential detail of abstracts to expand.

4.1. How does a random neural network in the visual cortex deconstruct/make sense of information from the Optic nerve ?

In the visual cortex input frequencies produce defined patterns within the random neural network by interfering at convergences and therefore changing the patterns of output frequencies (figure 3c and figure. 4a.) As the CAPs collide, the patterns they form within the visual cortex will always reflect the output from the retina. The information coded into the optic nerve's 100,000 neurons is a combination of information from adjacent (visual) gradients. The information contained, contains all the detail to reconstruct the full image from the outline to the detailed similar patterning. In the retina frequencies from the bipolar cells travel to the retinal ganglion cells (RGC) ensuring that all the information is encoded across all the optic neurons by the collisions and subsequent phase and frequency changes in the RGC. Assuming the optic nerve connections are formed randomly: the output from a few hundred of the optic nerve neurons therefore contains the information of large abstracts – basic colour, hue and definition and change. Each neuron within the optic nerve contains firstly the information from its own receptive areas (those directly connected by bipolar cells to cones or rods) (8), forming the main frequency outputs in each case. Information is then combined with the Horizontal cells connected to other receptive areas. Frequency is modified by phase by the horizontal cells to reflect the output of all other connected light cells. This computation is phase dependent and results in a distinct pattern of frequency being computed. This contains all the information regarding similar context of light including hue, colour, and saturation being coded by location of overlapping similarities. The resultant patterning of frequencies codes represents the abstracts patterns on the retina. The frequency and change of phase of each optic nerve therefore contains firstly, the information of its own connected cells and secondly, phase changes reflecting patterned similar abstractions (lines, corners, etc). The information from thousands, larger abstract shapes, and clearer definition are thus all coded by frequency and phase change. Selection of two or more optic neurons with overlapping receptive fields contains all the information of objects and abstracts within those fields. As the number of neurons increases so does the complexity. Thus, the relatively small connection between the LGN and thalamus contains enough information to synchronise large abstracts. As the information passes into the network of the visual cortex more intricate abstracts are revealed in its pathway. The information from all the neurons gives the complete picture. This mirrors the function of a contextual network figure 4b. We propose that the patterning of the visual cortex in response to stimulus is a result of activity being directed by quantum phase ternary collisions along defined pathways that respond to shapes on the retina. Patterning of the visual cortex has been observed (18, 19) concurring with our hypothesis. The implications of this only become apparent when considering the computation within the spatial dimension and connectivity of the visual cortex itself. For an analogy in a contextual network figure 4b and figure 4c. in the context of the label "vehicle" the labels "wheels, windscreen, metal" are positioned so that we can understand without the label what the object is. We can add detail to this to specify a car or bus and the initial perception can be added to by specifying detail. If we assume the object is "vehicle" then "car, windscreen etc" are all abstracts making up "vehicle". Each object is an abstract of other objects each can be combined and subtracted to form other objects. We can also guess what an object is in relation to its abstracts. In addition, if the object is moving, a "car" and we have already seen it we are able to remember the details from previous memory. In the visual cortex a similar deconstruction of recognisable abstracts takes place each placed within the network. Notice, to see the car moving, it is only necessary to recognise it once, movement can then be tracked separately by the object we propose this occurs in the brain through the LGN.

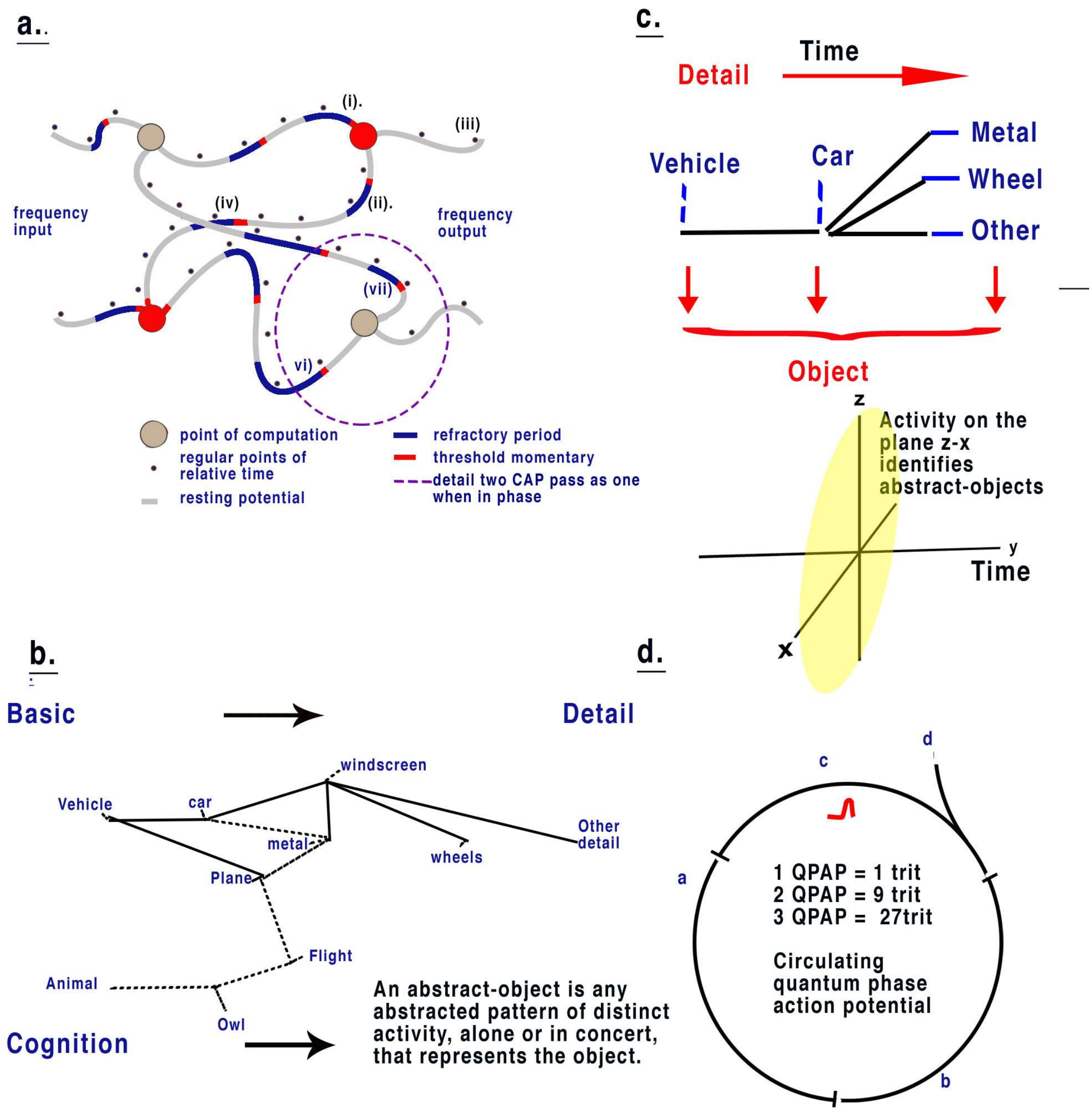


Figure 4. Action potentials travel slowly in comparison to electricity, in the unmyelinated neurons between 0.1 and 1m/s. In a random neural network parallel CAPs interfere (8) figure 4 a, randomly formed neural network showing quantum APPulse. Frequency inputs match corresponding frequency outputs. b. a contextual network. From left a vehicle is formed from a description of some and the more detail. c. Directionally the object is described by the z x axis while the detail is described along the y axis. d. 3 neurons with a circulating CAP contains 1 trit of memory, 2 CAP 9 trits and 3 CAP 27trits. A new CAP at "d" will change phase of the first if it collides changing memory. Repetition enables synchronisation and error redaction.

5.1. Spatial Memory.

In terms of object recognition, the formation of patterns passing through the network can be better understood if the random neural network is drawn according to timing of CAP. In figure 4b. context is gained by cognition as we discover the network reading from left to right so that complete understanding of the object takes time to examine first the larger object (vehicle) and then the detail of the vehicle figure 4c. Spatially information being filtered by a network will have directionally processing where x z coordinates code for each abstract and the y coordinate increasing detail. The Y coordinate is important because in the brain it is synonymous with the time taken for computation to take place. Y is relative to each individual and physiology. We propose the visual cortex functions as a contextual network and can be thought of as space where information flows directionally as described by figure 4. Optic nerve information on entering the visual cortex at the LGN is spread between 100,000 parallel neurons. The small world random network creates a system where the time taken for CAP to propagate from a synapse to a convergence or other synapse can be measured in phase differences. Thus, if the threshold precision or latency (proposed to be the beginning of the soliton) is one microsecond (1×10^{-6}S) then the distance occupied will be1 X 10^{-6}m. It is the differing latencies of neurons and synapses that create the random neural network. As CAPs interact any converging CAPs will be annulled and effective phase change if CAPs are less than 1 X 10^{-6}S separation. This results in diffraction of CAP through the random network figure 4 a, figure 4 b and figure 5a.

The frequency modulated parallel output from the optic nerve distributes itself through the LGN-visual cortex forming a pattern of excitation (figure 5a). The random architecture ensures that some of the paths are circuits (figure 5a). In the coding of the retina patterns formed from the computing frequencies spread according to the timing of the pathways. The optic nerve output passes this information into the visual cortex neural network. The random latencies of the neural connections disperse the output into a distinct pattern of separated dissimilar abstracts (figure 4b). CAPs follow discrete network patterns as frequencies pass deeper into the network reflecting increasingly complex deconstruction of the pattern of abstracts constituting the image. As information is retrieved it is passed into the cortex.

If Figure. 4c is changed to reflect direction of time through the random neural network (Figure 4c), we can see that the patterns of activity form abstracts. As patterns progress through the network vector y describes time and x y describes the abstracts and objects. For a complete image from the first pattern formation to the last abstracts of increasing complexity are passed to higher areas becoming clearer over time. The implication is that the visual cortex is deconstructing the signal into recognisable objects over time that can be sent by parallel CAP frequencies. The LGN passes basic information on the image to the cortex directly passing on the most rudimentary information on changes. In the visual cortex memory of each change is simultaneously formed so that future recognition of abstracts and object labels.

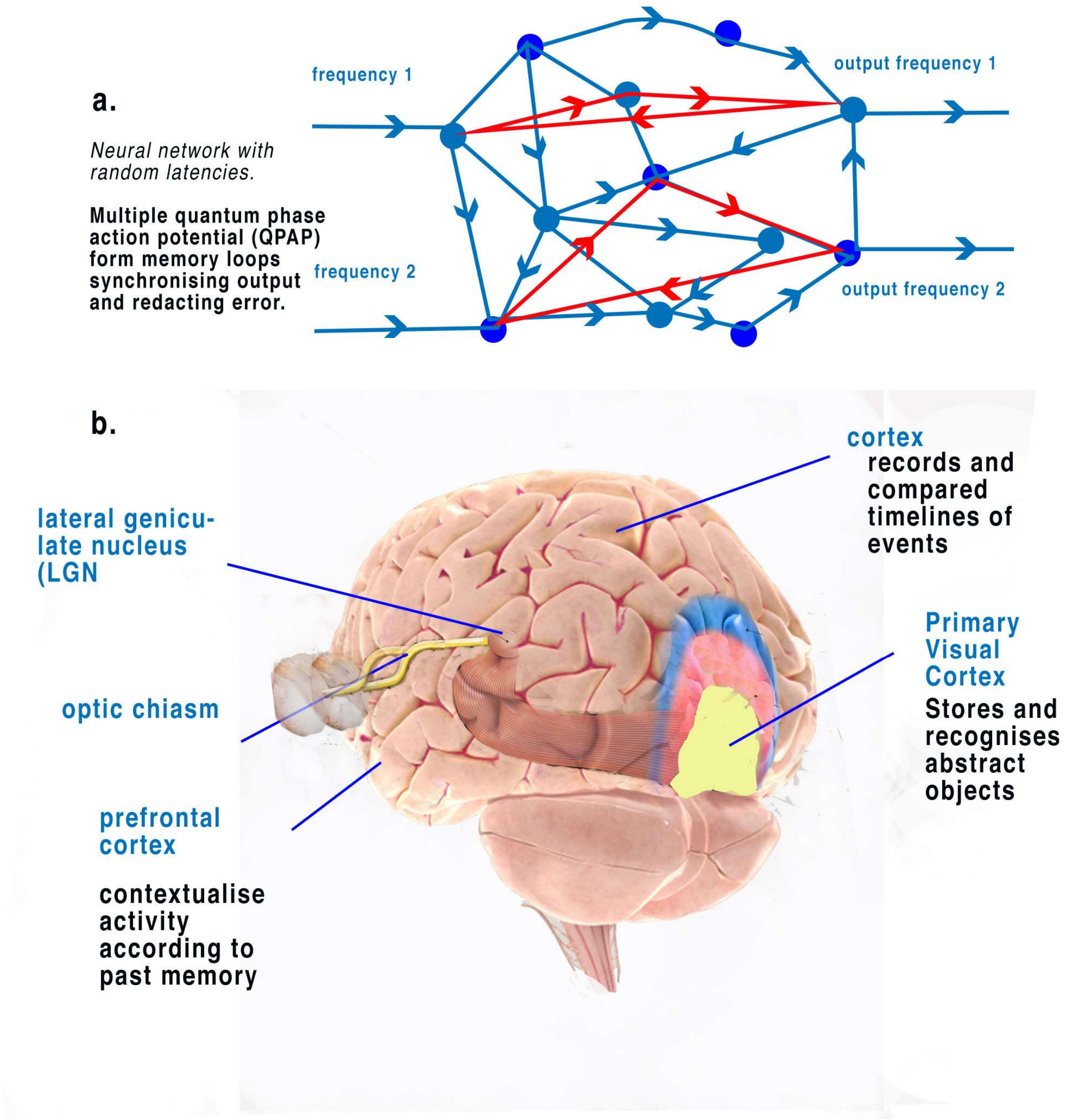


Figure 5. a. an illustration of a random neural network where latencies between nodes are formed from convergence and divergence. Phase ternary creates memory circuits or loops of trits within the circulating CAP. B. simplified illustration of the function of the cortex and neocortex showing areas of progressive perception. Attribution: Society for Neuroscience for the 3d brain image.

5.2. *Circuit Memory.*

Circuit Memory occurs in a random brain neural network with frequency modulated inputs and occurs because of recursive CAPs following circuitous routes figure 5a. The action potential is a ternary quantum object when acting in parallel this can be considered as a trit of information +1, -1, 0 (3, 4 ,7 8). A single action potential following a circuit passes 1 trit of information, two CAPs store 2 trits 3^2, and three trits 3^3. This is shown in red figure 5 a. In a random network circulatory loops of information can both store memory from changes in phase and redact error as the network will synchronise and stabilise to output. Theoretically, there is no limit to the number of circulating CAPs or the number of neurons for the CAPs to circulate. In a circulatory path with one CAP, a collision with another entering the circuit will shift the phase of the result changing the memory in the system. In a randomised small world neural network these circuits interact and eventually establish a natural synchronised equilibrium with incoming CAP maintaining memory by deviating into further

doi:10.20944/preprints202310.1594.v1

patterns. In each case the quantum ternary CAPs redact error from the system as parallel similar abstracts are formed from the inputs thus colliding and ensure phase precision through the network (8).

5.3. Active Circuit Memory forms a contextual database.

The activity of multiple circuit memory iterations forms a contextual database where every context of the abstract is linked by the circuit memory. In the network, circuit memory is held within specific neuronal pathways that permit CAPs to reverberate while phase changes record abstracts. (figure 5 a) Abstracts have context which when combined with others form the recognisable objects. An abstract is therefore a part of the spatial geometry of the neural network. A contextual database is indexed by context with multiple relationships. Firing patterns in the visual cortex therefore represent both passage of activity through the system and firing from activated circuit memory.

6. Discussion

In this paper we have described how quantum phase CAPs compute and follow distinct patterns in a neural network forming abstracts. This is a fast computational system where chemical synapses have a secondary role in providing latencies with electrical synapses the fastest (20) and in slow inhibition (8). Describing the action as a membrane quantum pulse has the advantage that we can logically explain non-classical neurons that do not produce spikes, as many CNS neurons are spike-less (20). Quantum phase ternary computation is feed-forward, fast, accurate and error free. We have also described the coding of the sensory systems in terms of vision provided by the retina, which is a small world network, and the role of CAPs. In our view such small world networks shown are repeatable and extendable and can be used to predict the detailed functioning of the CNS. Each individual iteration of the random small world network that forms an abstract representation of an image within the visual cortex can be replicated to produce objects.

The mechanisms described above are universal to neurons and neural networks and sensory systems in terms of neurocomputation and coding. All of this of course sits in parallel with, and accompanies, the physiological processes underlying sensory processing. These concepts will, in our view, also underlie the delivery of appropriate motor programmes. This implies that phase quantum processing occurs across the membrane of neurons converging due to the refractory period. The action potential refractory period and its significance were realised by Hodgkin Huxley (21) when they described the flow of ions that cause the action potential and realised it was propagated from the threshold. However, the measurements of the speed of processing of information at convergences confirms the beginning of the soliton (9, 10, 11, 12 13,18, 20) as the threshold and the model of the APPulse (4, 5, 9) as the mechanism of computation.

6.1. The Visual Connectome

Connectivity within nervous systems is vital, this may include more than just a specific connectome because even individual neurons are capable of computation and computational action potentials are considered quantal. We are entering a new and exciting research phase on nervous function, particularly in nonclassical brain connections, as we further investigate the connectome which appears to be underlain by interacting neurons connected by parallel distributed processing where the classical brain areas visual, auditory, motor, etc become understood as spatial connectivity of information.

We can but speculate about the mechanisms of what happens to the information of spatial abstracts coded in parallel. If the function of the visual cortex is to record and recognise objects and pass on this information, it is logical that the cortex acting similarly, is storing this information along with all other perceptions from the auditory system, taste, and all other sensory areas to compute whole perception and memorise it. The cortex is therefore able to process and store present activity as selected events, placing in memory activities of notable changes in the objects and representations forming sensory perception. Events refer to memory from all perception, sight touch taste hearing. This is summarised in Figure 6.

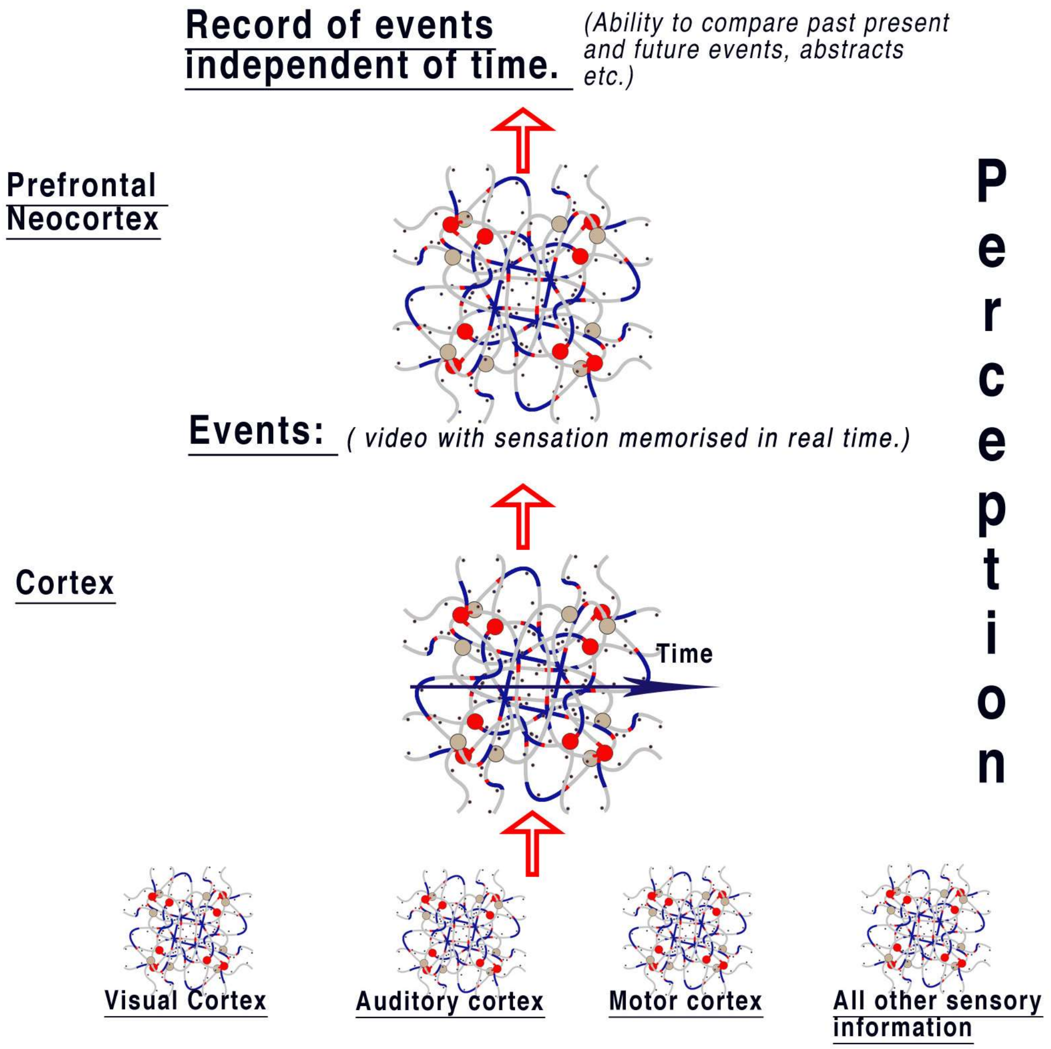


Figure 6. Model of perception from the diffuse brain areas. Sensory areas pass information to the cortex where events are reconstructed from sensory abstracts and memorised in real time therefore creating a “timeline” of events like a video including all senses. Information is therefore available to compare events to those already perceived in the cortex. When this information is passed to neocortex the event timeline is deconstructed with the implication that this area is responsible for the ability to think contextually irrespective of timeline. This gives the ability to the brain to compare objects in relation to the timeline. Therefore, the context between perception of events can be examined for example comparing every time an object is seen. An individual perceiving an object can then easily associate with all events.

It follows that the prefrontal cortex is computing another level from these events and contextualising and categorising them. For example, taking the events from the cortex and placing them in context of importance rather than time. The present (neocortex) can therefore compare events and objects with all previous similar events and objects, probably in the frontal lobes and objects held within them. The neocortex is therefore able to contextualise activity according to past memory. In terms of human behaviour this implies that we have a store of memory to refer to of all events in our life to compare current situations and memorise primarily by impact.

doi:10.20944/preprints202310.1594.v1

AI networks function according to Turing computing theory and not as a brain neural network. We have shown that the action potential is a quantum ternary structure able to pattern a neural network by frequency modulation and collisions (23). An AI network has programmed gates that form patterns on each iteration that end in unique output but that is where the analogy stops. The main difference is that an AI algorithm compares many like abstracts with a query to produce an output of the most likely abstract by probability. There is no evidence that the brain uses probability in selection, we show that CAP error and precision correct automatically, and the small world neural network is of unlimited depth. The decision of which events, objects and abstracts are activated in the brain for perception are chosen from context of past to present perception. The small world random brain neural network can index everything imaginable within a few neurons due to the one trillion synapses and connections in the brain. The system is therefore absolute and determinative giving a logic of "Yes, no, don't know". In the network of the visual cortex components of vision from the retina are split into patterns of abstracts containing information of recognisable objects in descending detail. The conditions under which a recognisable object is not recognised do not exist as any new object in an image is simultaneously memorised and considered as an object. AI networks and the visual cortex both compare abstract representations however the "don't know" in AI is determined by probability. By contrast the don't know in the visual cortex is produced from detailed synchronous circuit memory. This is important when considering facial recognition where AI is comparing faces as a probability of recognition. The brain either knows the face or doesn't. Similarly with self-driving vehicles the placing across the road compares similarity and then steers the vehicle on probability, a human subject steering a vehicle is programming motor coordination by comparing the present with all previous driving experience, road experience and any other relevant coordination in their past in context of them driving.

By storing events contextually, the cortex provides the neocortex with the ability to compare timelines so that events in the present can be compared to the past. The brain has the ability therefore to investigate the past and make decisions according to data presented to us from the context. Decisions in the human brain are therefore made based, on experience from the past, what is happening in the present, and the ability to use past context to predict the future from both.

Currently, we are at an interesting point of advance in neuroscience and evidence was recently presented to show that in addition to the computational events taking place in the cortex, there may also be non-classical brain functions due to quantum entanglement between systems, as described by Kerskens and Perez (23), which also supports our view that the brain uses quantum computation (5). Their observations require detailed verification but strongly suggest quantum entanglement between systems, not previously observed directly or physiologically identified (15).

CONCLUSIONS

- In the visual cortex there are many processes taking place simultaneously affecting the distribution of CAPs to form spatial abstracts: input coded parallel frequencies, action by synapses, error redaction and memory circuits.
- We have explained, coding and processing of CAPs into defined visual cortex patterning and give a logical explanation for memory and object recognition. The active memory of reverberatory CAPs within the network is reductive. Every change of pattern is registered in memory with context supplied by neurons exiting the memory loops.
- Although AI is useful as a tool, we have shown that AI systems are not functionally intelligent with the danger that their probable answers are accepted as being a judgement – this is especially true when using insufficient feed data. We have examined AI which we conclude is an insufficient model of brain functioning in almost all respects.
- In the retina we have elucidated the coding the decoding and function using only the properties of the CAP and the neural connectome properties. All neurons behave similarly, and we suggest that all areas in the brain function using quantum phase ternary computation.
- For philosophers we have answered the question, "Why do physical states give rise to experience?" This also confirms the environmental philosophy of being – we are a sum of our

experiences. The confines of the central brain and connections are created by a few thousand genes. With functioning determined by the positioning and type of a hundred billion neurons and a trillion synapses, all of which are susceptible to plasticity, genetic variation in a healthy subject is minimised.

Author Contributions: The basic conceptualization of this paper came from ASJ, based on our previous work. We then worked closely together to write it over several drafts.

Funding: No external funding was received from any sources.

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