Learnt Novelty with Overlapping Neural Cell Assemblies

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Abstract. Cell Assemblies (CAs) are central to many higher order cognitive processes such as perception, recognition, and recollection. Concepts are encoded as neuronal CAs in mammalian cortical areas, where CA formation and learning happen based on the Hebbian CA theory. Multiple CAs may share a common subset of neurons that produce dynamics that distinct, localist, orthogonal CAs do not exhibit, such as inherent support for generalisation and learnt novelty. This paper discusses implicit learning of novel behaviour in overlapping CAs, with a simulated agent based on a biologically realistic neural CA model.

Keywords: Artificial Intelligence, Neural Networks, Cell Assemblies

1 Introduction and Background

The CA [1] is the neural basis of the fundamental cognitive process of associative memory, and is the basis of many higher order phenomena [2], [3], [4], [5], [6], [7]. It is a reverberating circuit of spatially distributed groups of neurons that have high mutual synaptic strength [8]. Formation of CAs account for long term memory and their reverberating behaviour accounts for short term memory. CAs are learnt by a Hebbian learning rule, whereby modifications in the synaptic transmission efficacy are driven by correlations in the firing activity of pre-synaptic and post-synaptic neurons [9]. That is, repeated co-activation of neurons by a stimulus causes an increase in their mutual synaptic strength leading to the formation of a CA that is bound to the stimulus.

A CA may be activated when a subset of its neurons fire. The high mutual synaptic strength of its constituent neurons may cause it to reverberate as its neurons undergo cascades of activation, even after the stimulus that triggered it is removed. If the group of firing neurons happen to belong to more than one CA, activity may spread to other CAs. Prolonged co-activation may cause different CAs to merge, and learnt lateral inhibition may cause certain parts of a CA to overpower other parts, eventually forming separate CAs as a result of competitive learning. Such behaviour of overlapping CAs exhibit many interesting dynamics that disjoint CAs do not, such as the inherent ability to learn novel concepts and behaviour.

This paper discusses the nature of such overlapping CAs with a simulated agent that acquires novel behaviour via implicit, unsupervised learning.

2 Learning Cell Assemblies

The model discussed in this paper uses a neural network with simulated CAs based on *fatiguing Leaking Integrate and Fire* (fLIF) neurons that share many common characteristics with biological neurons [10]. Learning is driven by a correlatory Hebbian learning rule [1],[12], by which synaptic connection weights are modified based on the following equations:

$$\Delta^{+} w_{ij} = (1 - w_{ij}) * \lambda \tag{1}$$
$$\Delta^{-} w_{ij} = w_{ij} * -\lambda \tag{2}$$

w_{ij} is the synaptic weight from neuron i to j and λ is the learning rate. During each cycle, weights change based on the state of pre-synaptic and post-synaptic neurons. If both neurons co-fire, the weights increase as per the Hebbian rule (Equation 1). If only the pre-synaptic neuron fires, weights decrease as per the anti-Hebbian rule (Equation 2). Thus w_{ij} changes and approximates k, the likelihood of j firing if i fires.

Each neuron in the network is either excitatory or inhibitory, where all synapses leaving the neuron are either excitatory or inhibitory [13]. A similar learning rule applies to inhibitory neurons that makes the synaptic weight approximate $k - 1$ where k is the likelihood that the post-synaptic neuron fires when the pre-synaptic neuron fires.

Thus, the recruitment of neurons to different CAs may be due to repeated co-presentation of similar or ambiguous stimuli that increase their mutual synaptic strength. This suggests that events that tend to co-occur should somehow belong together. Every time these events occur in conjunction, they drive certain subgroups of neurons to fire in correlation, resulting in the association of the respective events [8]. Shared bit patterns in the Hopfield model are examples of a computational CA model [14].

Prior models based on disjoint CAs have been used to encode spatial maps, and sequential and many to many associations [10], but they show a relatively high degree of deterministic behaviour that arises from the limited ability to acquire novelty by learning due the disjoint topology of learnt CAs. Furthermore, biological CAs in the brain are known to be of overlapping nature [11].

3 The simulated agent

The simulated agent is driven by a network of 4000 fLIF neurons with distance biased connections [10]. The agent is able to perform three actions, move up, move right and move left, driven by three CAs. The CAs are labelled **UP**, **RIGHT** and **LEFT** respectively. Each action is executed based on the activation level of its corresponding CA. For instance, if **UP** has 20% of its neurons active, the agent moves up 20% of a unit distance.

Since all three CAs are in the same network, they have excitatory and inhibitory connections with each other. Training runs for 600 cycles [1], where patterns corresponding to **UP**, **RIGHT** and **LEFT** are presented for 200 cycles in succession, so that their respective CAs are learnt. The test phase lasts for 300 cycles, where random neurons of each of the three CAs are excited for 100 cycles each. That is, at cycle 0, **UP** is excited; at cycle 100, **RIGHT** is excited; at cycle 200, **LEFT** is excited. During the test phase, the agent executes movements based on the activity levels of CAs corresponding to the three actions.

The simulation is run in two separate modes; one with disjoint, orthogonal CAs, and one with overlapping CAs. The agent's movements in each mode is recorded so as to compare the behaviour emerging from orthogonal and overlapping CAs.

3.1 Behaviour from Orthogonal CAs

The patterns for each of the three CAs are presented for 200 cycles each in succession. The CAs are disjoint and do not share neurons. Each CA consists of 33% of the neurons of the entire network. The test was repeated on 10 different network configurations and the paths taken by the agent were found to be consistent 100% of the time. Figure 1 shows the path taken by the agent in the 300 cycles of test on one such run.

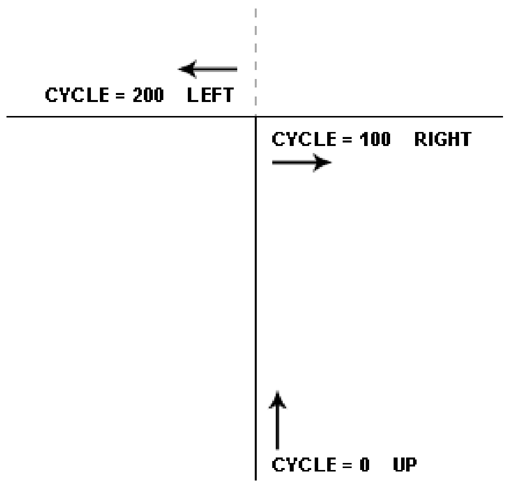

Fig. 1. Path taken by the agent with orthogonal CAs

[1] One cycle is 10 milliseconds in simulated time, when the neural network is updated based on the Hebbian learning rule (Section 2).

Since the first CA to be excited is **UP**, at the 0th cycle, the agent starts moving **UP**. Similarly, at the 100th cycle, the agent starts moving **RIGHT**, and at the 200th cycle, the agent starts moving **LEFT**. Each of these actions continue for 100 cycles. The disjoint nature of the CAs mean that the absence of shared neurons cause an active CA to suppress other CAs via learnt inhibitory connections. When the **UP** CA is active, the agent is solely moving **UP** without any deviations as other CAs are completely inactive. This is indicated by the linearity of the movements plotted in the figure. The dotted line marks the centre of the environment, at the base of which the agent starts.

3.2 Behaviour from Overlapping CAs

In the mode with overlapping CAs, the patterns share a 25% overlap of their constituent neurons with each other, where **UP** and **RIGHT** overlap, and **RIGHT** and **LEFT** overlap. That is, **UP** and **RIGHT** share 25% of each other's neurons, and **RIGHT** and **LEFT** share 25% of their neurons. **UP** and **LEFT** do not physically overlap, but over the course of learning, they form shared sub-CAs via their overlaps with **RIGHT**.

The patterns for each of the three CAs are presented for 200 cycles each in succession in the training phase, so that their corresponding CAs are learnt. In the test phase, each of the three CAs are partially excited for 100 cycles one after the other.

Figure 2 shows the path taken by the agent over the course of the test. The path is visibly erratic compared to that in Figure 1, and the agent seems to have moved **UP**, **RIGHT**, and **LEFT** at the same time at relatively the same rate. The largest deviations in the path are at cycles 0, 100 and 200 respectively, when the corresponding CAs receive external excitation. Over the next few cycles, the movement settles into novel pseudo-stable states which seem to be combinations of all three CAs.

4 Discussion and Conclusion

The simulated agent with overlapping CAs has been shown to develop novel concepts from the three base CAs it was trained with. The resulting behaviour is dynamic, compared to the relatively deterministic behaviour from orthogonal CAs. The novel pseudo-stable CAs formed from the overlaps change over the course of time, all via implicit learning.

The CA model used in the simulation is based on fLIF neurons that have biological plausible characteristics such as distanced biased topology, and excitatory and inhibitory properties. CAs in the network are learnt gradually over a course of many cycles via external stimuli.

The agent driven by overlapping CAs manages to learn implicit sub-actions dynamically from varying combinations the base actions **UP**, **RIGHT** and **LEFT**, as indicated by the nature of its movement. Figure 2 shows movements such as **UP-RIGHT**, **UP-LEFT**, **UP-RIGHT-LEFT** and **LEFT-RIGHT**.

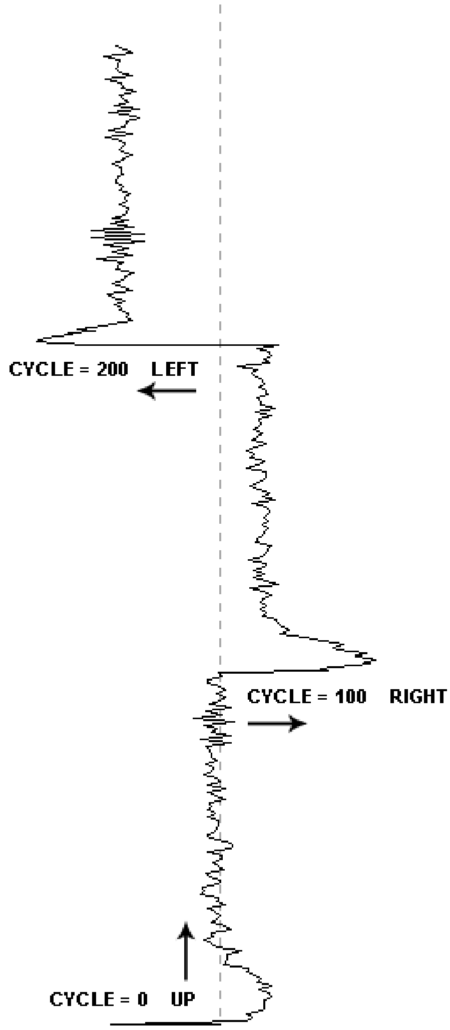

Fig. 2. Path taken by the agent with overlapping CAs

Even though there is no physical overlap between **UP** and **LEFT**, **UP-LEFT** seems to have emerged from their interactions with **RIGHT**. Also, the strength of these novel pseudo-stable combinations can be seen to vary dynamically over the course of time, where for instance, **UP-RIGHT** is dominant compared to **UP-LEFT** at certain points.

Overlapping CAs overcome the relatively deterministic behaviour that disjoint CAs (or other similar models) exhibit. They introduce a certain degree of randomness that eventually settle to pseudo-stable sub-states leading to the emergence of many interesting dynamics, which many other esoteric models seem to lack. Another benefit of overlapping CAs are their inherent support for generalisation [15], where prototypicality emerges from CAs that share common attributes. Also, shared neurons between different CAs have the ability to participate in different kinds of information processing [16]. Overlapping CAs may also help overcome capacity constraints in neural networks, where shared neurons make it possible to have more CAs than the total number of neurons in a network [17].

While the above discussed simulation demonstrates how overlapping CAs can implicitly acquire novelty, other simulations have used overlapping CAs to model different cognitive tasks [18], [19]. It is also suggested that human cortical semantic memories are distributed and overlapping in nature [20]. This would enable unique episodical memories and context-free information to be encoded as a part of a larger semantic network, where overlapping patterns may make possible distributed access to the entire knowledge structure [21].

It seems likely that overlapping CAs, with their inherent ability to learn novelty among many others, are important for implementing biologically realistic neural models. This work is intended at furthering the understanding of dynamics of neural processing.

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References

[1] Hebb, D.O.: The organization of behavior. Wiley, New York (1949)
[2] Harris, K.: Neural signatures of cell assembly organization. Nature Reviews Neuroscience 6, 399–407 (2005)
[3] Maurer, A.P., Cowen, S.L., Burke, S.N., Barnes, C.A., McNaughton, B.L.: Organization of hippocampal cell assemblies based on theta phase precession. Hippocampus 16(9), 785–794 (2003)
[4] Pulvermuller, F.: Words in the brain's language. Behavioral and Brain Sciences 22, 253–336 (1999)
[5] Pasupathy, A., Connor, C.: Population coding of shape in area v4. Nature Neuroscience 5:12, 1332–1338 (2002)
[6] Funahashi, S.: Neuronal mechanisms of executive control by the prefrontal cortex. Neuroscience Research 39, 147–165 (2001)
[7] Foster, J., Alexander, G.: Neuron acitivity related to short-term memory. Science 173, 652–654 (1971)
[8] Wennekers, T., Palm, G.: Cell assemblies, associative memory and temporal structure in brain signals. In: R.Miller, editor, Time and the Brain. Conceptual advances in Brain Research, Vol. 2. pp. 251–274. Harwood Academic Publishers (2000)
[9] Gerstner, W., Kistler, W.K.: Mathematical formulations of Hebbian learning. Biological Cybernetics 87(5-6), 404–415 (2002)
[10] Huyck, C.R., Nadh, K.: Multi-associative memory in fLIF cell assemblies. In: A. Howes, D. Peebles, R.C.E. (ed.) 9th International Conference on Cognitive Modeling - ICCM2009. pp. 81–87. Manchester, UK (2009)

[11] Sakurai, Y.: The search for cell assemblies in the working brain. Behavioural Brain Research 91, 1–13 (1998)
[12] Huyck, C.R.: Overlapping cell assemblies from correlators. Neurocomputing 56, 435–9 (2004)
[13] Eccles, J.C.: Chemical transmission and dale's principle. Progress in Brain Research 68, 3–13 (1986)
[14] Hopfield, J.J.: Neurons with graded response have collective computation properties like those of two-state neurons. In: Proceedings of the National Academy of Sciences. vol. 81, pp. 3088–3092 (1984)
[15] Nadh, K., Huyck, C.R.: A pong playing agent modelled with massively overlapping cell assemblies. (Manuscript submitted for publication).
[16] Sakurai, Y.: How do cell assemblies encode information in the brain? Neuroscience & Biobehavioral Reviews 23(6), 785 – 796 (1999)
[17] Wickelgren, W.A.: Webs, cell assemblies, and chunking in neural nets. Canadian Journal of Experimental Psychology 53(1), 118–131 (1999)
[18] Garagnani, M., Wennekers, T., Pulvermuller, F.: Recruitment and consolidation of cell assemblies for words by way of hebbian learning and competition in a multi-layer neural network. Cognitive Computation 1(2) (2009)
[19] Huyck, C.R.: Creating hierarchical categories using cell assemblies. In: Connection Science. vol. 19:1, pp. 1–24 (2007)
[20] Karalyn, P., Peter J. Nestor, T.T.R.: Where do you know what you know? the representation of semantic knowledge in the human brain. Neuroscience 8(12), 976–987 (2007)
[21] Eichenbaum, H.: How does the brain organize memories? Science 277(5324), 330–332 (1997)