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Investigation of a moderate cortical model synchronization created using BRIAN simulator

Sadeem Nabeel Saleem Kbah
Biomedical Engineering Department, Alkhwarizmi College of Engineering
University of Baghdad, Baghdad-Iraq, 10071
Email: sedeemkubba@gmail.com

***Abstract*—Obtaining computational models for the functioning of the brain gives us a chance to understand the brain functionality thoroughly. This would help the development of better treatments for neurological illnesses and disorders. We created a cortical model using python language using BRIAN simulator. The dynamic connection model has multiple parameters to ensure an accurate simulation. We concentrated on the connection weights and studied their effect on the interactivity and connectivity of the cortical neurons in the same cortical layer and across multiple layers. As synchronization helps us to measure the degree of correlation between two or more neuronal groups, the synchronization between neuronal groups, which are connected across layers are considered.**

***Keywords*-Izhikevich neuron model; cortex; large-scale networks; synchronization; neuron connections.**

I. INTRODUCTION

In the last decade, efforts towards obtaining computational models for the brain has been increased tremendously. The most accurate modeling of the human brain occurred in a Japanese university, using a supercomputer, it took 40 minutes to simulate 1% of the human brain neuronal connectivity working for 1 second [1][2][3].

In this work, we are inspired by Izhikevich and Edelmans work on large-scale brain model, we simulated 10000 neurons activity where 22 different types of neurons are considered. The model is constructed with BRIAN (v1.4) simulator and this work gives an example of realizing a large-scale model of the brain using a computer with ordinary computational properties [4]. We investigated also the effect of changing the connection weights on synchronization.

Synchronization is the degree of correlation between two or more spiking neuron activity in the same time interval[2][5][6]. It has many applications in monitoring the activity brain functionality, predicting the behavior for long-term neuronal interaction which is important in detecting and measuring the degree of brain disorders [7], inspire new learning techniques, and can be used also to study the role of short-term plasticity and STDP on learning as in [8][3][9][4].

Table I: Type of spikes available in the brain cortex.

Spiking type symbol	Spiking type name
RS	regular spiking
IB	intrinsically bursting
CH	Chattering
FS	fast spiking
LST	low- threshold spiking

Table II: List of parameters a, b, c, and d.

Spiking	Values	of	parameters	
type symbol	a	b	c	d
RS	0.02/ms	0.2/ms	-65*mV	8*volt/second
IB	0.02/ms	0.2/ms	-55*mV	4*volt/second
CH	0.02/ms	0.2/ms	-50*mV	2*volt/second
FS	0.05/ms	0.2/ms	-50*mV	2*volt/second
LST	0.1/ms	0.25/ms	-50*mV	2*volt/second

It helps, with brain modeling, the investigation of the active brain areas during some activity like movement or cognition [10][11]. Especially in new approaches in machine learning, such as Bartoet.al.s reinforcement learning [4], Grossbergs adaptive resonance theory [9]. Spiking neuron models are also considered in developing new machine learning methods [12][13].

II. MATERIALS AND METHODS

A. Creating the Cortical Layers

The differential equations in [14] has been used to create the single neuron model as in [15] with parameters (a, b, c, and d) listed in Table (II), these parameters are responsible on giving the spike its characteristic shape. created single neurons then used to created two groups each one consists of different types of neurons, with 80% excitatory and 20% inhibitory [16], details of the used neurons can be found in tables (III) and (IV).

In BRIAN environment, the connections between groups realize by certain $weight$, $spareness$, and dynamic variable (g_{ampa}) see equation (1) [15]. (τ_{ampa}) is the recovery time,

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Table III: Excitatory groups, its neurons information

Type of neurons	Existence in cortex	Actual number of neurons used in our model	Percentage of existence	Spiking type
Pyramidal cells	L2/3	2500	25%	RS
Pyramidal cells	L4	1000	10%	RS
Pyramidal cells	L2/3	500	5%	CH
Pyramidal cells	L5/6	100	1%	IB
Pyramidal cells	L4	1400	14%	CH
Pyramidal cells	L5/6	500	5%	IB
Spiny cells	L4	1000	10%	RS
Spiny cells	L2/3	1000	10%	RS
Total number of all EXCITATORY neurons		8000	80%	

Table IV: Inhibitory groups, its neurons information

Type of neuron	Existence in cortex	Acual number of neurons used in our model	Percentage of existence	Spiking type
GABA$_{nb}$	L1	200	2%	LTS
GABA$_{nb}$	L2	400	4%	LTS
GABA$_{nb}$	L4	200	2%	LTS
GABA$_{nb}$	L5	100	1%	LTS
GABA$_{nb}$	L6	200	2%	LTS
GABA$_{b}$	L2	200	2%	FS
GABA$_{b}$	L4	400	4%	FS
GABA$_{b}$	L5	100	1%	FS
GABA$_{b}$	L6	200	2%	FS
Total number of all INHIBITORY neurons		2000	20%	

Table V: The dynamic variables g used in this model.

Neuron cell	Dynamic variable g	Type of action
Pyramidal neurons (L2,L4)	AMPA	Excitatory
Pyramidal neurons (L3,L5,L6)	NMDA	Excitatory
Spiny neurons	AMPA	Excitatory
GABA$_{nb}$, GABA$_{b}$	GABA	Inhibitory

which is the time required by the membrane to return to its rest potential, each neuronal group has its own dynamical variable and recovery time (τ). The whole types of dynamic variables (g) used in our model are listed in Table (V).

$$dg_{ampa}/dt = -g_{ampa}/\tau_{ampa} \tag{1}$$

$spareness$ denotes the probability of a connection between two groups of neurons to occurs and its value is taken to be between (0.1-0.2) [16]. The synaptic $weight$ between the neurons can also be changed dynamically, $weight$ here denotes the values added to the dynamical variable (g) of each connection to increase or decrease the strength of the connection.

Once connected neurons start to fire, the strength of the synaptic connections between them will either increase or decrease according to the functional property of the neurons considered (excitatory neurons or inhibitory neurons). These changes in the synaptic connections due to firing of neurons

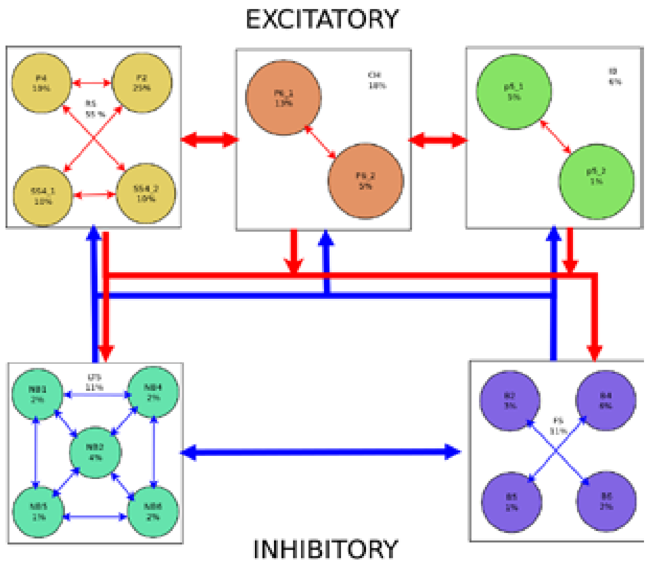

Figure 1: The entire cortical neuronal groups, (RS, CH, IB) are the EXCITATORY groups, (FS, LTS) are the INHIBITORY ones. Arrows are coloured as red for excitatory and $blue$ for inhibitory.

are called Hebbian rule and it is specified by changing the weights of connections [17].

The entire network proposed for the cortex with connections properties and different cortical neuronal groups is shown in Figure (1), this model is capable of simulating the behavior of microcolumns in the cortex, even in its learning capabilities [18].

B. Measuring Synchrony

Synchronization measures the degree of effectiveness of each layer by the action of the other layers, and the estimation of connectivity in cortex [19]. The synchrony measure for neuronal activity of N neurons is given as follows [11]:

$$X^2(N) = \frac{\sigma^2_{V(t)}}{\frac{1}{N}\sum_{i=1}^{N}\sigma^2_{V(t)_i}} \tag{2}$$

Where X^2 is the synchrony measurement factor, $V(t)$ represents the mean of the neuron membrane voltages during the running duration, while $V(t)_i$ is the single voltage value at specific time. $\sigma^2_{V(t)}$ is the variance of the activity of all neurons.

The synchrony measure X is calculated while changing the connection weights in an interval of (1 to 100) incrementing each time by 10 mV for inhibitory and excitatory groups, Regular spiking (RS) and Chattering (CH) neuron behaviour in excitatory group while the inhibitory group has Fast spiking (FS) neurons. The simulation results of excitatory groups are given in Figure (3).

III. Results

The simulation results can be seen in Figures (2,3). In figure (2) the first row represents the raster plot of the firing neurons and their temporal location per time (in our model 1 ms), the second row is the voltage plot of a single spike which in our case is (RS) type. The third row is variable u is the recovery time or refractory period of this neuron group, the fourth row is the dynamic variable g and finally the fifth row is the firing rate.

If we have a second look at Figures (2) and by examining the rhythmic behavior of the first and fifth rows, we can see that the spiking of the group have a random behavior compared the single spiking behavior shown in the second row of the same figures. This behavior is a sign of the existence of an interaction between different groups in the model. This interaction between this group and the other groups can be measured by the degree of synchrony occurred between them, see Figure (3).

In Figure (3) we plotted the synchrony measurements of excitatory groups, here the y-axis is the degree of synchronization which is normally between (0-1), were (0) means no synchrony at all and (1) means total synchronization between this group (under study) and the other groups in the model. The x-axis is the values of weight of connection, we can see its in mV and it changes during the run in each iteration.

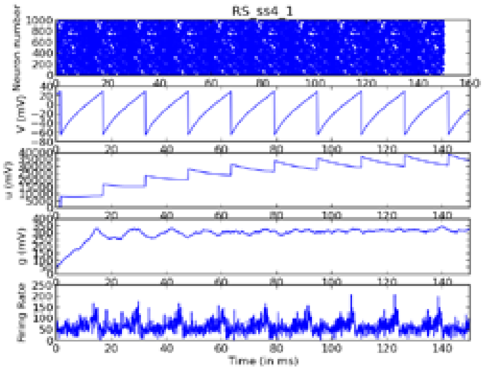

Figure 2: This figure shows some of the simulation results of the EXCITATORY groups.

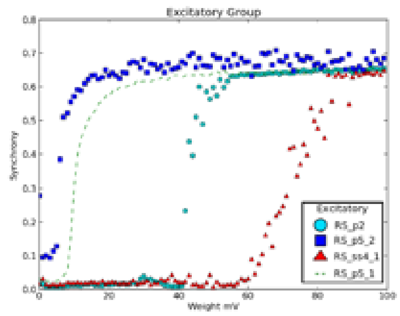

Figure 3: This figure shows some of the simulation results of *synchronization measurements* of the EXCITATORY groups

IV. Conclusion

The effect of connection weights over the strength of the connection is investigated. The degree of connectivity was tested thoroughly by calculating the synchronization between the connected neuronal groups. Even though synchronization within a group has been considered in previous works, the synchronization between groups is considered for the first time in this work up to our knowledge. The result shows that there is an increase in the synchronization factor with the increase occurs in the connection weights, which shows that there is an increase in the connectivity between neurons. This conclusion can use in multiple applications especially in machine learning and cognitive research fields.

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