Article

Neural Assemblies as Precursors for Brain Function

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Abstract: This paper describes some neural representations that may be helpful for realising intelligence in the human brain. The ideas come from the author's own cognitive model, where a number of algorithms have been developed over time. Through developing and trying to implement the architecture, ideas like separating the data from the function have become architecturally appropriate and there have been several opportunities to make the system more orthogonal. Similarly for the human brain, neural structures may work in-sync with the neural functions, or may be slightly separate from them. Each section discusses one of the neural assemblies with a potential functional result, that cover ideas such as timing or scheduling, inherent intelligence and neural binding. Another aspect of self-representation or expression is interesting and may help the brain to realise higher-level functionality based on these lower-level processes.

Keywords: neural; brain; structure; function; process; cell expression

1. Introduction

This paper describes some neural representations that may be helpful for realising intelligence in the human brain. The ideas come from the author's own cognitive model, where a number of algorithms have been developed over time. Through developing and trying to implement the architecture, ideas like separating the data from the function have become architecturally appropriate and there have been several opportunities to make the system more orthogonal. Similarly for the human brain, neural structures may work in-sync with the neural functions, or may be slightly separate from them. Having more than 1 information flow actually makes the problem of how the human brain works much easier to solve. Another aspect of self-representation or expression is interesting and may help the brain to realise higher-level functionality based on these lower-level processes, maybe even natural language itself. The cognitive model is still at the symbolic level and so the neural representations are also at this level. The neuron discussion is therefore at a statistical or biophysical level rather than a biological one.

The rest of the paper is organised as follows: section 2 describes some related work. Then the other sections discuss one of the neural assemblies with a potential functional result. Section 3 describes earlier work on a timer or scheduler. Section 4 describes how intelligence may be inherent in the neuron conversion process. Section 5 describes how the neural binding problem can be simplified and section 6 describes how natural language may have evolved naturally from lower-level brain structures. Finally, section 7 gives some conclusions on the work.

2. Related Work

The paper is based mostly on the author's own cognitive model, who comes from a computer science background. This has been described in detail, in particular in the paper series 'New Ideas for Brain Modelling' 1 – 7 [10][8]. Most of the Artificial Intelligence technology is therefore described in the following sections, but a background to supporting biological work is described next. There is biological work that can be used to support the ideas, for example [14][18][26][27], and also biophysical or statistical work, for example [15][28]. Having more than 1 information flow has been studied extensively. For example, the paper [27] describes that more than one type of sodium channel can be created and that they interact with each other, producing a variable signal. Small currents are involved, even for Ion channels and they work at different potentials, etc. It is also described how neurons can change states and start firing at different rates. Memory is a key topic, where the paper [18] describes that positive regulators can give rise to the growth of new synaptic connections and this can also form memories. There are also memory suppressors, to ensure that only salient features are learned. Long-term memory endures by virtue of the growth of new synaptic connections, a structural change that parallels the duration of the behavioural memory. There is also some mathematical background, where the paper [26] was the basis for the simulation equation of [11] and the book [14] is a critical work on the neocortex and higher brain functions. The argument is still at the symbolic level, where the papers [15][28] both try to describe how the brain might organise itself through statistical processes. The pioneering work of Santiago Ramón y Cajal[1] may be supportive, in relation to pacemaker cells. Then a new theory by Tsien [25] suggests that perineuronal nets, discovered by Golgi[2] may be key to how the brain stores long-term memories and it is the basis for the cognitive model of this paper as well. The idea of an extracellular matrix was actually rejected by Cajal. Neural binding is discussed in one section, but with a view to making it less holistic, where contrasting biological work might include [1][4]. Other biological work on simpler organisms includes [17][22][23][29] and is noted in the following sections.

3. Timing

This was an early discovery for an automatic scheduler or counter [11]. It is not as relevant to the other sections, but it does offer an automatic construction for an intelligent process. The paper considered using nested structures, not only for concept ensembles, but also for more mechanical processes. If the structure fires inwards, then the rather obvious idea would be that an inner section would fire inhibitors outwards that would eventually switch off the source to its activation. It may also fire positively inwards, when the process would repeat with the next inner section, and so on. This switching on and off of nested sections could lead to a type of scheduling or timing, if each section also sent a signal somewhere else. A simulation of this process was run, using a simplified version of an equation from [26] that processed at a pattern level, not a synapse level. It showed the expected result of how the pattern excitatory value would flow through the nested levels, rather like a colonic movement, for example. Cajal discovered Interstitial cells [23] that serve as pacemaker cells, to electrically contract the gut muscle and so an appropriate type of energy source is available. This is therefore one of the most basic processes in a human and other much simpler animals. The elegans worm is much studied, for example, because it has a brain of only about 300 neurons that can be mapped accurately. It has been found that 'most active neurons share information by engaging in coordinated, dynamical network activity that corresponds to the sequential assembly of motor commands [19].' While the neural assemblies might not be nested, there is a circular arrangement to the behavioural network [29] that is a sequence of behaviours. The worm also has pacemaker-like cells to activate some behaviours [17].

4. From Neuron to Network

It is proposed in this paper that the neuron and the brain network use a similar functionality. The proposed architecture for the neuron is the standard one of soma body, dendrites as the input channels and the axon as the output channel. The input is an amalgamation of other neuron signals, which gets sorted in the dendrites and soma into a more specific signal that is then transferred to the axon for sending to other neurons. In essence, the process converts signals from being set-based to being type-based. This would be a

[1] http://www.scholarpedia.org/article/Santiago_Ramón_y_Cajal

[2] https://en.wikipedia.org/wiki/Camillo_Golgi

well-accepted filtering process and it is argued that the conversion from a set-based 'scenario' to more specific and local types in the output, is key to generating intelligence from the structure. This may also help with the author's own ensemble-hierarchy structure ([8] and earlier papers). Note that a type however is simply something more singular. It does not have to represent only one input signal, for example, but represents a consistent set of input values. With this architecture therefore, the signal from one neuron to another must also be type-based, but the ensemble input is a set of signals from several neurons. Each set may get sorted differently and therefore create a different set of output types, and so the neuron can be part of more than 1 pattern at any time, where the timing of receiving a signal type would be important. The neuron can therefore be part of several patterns, making it quite flexible with regard to the information flow and also the signal type it then emits. If the input has a chemical bias, for example, then that may allow the synapses related to that particular chemical type, to form and gather sufficient energy to release the signal to other neurons. This would be stigmergic [6] in nature. For example, if a neuron fires a signal of a particular type and that is then sent through a network and back to the neuron again, the neuron will already be able to reinforce its current state. It may also now be prepared for the signal [14] and be able to emit it more easily again. This means that the output from a neuron can be sent anywhere, but as with biophysics [28], where there are similar concentrations of a particular type, then the network will start to fire and form patterns relating to that type.

This type of architecture still does not require any intelligence. Thinking about more cellular organisms again, at the SAI'14 conference[3], the speaker asked 'why' an amoeba has a memory and not just how. If it is not to think, then it must be for a functional reason and this function must have evolved from the genetic makeup of the amoeba, hinting that such a mechanism can evolve naturally. So, why did the amoeba develop a memory? The obvious answer would be an evolutionary development for survival, but the author would like to postulate further and guess that it may also be because a living organism has a need to express itself. This desire may go back to the reproduction process itself. An earlier paper argued that true AI cannot be realised because we cannot simulate the living aspect of human cells [13], for example, and that may include this expressive nature. As with a stigmergic build-up, if the amoeba has set itself-up for a particular type of input, maybe it does not react to other input immediately but can only react to the specific input again, even after a short delay. The paper [22] models the amoeba behaviour as a memristor, which is a similar type of electronic circuit. They note that: the model however does not fully explain the memory response of the amoeba and does not take into account the fact that, at a microscopic level, changes in the physiology of the organism occur independently of the biological oscillators. These changes also occur over a finite period of time and must be dependent on the state of the system at previous times. This last point is particularly important: it is in fact this state-dependent feature which is likely to produce memory effects rather than the excitation of biological oscillators. It is thus natural to argue that in the very same way that a memristor has its inherent memory, the Physarum acquires a memory through the interactions of the gel-sol solution, specifically through the formation of new, low-viscosity channels. Therefore, at least 2 processes are at work in this single celled organism, where one is slow moving and one is much quicker. The slow-moving viscosity channels would be tuned-into by the oscillator types, that would maintain a behaviour until the channels changed.

5. Neural Binding

This is an important question from both the psychological and the mechanical aspects of the human brain. It asks why the brain does not confuse concepts like 'red square' and 'blue circle' unless these are fully defined by brain patterns first [4]. Why is 'red' and 'blue'

[3] Prof. Chen's Talk, SAI'14.

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not confused, for example. The problem is that it would not be possible to store every memory instance combination in the brain and so (dynamic) linking of concepts is required. The paper [4] includes the idea of consciousness and how the brain is able to be coherent, but while there are lots of theories, there are not a lot of very specific results for the binding mechanism itself. Some models may include temporal logic or predicate calculus rules to explain how variables can bind with each other. Quantum mechanics is another plausible mechanism for merging patterns [20]. The paper [1] is quite interesting, where they describe a framework called the Specialized Neural Regions for Global Efficiency (SNRGE) framework. The paper describes that 'the specializations associated with different brain areas represent computational trade-offs that are inherent in the neurobiological implementation of cognitive processes. That is, the trade-offs are a direct consequence of what computational processes can be easily implemented in the underlying biology.' The specializations of the paper correspond anatomically to the hippocampus (HC), the prefrontal cortex (PFC), and all of neocortex that is posterior to prefrontal cortex (posterior cortex, PC). Essentially, prefrontal cortex and the hippocampus appear to serve as memory areas that dynamically and interactively support the computation that is being performed by posterior brain areas. They argue against temporal synchrony, because of the 'red circle blue square' question and prefer to argue for coarse-coded distributed representations (CCDR) [16] instead. With CCDR, the concepts themselves can remain separate and it is not necessary to declare every binding instance explicitly, but it can be obtained from a local coding scheme. The author has argued that patterns can be aggregated to some extent ([8] and earlier papers), when manipulation of them can then be done with much fewer neural connections over the aggregated representations. He has also argued that simply 2 layers with the same node representations can produce the required circuits. But to realise these two concepts, still requires linked formations that either contain read and square, or blue and circle and so CCDR looks like a neat solution to this. But it might be a question of whether the links are permanent or created 'on the fly'. There is also the problem with imagination that can create new images. If the ensemble structure does not exist, then it would have to be constructed dynamically.

The author has also argued, or asked, why the senses are not part of the human conscious [9]. Recent science however, is beginning to suggest that the whole nervous system is the conscious. We have eyes, ears, voice box, and so on, which we use as external mechanisms to the brain function and the paper [9] argues that when the brain thinks, it sends signals back to these organs and that they are essential to realise what the brain is thinking. If we consider the 'red square, blue circle' problem again, then one problem with current philosophy may be that we assume the pattern formations are translated only by the brain. One problem here is that the conscious would see every pattern and pattern part as the same, and so much more intelligence would be required to try to differentiate. The 'red' concept has the same makeup as the 'square' concept to the brain conscious, for example. If it is possible to introduce different functions to the problem, then a solution may be much easier to explain and for the author, this would mean feedback to the external sensory organs. Considering the eye and for the sake of argument, let it produce only image shapes and colours. What if one signal could request the eye to produce an imprint of a shape on it and then a second separate signal requests that the eye gives it a particular colour. If this was possible, then the two signals would not necessarily have to be linked first, where that requirement has changed over to one about sending different function requests to the eye. This would make the neural-binding problem much easier, because the orthogonal function requests do not require all of the combinations that the more holistic conscious might require. Part of the binding has been moved to the eye itself. It may be the case that this could be for more long-term memory however, where a holistic memory store of recent images could still operate. Also with this setup, the functional signals do not need to be fully-linked patterns, but can be single links, for example, while the concept patterns can still be fully linked. The patterns are maybe more horizontal and the functions more vertical. The paper [9] tried to measure intelligence at a low level, but made a connection between the optimising Kolmogorov coding theory [3] and Shannon's entropy-based information theory [24]. The algorithmic solution suggests, for example, that if we want to hammer a nail into a post, we move the hammer and nail to the post in a single optimal step and then take several entropy steps to hammer it in. There is therefore a loose association with entropy-based patterns that are activated by single-step functions here, if the entities can indeed be separated.

6. Natural Language Development

The original cognitive model [13] had an architecture of 3 levels of increasing complexity, but also a global ontology that any of the 3 levels could use. The idea of an underlying global representation raises some interesting ideas. The author's background is in computer science, distributed systems and even the Internet, where the SUMO ontology (and others) [21] has been previously suggested. SUMO has been created to be a common language for the Internet. It is more expressive than object or semantic recognition, but not as much as natural language. Base concepts include 'object' and 'process', for example, but being an ontology, it includes relations between the different ontology entities. The author has worked on a cognitive model for several years and it is at an early stage of development, with an even simpler ontology at its base. It is not even an ontology, but levels of symbolic node clusters, where a lower-level contains more frequently occurring symbols or concepts. The clusters are not linked together, but they offer some kind of global ordering over the stored symbolic representations. One example may be the 3 short stories – 'fox and crow', 'fox and stork' and 'fox and grape'. If a basic word count is done on each story, then for the 'fox and crow' story, the crow word occurs more frequently and so if using the concept tree counting rule [12], it would be placed as the root tree node. In a global sense however, the fox word is more common, because it occurs in all 3 stories. Therefore, the global ontology would in fact re-order the local 'fox and crow' instance, to place 'fox' at the root node and then 'crow' one level above that. For this architecture therefore, the local story instance provides what concepts are available, but they are then re-ordered by the global ensemble. It is the same idea as the natural ordering for concept trees described in [12], section 6.4. With that, a road would always be placed below a car, for example, because a car would run on the road. With the cognitive model implementation therefore, there is the global ensemble of concepts at the base as the memory structure. Each of the 3 cognitive levels – pattern optimisation, pattern aggregation and more complex concepts – also write a simplified view of their structures to the memory database. Then when any level wants to read from memory, it uses the global database to retrieve whatever memory type it requires. The global memory structure therefore has an ensemble at the base and then different levels of tree structure representation that reference the ensemble clusters. It is also a common view of the information in the system, where any module can read and understand what a memory node is, because the more complex functionality that may be specific to any module is missing.

In the human brain, there are more simple cells, like glial cells or interneurons, for example. More recently the perineuronal network [25] has received a lot of attention and may be exactly the memory structure that this section is describing. If the memory structure is sightly separate therefore, this can lead to at least two different information flows for both memory and function. For example, the paper [27] notes that multiple sodium channels can flow through the brain and at different rates as well. If the Perineuronal network is made of the glial cells - astrocytes and deodendrocytes, for example, then astrocytes are also known to produce energy for neurons and so successfully syncing with the memory structure might also provide an energy supply.

It may be interesting then that there is now some separation between the global representation and the original sources, and also a little bit of autonomy for the global representation. Tokenized text, for example, might be stored largely as nouns and verbs, without all of the natural language. The architecture also works with images. The author is using a new idea called Image Parts [7], which scans an image and splits it up into parts,

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but is currently only useful for object recognition. The parts can then be stored in a database, where a whole image can be represented by its parts and their relative position. One part may be north of another part, for example. The algorithm is not very accurate, achieving only 80% accuracy, where neural networks would achieve closer to 100% accuracy, but it is also explainable. For the cognitive model, the image parts would be stored in the global ensemble and then any new image would be described in terms of them. So, the homogeneous input image is split up into the tokens, or pattern blobs, of the global ensemble. Then when other modules want to interface with the image, they can make use of the same ensemble parts, structured by an abstract tree representation. The author postulates that this is like the brain architecture itself making use of a common language, to allow the different modules to interact with each other. The homogeneous input is converted over to a different tokenised representation, that is then used to describe the input to any other part of the system. If that process is internal to the brain itself, then it may be a reason why humans have developed their natural language, in order to try to express their internal structures and processes. Nouns and verbs are the basis of the real world as well, for example and the paper [5] concludes that: 'The available studies on the neural basis of normal language development suggest that the brain systems underlying language processing are in place already in early development.' The suggests that the structure for natural language is in place from a very early age. The paper [2] states that deep learning algorithms can produce, at least, coarse brain-like representations, suggesting that they process words and sentences in a human-like way. Word vectors may be superior to tree linking, but it is still a distributed and tokenised AI algorithm that can be mapped to brain regions. They note that whether an algorithm maps onto the brain primarily depends on its ability to predict missing words from their context, but this may suggest some underlying instability, where other research showed that random or untrained networks can also map to brain regions.

7. Conclusions

This paper suggests neural structures and cognitive processes that are consistent with the author's own cognitive model. As such, they may or may not be part of real human brain functions, but there appears to be a consistency about them and some biological and mathematical evidence that they could be valid. One idea is that intelligence can be realised automatically by converting from ensemble input to type-based output. The realisation of the types will produce some understanding and therefore intelligence. Another idea is that the neural binding problem is constrained by current thinking about a holistic conscious and if it can be made more orthogonal and receive help from other organs, the problem will become much easier to solve. An early idea about scheduling through nesting seems to have some validity and may also be found in some form, in simpler organisms such as worms.

It would be interesting if there is an underlying global memory structure to the brain, which can abstract and even re-structure input signals, and communicate this to other modules. This can be the case with either symbolic, textual input, or images. Images may be stored as whole representations in the short-term memory, for example, but when they are moved into long-term memory, they become tokenized and abstracted. This might produce clusters that can be inclusive or exclusive of each other as well, supporting a logic-based relationship and this might again be seen in simpler animals. Higher-levels of aggregation can also take place, or for simpler animals, maybe only the lowest-level is present.

Most interesting then may be the idea that a cell or organism evolves, not only to survive, but also by expressing itself. The expression is a result of its own internal structures and processes. In this respect, the global memory ensemble would be a precursor to our own natural language. The structural transformation from input to tokenized ensemble results in a communication process that is akin to a common language. The higher cognitive processes, if you like, have built themselves on the lower-level structures and processes.

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