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SYNCHRONIZED NEURAL FIRING FOR CONTROLLING CYBER PHYSICAL SYSTEM

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ABSTRACT

Objective: Plasticity of the neurons and the synchronization features are essential to bring out the intelligence in a biological specimen. Thus, in this study, we model the synchronistic behavior of neuronal firing to avail control system of cyber-physical system.

Methods: We model and study the correlations between two or more neurons that belong to the same sets connected through a chain of networks. This will allow the synchronous controlling of several tem temporal cyber physical system. Furthermore, a brief review of neuronal oscillations is also discussed.

Results and Discussion: Once the reliability of a chain activates neurons that of the other chain consequently, it gets merged and this merging is what forms the model formation at the neural level. This will aid us in understanding nature of functioning of cortical circuits which maintains synfire chain to give rise to appropriate computations.

Keywords: Neuronal plasticity, Neuronal oscillations, Cyber-physical system, Control system.

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INTRODUCTION

Synchronous firing chains or synfire chains is a feed-forward network of multi-layered neurons, wherein neuronal spiking activity broadcast itself to other neurons in a synchronization with other neuronal firing activities [1]. Sets of neuron receive afferent inputs the previous sets of activated neurons, thereby projecting its output to other neurons of consecutive sets for activation. Hence, as a whole, a neuron receives other afferents from the collectively coactivated networks and dispatch outputs to other neurons in the neural network. The idea behind pulse packet was developed in [2], where it was found that for neural network of size large enough, the pulse packet converges to the pattern of synchronous firing, on the other hand for small sized network, the pulse packet dispersed and remains indistinguishable from the background neural activity. It's because in randomly connected balanced sparse network, where each neuron from this balanced network gets equal and proportional inhibition as excitation [3], forms an integrated fire neurons which in turn is known to have procedural parameters of activation for internetworked neuron with stable asynchronized irregular activity [3,4]. When a balanced network is set to function in a domain of asynchronized irregular activity; then, the neuronal firings are driven majorly by the fluctuations of input than of its mean input. Thus, the neurons activates irregularly even they are integrated to a large sum of inputs. This property of balanced networks and quick response to external stimuli [5,6]; put them a suitable regime for modeling and testing a cortical neural network. In the past, studies on isolated neocortical microcircuits showed that such spontaneous activity could be temporally precise even in the absence of sensory stimulation [7,8]. Precise repetitions of such pattern of neural activity serve as pathway for numerous other neural functions which guarantees a fixed level of network activity while allowing to learn and reproduce complicated spatiotemporal firing patterns.

This will aid us in understanding nature of functioning of cortical circuits which maintains synfire chain to give rise to appropriate computations. Thus, for learning it is prerequisite that the same training stimulus is feed to the system in repeated intervals. This stimuli is represented as sequences of activation patterns which latter drives the network; thereby forming a rule for network connectivity, developing rules for learning and finally used to build model of the problem. The previous studies showed that self-organizing neural networks with binary units can learn and represent temporal sequences of sensory inputs [9]. In this study, we aim to show that computational results developed in the modeling of a self-organizing neural network driven by synfire chains reproduce the same experimental data of fluctuations for synaptic connection strengths in cortex and hippocampus, offering an explanation for the experimentally observed distribution of synaptic efficacies and model building [10], which can later be used to form a structure of self-learning artificial neurons to carry various task of data processing.

METHODS

We begin the modeling by studying the correlations between two or more neurons that belong to the same sets connected through a chain of networks [11-13]. This connectivity between chain of networks is not assumed to be entirely random nor structured. Therefore, our model consists of many pairs of neurons that share at least sets of network as their common inputs and also deprived from any specific wiring unlike a random network; wherein pair of neurons shares a small number of common inputs.

Let us supposed that we have a total of excitatory neurons (E_N) and inhibitory neurons (I_N) where they are in the ratio of $I_N = 0.2 \times E_N$. Now, that we need to find an evolutionary Hodgkin-Huxley equation for self-managing neurons. Therefore, to model the phenomenon of building the learning model for biological neurons, we require to merge the properties of artificial neural network with the biological neurons. Where the sequence of inputs of the firing neurons is affects the other subsequent sequence and consequently synapse formation before giving a unitary idea of stimuli. Thus, W_{ij} be the weightage for the connection strength from neuron i to neuron j, similarly W^{IE}, W^{EE} and W^{EI} represents weightage for inhibitory to excitatory connections, excitatory to excitatory and excitatory to inhibitory connections, respectively. The W_{EE} and W_{EI} are initialized as sparse random matrices with the range of connection probabilities between the value of 0.1 and 0.2. Initially, the W_{IE} connections are meant to freeze at their random initial values which are depicted from uniform distribution, latter followed by normalization [13,14]. Altogether, the sum of connections entering a neuron is in a sequence of 1 and 0; thereby, the binary vectors are given by $x(E_N) \in \{0, 1\}$ and $y(I_N) \in \{0, 1\}$ for the excitatory and inhibitory neural activity at time step t, respectively. Hence, the sequencization of the network states at time step t + 1 is equivalent to:

$$x_{ij}(t+1) = \theta\left(\sum_{j=1}^{E_N} W_{ij}^{EE}(t)x_{ji}(t) - \sum_{k=1}^{I_N} W_{ik}^{EI}(t)y_{ki}(t) - T_{ij}^{E}(t) + \xi E_i(t)\right)$$

for activation of neuron

$$y_{ki}(t+1) = \theta\left(\sum_{j=1}^{N^E} W_{ij}^{IE}x_j(t) - T_i^I(t) + \xi I_i(t)\right) \text{ for growth of neurons}$$

As the network equation continues to evolve x_{ij} and y_{ki}, the synaptic weights is given as:

$$\Delta W_{ij}^{EE}(t) = \eta\left(x_{ij}(t)x_{ji}(t-1) - x_{ij}(t-1)x_{ji}(t)\right)$$

$$\Delta W_{ij}^{EI}(t) = -(1-\eta)y_{ji}(t-1)\left(1 - x_{ji}(t)\left(1 + \frac{1}{\mu_{ji}}\right)\right)$$

θ is the Heaviside step function; T^E and T^I are the threshold values for excitatory and I_N, where it is initially drawn from the uniform distribution within the interval $[0, T_{max}^E]$ and $[0, T_{max}^I]$. $\xi E_i(t)$ and $\xi I_i(t)$ are white Gaussian noise processes with μ_ξ [0.01, 0.05]. Here, one time step corresponds roughly to the duration of window of the spike time dependent plasticity. η is the learning rate.

Now, that the threshold value of the E_N in response for a sequence of activated neurons is made pass through the previously generated targeted sequence code blocks of firing neuron states $S_{ij}^{\text{code block}}$; which is determined by the adaptation rate η_{AD} as:

$$T_{ij}^{E}(t+1) = T_{ij}^{E}(t) + \eta_{AD}\left(x_{ji}(t) - S_{ij}^{\text{code block}}\right)$$

The inhibitory spike-timing dependent plasticity ji rule regulates the weights backward from inhibitory to E_N which stabilizes the amount of excitatory and inhibitory to drive sensory information through the E_N. Therefore, the evolutionary dynamics of the neuronal membrane potential that mediates the excitatory and inhibitory sequences through the network of membranes is governed by the above-deduced equation.

RESULTS AND DISCUSSION: DEVELOPMENT OF MICRO BRAIN (MB) FOR SIMULATING SENSATION

The response of synfire chain growth in training was remained stochastic but in our mathematical model of internetworked neurons we've found that repeated stimulations for training neurons changes the weights of the synaptic distribution and consequently forms a stable and strong connectivity within synaptic chain. Thus, the selection of postsynaptic targets is crucial for the formation of loop of synfire chains that stops its growth for the similar stimulation but keep on adjusting weights with chain growth emanating from the training neurons. Due to the spike time dependency plasticity rule, the targeted neurons spontaneously spike shortly after the training neurons. It is observed that the training neurons spike synchronously and make convergent connections to the same sequential set of neurons and strengthens these connections. Once strengthened connections are developed the prominent sets of neuron spikes is readily evoked in these targets on every run of the stimulation. For the targets, to overcome membrane noises, it is important that the synapses are cooperated through the convergent synapses. The next step follows for the closed loop of synfire chain is to propagate the firing chin to other neurons to recruit the new group in association with the previously recruited neurons. This iterative process yields stable topologies of synfire chains which are actively efficient in producing long stereotypical sequences of spikes for mediating training sets to other neurons; such that this chains consists of introductory sequence generated by training neurons in the first step and feeds this loop of strong synaptic connectivity to other pools of neurons, as network size is increased. Thereby, forming an interconnected network of neurons such as examples of which is displayed in Fig. 1. The internet worked structure of neurons is reacted in raster plots of the activity of the neuronal population consisting of inhibitory and E_N, during a typical trial after the chain is fully formed.

In our mathematically framed large recurrent networks the potentiation decay of synapses, we found emergence of long and sequences of spikes. The sequences are produced by stable synfire chain topologies which self-organize through the growth process mentioned above. The localized distributions of synfire chain loops influence the rate of potentiation decay in the synaptic plasticity which primarily controls the shape of the global distributions of responsive stimulus emerged from the network in dynamically distributed synaptic weights and remains vulnerable until the synchronization is formed with the sequence from recruited neurons are synaptically withheld. As the sequence begins to emerge the neurons in the pool of networks are more likely to target the neurons in the chain. Such that this response of synapses throughout the network coevolved the spike activity forming an the emerging sequence and newly framed synaptic topology in awe of preferential targeting. This generalizes to other recurrent network developed in the previous

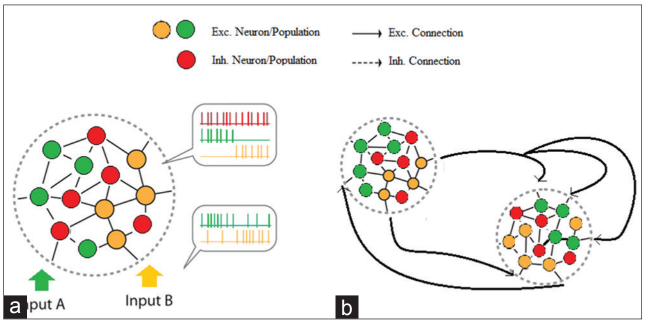

Fig. 1: Illustration of the network model. (a) For a closed neural network where inputs are read through population of several inhibitory and excitatory units and develop an internal model based on sequence of connections from the reception of global inhibitory feedback from that unit, (b) volumetric transfection of inputs to excitatory and inhibitory inter-networked neurons through the input channel they are connected to different sources. Note that, each node a pool of population of neurons distinguished by different color and associated features

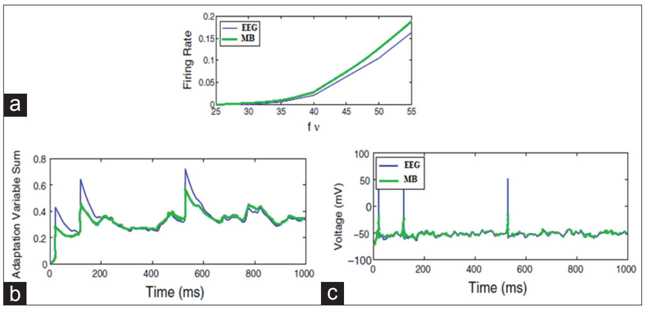

Fig. 2: Network dynamics of cortical networks during the task using electroencephalography (EEG) and MB model. (a), The firing rate comparison with the frequency based oscillation of the two networks showing similar properties, (b) the sum of the activation variables for EEG and MB models are found to be approximate, and (c) its voltages traces coincide with the EEG data. Simulation time was 1000 ms

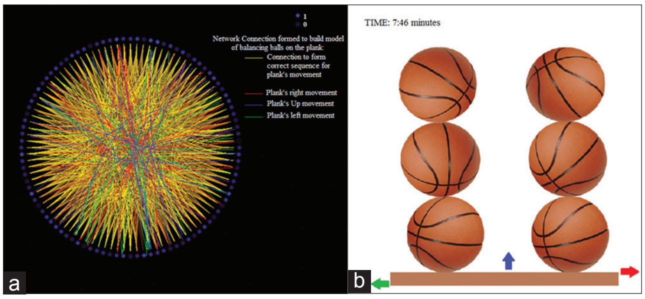

Fig. 3: (a) The network of connections formed during the turing of the micro brain to reveal the right sequence (in the binary form, i.e., 100010…) to formulate a connection that stabilize and balances the basketballs stacked on one another over a plank during the simulation, (b) An instance from the simulation showing the attainment of control by the computational micro brain. The simulation is only meant to control the movement of plank in three directions under the influence of gravity

steps mentioned above in which spike sequences emerge. Thus, when excited by the stimulation the response is in the form of coevolution of the sequence of network activity and its topological connectivity which is reflected back in the spectrum of sequence and length of the synfire chains and its distribution. The same is experimentally found similar (Fig. 2) between the electroencephalography data of cortical network and mathematically modeled MB. Note, that not every neuron is part of the chain formed in our study.

A natural extension of this mathematical investigation is to carry out the real-time problems with the MB so developed in the study in this way we found emergence more complex asymptotic synaptic topologies emerge. Hence, as shown in Fig. 3, we have simulated the MB to carry out the task to balance the 6 balls placed on one another 3 balls each and the MB is given control of the plank on which the forces in right, left and upward direction can be applied by it to stabilize the system under the influence of gravity with downward acceleration of 9.8 m/s^2. This task and the learning involved in it is similar to the complex motor behaviors of a juggler, which spends most of his life in perfecting the technique. Thus, our goal herein is to employ the computational MB to learn the techniques of balancing autonomously by framing models of its own for the given condition and variables. From ordering of distinct elements involved within the task, we observed an emergent behavior with multiple complexity. For the successful completion of task, a single synfire chain is not capable to capture this tasks complexity therefore multiple branching chains are offered by the developed MB. In Fig. 3, we display the results of MB connectomes growth revealing the ideal sequence to adjust the plank and balls positions through hierarchical model formation from mediating synfire chain formations and consequently updating the self-built model of balancing at each step. Hence, the several groups of chains developed individually were ultimately merge to a single chain. Emergence of synfire groups encodes two disjoint sequences in the internetworked neurons, and these sequences are perfected at each step of loop formation for synfire chains. Although, occasionally this chains activated by spontaneous activity and influencing neurons in the network pool to preferentially target the partial chains. Once the reliability of a chain activates neurons that of the other chain consequently, it gets merged and this merging is what forms the model formation at the neural level. We believe the success of our work will aid in forming autonomous intelligent systems or autonomous data processors, or even soon we could digitize the human personality.

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