

# Studies on Sparse Array Cortical Modeling and Memory Cognition Duality

K. K. Majumdar and R. Kozma

**Abstract—** In this paper we have suggested a sparse three dimensional array model for the brain. Entries of the array are synaptic weights as functions of time. This is a typical four dimensional spatiotemporal model, where each event has three spatial and one temporal dimension. Here we have concentrated on cortical computation over this model. Our model naturally indicates a duality between memory (both working and long term) and cognition, in the sense that they are mutually transformable in either direction. It also gives some support to the notion of grandmother cells [12].

**Keywords** — Cortical computation, synaptic plasticity, cognition, memory.

## I. INTRODUCTION

THE explosive growth of new information in neuroscience is an exciting development in an inherently exciting field of inquiry. However the vast increase in knowledge still leaves us fundamentally ignorant of how brain cells work together – to achieve recognition, evaluation of sensory input, selection and coordination of response. We are rich in knowledge of mechanisms at the level of components: molecular, intracellular, even some circuits. We are still poor in understanding higher levels, for example, cerebellum, striatum and cerebral cortex or feature extraction, repertoire selection and motor control, and still poorer in respect to volition, cognition and learning, in spite of spectacular advances in each of these areas [1]. Cortical computation, which deals with organizations at the system level, is an important tool to understand the higher level brain functions like, perception, cognition and awareness. If there are common foundations for cortical computation then a central goal of neurobiology must be to discover what they are and how they are embodied in cortical structures and processes [2]. In this paper we propose an elementary model of cortical computation on a few fundamental preliminaries, which perhaps every cortical computational model should consider as basic premises. The model through its action can generate cognitive processes as well as can store memory. In fact,

memory and cognition can transform into each other in either way in this model.

## II. PHYSIOLOGICAL PRELIMINARIES

In this section we shall describe a few physiological preliminaries, which should be fundamental to any cortical computational model. They are however not independent, but mutually interdependent:

- (a) Connectivity of neurons in terms of synaptic topology – In reality there may be tens of millions of *kinds* of neurons in the human brain, on all criteria of nonequivalence, and far fewer in goldfish and lobster [3]. Here we shall be concerned about firing or not firing of a neuron only.
- (b) Rapid firing of neurons, where frequency of firing will be a fundamental variable in describing the model [4]. Here we will be most interested in the  $\gamma$  frequency range, i.e., the frequency range between 20 and 80 Hz for the human brain [5]. This is the frequency range in which most of the binding occur across many species (Table 1 of [6]).
- (c) Time of firing of neurons – The temporal structure of synchronous firing of neurons is the defining mechanism for brain functions like perception [5], [7] and awareness [6]. In all systems and species studied, synchrony can be very precise, with a coincidence window of about 10ms [6].
- (d) Gain of synaptic transmission between pairs of neurons – In the overwhelming majority of instances, the many synapses maintained by any one neuron on other neurons have the same effect on their targets, either increasing or decreasing the target activity, so in the following discussion we shall refer to them as excitatory neurons or inhibitory neurons to denote the effect they have [5]. In the spirit of Hebbian rule we will understand that in the former case gain of synaptic transmission between the presynaptic and postsynaptic neurons has increased and in the latter decreased.
- (e) Electrical and chemical field effects, which operate over many micrometers, taking us beyond the classical synaptic transmission [1].
- (f) Release of neurotransmitters – Gain of synaptic transmissions is intimately related to the release of neurotransmitters and its efficacy at the receptor level.

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### III. COMPUTATIONAL MODEL

The architecture indicated by (a) of section 2 is obviously a circuit. Cortical computation, which is widely used to understand higher order brain functions like cognition, long term memory storage and retrieval, etc. is heavily dependent on the circuit model of the cortex. Validity of circuit models of the brain from a neurophysiological stand point has been discussed in [8].

The closest computational analog of a brain circuit like (a) is a directed multigraph, whose each node will represent a neuron and each edge a synapse. It can be represented as a three dimensional matrix – a three dimensional array  $a[i, j, k]$ . If there are  $k$  different synapses joining the neuron  $i$  with the neuron  $j$  (assuming that all neurons in the brain have been numbered) then  $a[i, j, k]$  will give the weight (the gain in synaptic transmission) of the  $k$ th synapse joining the neuron  $i$  with the neuron  $j$ . If the synapse transmits signal from  $i$  to  $j$  then  $a[i, j, k]$  will be positive, if it does so from  $j$  to  $i$  then it will be negative. For given values of  $i, j$  and  $k$   $[i, j, k]$  uniquely determines a synapse and  $a[i, j, k]$  gives that synapse up to its gain in transmission. In general  $a[i, j, k]$  will be a function of time and we shall write it as  $a[i, j, k](t)$  or  $a_{ijk}(t)$ , where  $t$  denotes time.

Each of the approximately  $10^{11}$  neurons present in a human brain is connected to the order of  $10^4$  synapses. So there are altogether  $10^{15}$  synapses in the human brain [9] and therefore the number of nonzero entries in at least  $10^{11} \times 10^{11}$  number of different values, for the collection of all  $a_{ijk}(t)$  for a fixed  $t$ , is at most  $10^{15}$ . This means that if  $10^7$  entries are sampled at random from  $a_{ijk}(t)$  (for a given  $t$ ) then on an average only at most one out of them will turn out to be nonzero. The three dimensional array  $a_{ijk}(t)$  is very sparse indeed at any given time  $t$ . Sparseness of connectivity of the brain circuit is a well documented fact [9], which is exhibited by our model.

As soon as we receive information from the environment through our sensory excitatory neurons they activate a sub-circuit of the whole cortical circuit to start a cortical computation in order to process those information, which culminates in some form of cognition (with or without action in general). Let us denote all active receptor neurons as  $T_0$  or target 0 neurons. The neurons fired by  $T_0$  be called  $T_1$  neurons or target 1 neurons. In general  $T_i$  be the class of neurons fired by the class of  $T_{i-1}$  neurons. These classes are not mutually exclusive. Some forward class neuron can

excite back an earlier class neuron and in fact this happens quite often. Several retrograde messengers have been identified that once released from dendrites act on presynaptic terminals to regulate release of neurotransmitters [10]. To account for any retrograde effect we shall just change the sign of the synaptic weight (gain in synaptic transmission) function  $a_{ijk}(t)$ .

Now consider the set  $V_{i-1} = T_{i-1} \cup T_i$  for all  $i$ . Consider the (simple) graph whose vertex set is  $V_{i-1}$ . There is an edge between two nodes of  $V_{i-1}$  if the two neurons are connected by a synapse (here node and neuron are same). Now consider the adjacency matrix of the graph. If the  $(i, j)$ th entry is 0 we leave it as it is. If it is 1, we replace the entry by a one dimensional array whose length is equal to the number of synapses between neuron  $i$  and neuron  $j$ . Each entry of the array will contain the weight of the respective synapse up to sign ( $a_{pqr}(t)$ ,  $p$ th neuron belongs to  $T_{i-1}$ ,  $q$ th neuron belongs to  $T_i$  and  $r$  varies over all the synapses connecting the  $p$ th neuron with the  $q$ th). Now exactly the same way the scheme will keep iterating from  $V_{i-1}$  to  $V_i$  and from there to  $V_{i+1}$ , so on. We call each iteration a *cognitive cycle*.

Initially  $T_{i-1}$  neurons are fired by  $T_{i-2}$  neurons (according to the synaptic weights carried the signals, which is controlled by neurotransmitters), but if  $T_{i-1}$  cannot expect the goal they will soon come to rest and no significant cortical computation will be performed or cognition will form at the level of  $T_{i-1}$  neurons. On the other hand if they can anticipate the goal they will keep firing rapidly and only those neurons will be firing rapidly which have ‘past experience’ to anticipate the goal. Synchrony will be sustained by the anticipating neurons only. When a neuron fires it propagates nonsynaptic electrical and chemical fields. When spatially contiguous neurons fire in synchrony they create very strong electrical field detectable as a spike in the EEG signal on the skull. In this sense if the brain electric field is  $E_B(t)$ , we can write  $\nabla \cdot E_B(t) = \text{action potential} = \text{spike amplitude in the EEG}$ . As long as the synchrony is observed within windows of 10ms range they are all occurring at a level  $T_i$  for a particular  $i$  (i.e., within the same cognitive cycle), because transition from  $T_i$  to  $T_{i+1}$  will take second, minute, hour or even longer time (cognition from one cycle to another may even take months or years, e.g., solving an outstanding mathematical conjecture by a seasoned mathematician). Prominent cognition will occur at the  $\gamma$  frequency range. At a much lower frequency the cortical sub-circuit (engaged in the current computation) will produce no cognition, but it will only act as the storage for a

volatile memory (discussed in the next section).

In case of visual sensory input this will be true for relatively ‘simple’ scenes. The scenes are *simple* in the sense that perception will be formed within a few tens of milliseconds. When scenes are *complex*, such as, a complicated mathematical formula written on a black board, the meaning will take much longer time to form in our mind. In other words, the cognition will be a long process. Visual perception will quickly form the meaning of each symbol in a trained mind, but the over all meaning of the collection of all those symbols, in that particular order, will take a much longer time to precipitate. Here the binding problem will typically take several cognitive cycles as described above. It may well happen that even after several cognitive cycles no meaning emerges at which the cognitive cycles can stop. When a seasoned mathematician is trying to prove or disprove a difficult formula the cognitive process may actually not stop unless a definite solution is reached, which may take a very long time. It may only get buried at times under other cognitions. The formula cognition may come into full attention, as for example, by some visual clue (environmental stimulus) like seeing another mathematical formula in a book or paper (which may be relevant to the one at hand).

Here binding is stimulus driven as well as goal driven. Several (possibly) overlapping cortical circuits remain busy at the same time in several cognitive tasks. The task whose corresponding circuit gets the most favorable flow (in some sense) of neurotransmitters, becomes the most dominant. This we may call *binding by feelings*. Apart from synaptic transmission binding by feelings will also depend on nonsynaptic (electrical and chemical) field effects. This type of binding will be very resource efficient in face of the huge resource demand associated with the combinatorial nature of visual images [11]. Typically at each iteration the number of neurons involved becomes less compared to the previous one. When the cognition of the visual object completes after a number of iterations, the object is represented in brain by only a few cells. The idea has been further supported by a recent work reported in [12]. Clearly the neurons with more number of axonal projections will remain present in greater number of iterative steps (in more  $V_i$ s) and therefore the advanced steps are more likely to converge to the neurons with more number of axonal projections, whose number is relatively less. This is exactly the *binding by convergence* [11], [13]. Binding by convergence is not driven by feelings alone. It is also goal driven. It has been observed that neurons keep firing in anticipation of a goal based on past experience [4]. Several neurons may start firing in similar manner in anticipation of the same goal, which will then give rise to a goal or hypothesis driven binding. This will also play a substantial role in binding. In this sense binding is both a top down and a bottom up approach (in the sense of [4]).

#### IV. COGNITION MEMORY DUALITY

Various aspects of cognition like representation [14], awareness [6] and perception [4] have been modeled by assemblies of firing neurons. Long term memory on the other hand is preserved through structural changes in our brain [15]. In case of binding by feeling a cognitive task will get attention according to the combination of flow of neurotransmitters. (Flow of neurotransmitters mediates synaptic strength, which in turn will single out a particular task from among many others. This may be thought as a form of predictive filtering as indicated in [2].) This will keep the cognitive cycles alive. The on going cognition then becomes part of *working memory* (or *short term memory*). After some time some other cognition gets the attention and the combination of flow of neurotransmitters to the previous cognition does no longer remain as earlier and hence it can no longer remain at the center of attention. However since the cognitive process is a cycle consisting of two complementary sub-processes, one is goal driven (feed back or top down) and the other is stimulus driven (feed forward or bottom up), the associated cortical circuit still maintains its flow of neurotransmitters at a level and combination, such that, all  $a_{ijk}(t)$  associated with the circuit are close to medium. When  $a_{ijk}(t)$  are at medium for all  $k$ , neurons  $i$  and  $j$  are at rest [7]. This means that the neurons within the circuit involved in the cognition are close to rest and therefore the cognitive process is in rest within the circuit as memory (the neurons are still firing, but very faintly). We may call this as *volatile memory* in the sense that, if the flow of neurotransmitters becomes such that the neurons go to complete rest then the information will be lost completely. When ever appropriate environmental stimuli are applied to the circuit many  $a_{ijk}(t)$  will become high, such that, the neurons start firing in appropriate synchrony and the volatile memory becomes an on going cognition.

To make a volatile memory into a permanent one the circuit may have to be brought into cognition for a large number of times (through prolonged training) or the input (environmental stimuli) will have to have an extraordinary impact. In the first case the flow of neurotransmitters will be somewhat high for a prolonged period and in the second case the flow of neurotransmitters will be quite high for a short period. For specific neurotransmitters these may cause synaptic growth or regression leading to structural changes in the cortical circuit. This is believed to be storing long term memory in our brain [15].

A single neuron usually participates in several cognitive tasks depending on which sub-cortical circuit is sharing it. If two or more circuits have substantial overlapping then the corresponding cognitive tasks will form a context. We shall call any cognitive task related to a context a *contextual cognition*. Now say, any one of these circuits stores a long term memory by synaptic modification (as outlined in [15]). In this scenario any contextual cognition may pump neurotransmitters in right combination and amount into the

overlapped circuit, which is a substantial part of the long term memory circuit. The long term memory circuit, by virtue of its synaptic design, may become fully activated due to activation of a large part of it already. This is exactly the situation where the long term memory becomes an on going cognition due to contextual stimulus [16]. Contextual cognitions become contextual memory in the same way a cognitive task becomes a memory.

#### V. CONCLUSION

In this paper our aim had been to out line a model for the cortex as a circuit consisting of neurons and synapses, and synchronous and asynchronous firing patterns of neurons. The main variable in our model is  $a_{ijk}(t)$ , where  $i, j, k$  the spatial position of the synapse in terms of its presynaptic and post synaptic neurons in the network topology.  $t$  gives the time on which plasticity of the synapse (denoted by  $a_{ijk}(t)$ ) depends. How plasticity of the synapses determines the firing of the post synaptic neuron remains an open question to be investigated in future works.

Although without the modeling of neuronal firing our model remains incomplete, it still shows very clearly the close relationship between cognition and memory. Based on our model we have shown how they transform into each other (memory to cognition and cognition to memory). Since our model is based on some of the most basic physiological preliminaries of the brain, the memory cognition duality seems to be a very fundamental feature of our mind (as made up by the brain [5]).

Up to now the model has remained largely combinatorial. In future we shall extend this model to incorporate the field aspect too [17].

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#### REFERENCES

[1] T. H. Bullock, "Integrative systems research on the brain: resurgence and new opportunities," *Annu. Rev. Neurosci.*, vol. 16, pp. 1-15, 1993.  
 [2] W. A. Philips and W. Singer, "In search of common foundations for cortical computation," *Behavioral and Brain Sciences*, vol. 20, pp. 657-722, 1997.  
 [3] T. H. Bullock, "Reassessment of neural connectivity and its specification," In *Information Processing in Nervous System*, H. Pinsky and W. Willis (eds.), Raven, New York, pp. 199-220, 1980.

[4] A. K. Engel, P. Fries and W. Singer, "Dynamic predictions: oscillation and synchrony in top-down processing," *Nature Rev. Neurosci.*, vol. 2, pp. 704-716, 2001.  
 [5] W. J. Freeman, *How Brains Make up Their Minds*, Columbia University Press, New York, 2000.  
 [6] A. K. Engel and W. Singer, "Temporal binding and neural correlates of sensory awareness," *Trends Cog. Sc.*, vol. 5, pp. 16-25, 2001.  
 [7] C. von der Malsburg and W. Schneider, "A neural cocktail-party processor," *Biol. Cybern.*, vol. 54, pp. 29-40, 1986.  
 [8] A. Destexhe and E. Marder, "Plasticity in single neuron and circuit computations," *Nature*, vol. 431, pp. 789-795, 2004.  
 [9] D. B. Chklovskii, B. W. Mel and K. Svoboda, "Cortical rewiring and information storage," *Nature*, vol. 431, pp. 782-788, 2004.  
 [10] L. F. Abbott and W. G. Regehr, "Synaptic computation," *Nature*, vol. 431, pp. 796-803, 2004.  
 [11] W. Singer and C. M. Gray, "Visual feature integration and the temporal correlation hypothesis," *Annu. Rev. Neurosci.*, vol. 18, pp. 555-586, 1995.  
 [12] R. Quiñan Quiroga, L. Reddy, G. Kreiman, C. Koch, I. Fried, "Invariant visual representation by single neurons in the human brain," *Nature*, vol. 435, pp. 1102-1107, 2005.  
 [13] W. Singer, "Neuronal synchrony: a versatile code for the definition of relations?" *Neuron*, vol. 24, pp. 49-65, 1999.  
 [14] C. A. Skarda and W. J. Freeman, "How brains make chaos in order to make sense of the world," *Behavioral and Brain Sciences*, vol. 10, pp. 161-195, 1987.  
 [15] C. G. Bailey and E. R. Kandel, "Structural changes accompanying memory storage," *Annu. Rev. Physiol.*, vol. 55, pp. 397-426, 1993.  
 [16] X. Chen, M. G. Garelick, H. Wang, V. Li, J. Athos and D. R. Storm, "PI3 kinase signaling is required for retrieval and extinction of contextual memory," *Nature Neurosci.*, vol. 8, pp. 925-931, 2005.  
 [17] W. J. Freeman, "A field-theoretic approach to understanding scale-free neocortical dynamics," *Biol. Cybern.*, (to appear).