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Opinion

Shortcomings of Current Artificial Nodal Neural Network Models

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The usefulness of small-networks to model large-networks is limited in biological systems and synaptic studies give little insight into conduction in more highly evolved brain-neural-networks where axon conduction is diverse and seemingly unreliable [1-3] with an alarming amount of noise, reduction of which must be taken into consideration for any neural network of depth. Reverse engineering models [4,5] assume processing works like a conventional binary computer and neglects speed of cognition, latencies and error in nerve conduction and the true dynamic structure of the brain neural network: any model of nerve conduction that claims inspiration from nature must include these prerequisite parameters.

Historically research has followed the progression of computational science; literature film academic and non-academic articles almost universally speak of the action potential being binary and binary mathematics has been assumed by force of popular acceptance to mediate computation in the brain. A superficial examination of the history of computing and the action potential itself quickly dispels these assumptions; at the time the action potential was discovered the field of computation was pre-transistors and any base or indeed analogue was considered though not a compound ternary-phase pulse structure. The availability of cheap binary transistors ended investigation into ternary computing. Because of the latencies involved in slow moving pulses, phase computation was not considered practical [6]. However this predated understanding of relational-databases or neural networks and their function. For the brain neural network to function as an associative database (multiple associations) it must have a depth of many thousands of nodes allowing multiple associations within the first layer mounting exponentially with every layer. Using the compound phase action potential within a deep small-world neural network overcomes the restrictions of synapse mediated memory redacting error, and counter-intuitively as depth increases timing between association decreases, so that the deeper the network the more efficient it becomes in respect of time. This is a natural consequence of the small world network where collision points represent the nodes so that every possible conceivable connection from a node can be represented as a potential associated memory. Computation in a network may occur in a number of ways and a binary notation is not exclusive, logic may use other base forms and timings. Superficial calculations on timing, facility of computation and error demonstrate that only a few current models are applicable to vertebrate brains or those of advanced invertebrates and almost all can be immediately discounted.

Reasons for reinterpreting and modifying artificial nodal network models.

1. The modus operandi of action potentials is unlikely to be binary and is probably driven by compound ternary structures.

2. Depth of neural network– the human neural network is unrestricted in its ability to learn sequentially. Histology and genetic studies demonstrate that the neural network is not fixed, is randomly connected and randomly assigned directionally. In addition plasticity ensures that no one connection can be considered ‘fixed’.

3. Fixed latencies between neurones– the neurons of the brain are of different sizes, length and composition; it is almost impossible for action potentials to arrive synchronously. The speed of axon transmission is discussed in more detail in the Action Potential Pulse [7].

4. Speed of cognition and speed of connections [8] – the modelled computational speed of an artificial neural network cannot explain the speed of cognition and learning unless speed of connections is ignored.

5. Energy requirements– artificial neural network modelling of synapses to produce 'weighting' is inefficient, as it requires additional steps for computation and timing.

6. Algorithms or processes for each decision indicate that a further mechanism must be instigated. Bayesian calculations are time-inefficient, at action potential speed, to produce a weighted result and there is little evidence such a system works in the brain– there is also no evidence of any corrective mathematics in the brain that would compute as software or redact error.

7. Error– use of synapses creates additive error and inefficiencies in the network making a very deep unsupervised learning network unreliable. Error in the neural network approaches that of activity but memory in both animals and humans persists over many years with a high degree of accuracy indicating that error is redacted. Using synapses as gates creates analogue error that would prevent an associative matrix and further decrease the level of memory and sequential computation. Balanced ternary phase computation in contrast natively reduces error to zero by parallel pathway negation of "of-of" synchronisation of action potentials.

8. Genetic considerations. There are not enough genes to denote positions of any but main pathways – neurons and connections are likely to be positioned randomly and multidirectionally.

9. Plasticity in the system where synapses hold memory would act detrimentally. In a phase system plasticity enhances system efficiency providing additional pathways and memory where and when required.

10. Measurement of memory needed to sustain cognition in a network. The number of synapses would be barely enough to sustain a life using synapses to control or retain memory when considering that there must be a large proportion given over to calculation and error – none of which is covered adequately by conventional models.

In the near future we will examine these networks and the above assertions in further detail and make suggestions for their modification. The nature of action potentials has already been discussed in the context of neural network efficiency [7,9].

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