UNIVERSITY OF TEHRAN

COLLEGE OF ENGINEERING

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

INTERNSHIP REPORT

<u>RESEARCH ON NEURAL CODING</u>

TELECOMMUNICATIONS INNOVATION LAB

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2 ABSTRACT:

Neural coding describes the study of information processing by neurons. Such studies seek to learn what information is used, and how information is transformed as it passes from one processing stage to another. The field of neural coding seeks to synthesize information arising from many levels of analysis and to explain how integrated behaviour arises from the cooperative activity of the neurons in the brain. It is natural to consider the brain as an information processing machine. It takes in information from physical changes in the environment, including light, touch, and sound, integrates this information with remembered or genetically coded information and then produces organized behaviour. In any information processing system, issues to be considered are what is being encoded, what is the code used to transmit the information, how reliable (noisy or not) is the code, and how the information is utilized or decoded. Much is known about the biophysics of neuronal responses – that is, how a spike is generated, how the spike acts on the axonal terminal to cause transmitter release, and how transmitters act on the target neuronal receptors. However, the impact of series of spikes is not well known, and it is even less clear what information has been encoded and how that information will be utilized in subsequent processing stages. At the base of this cascade of information processing is the information transformed and transmitted by single neurons. The signal on dendrites and cell body is reflected in fluctuations in the potential difference across the membrane. The signal that is transmitted down the axon is quite different; it is the action potential. This action potential propagates rapidly down the axon. At the axon terminal the arrival of the action potential generally causes the release of a transmitter that affects the membrane of the target neuron. The action potentials mark times at which the cell membrane at the neuronal cell body reaches the firing threshold. Thus, there is a sequence of action potentials containing information about the membrane potential at the neuronal cell body, and it is the information carried by the train of action potentials that provides information at the projection targets for the neurons. This train of action potentials (the spike train) can be considered as elements of a neural code. A model is presented that reproduces spiking and bursting behaviour of known types of cortical neurons. The model combines the biologically plausibility of Hodgkin Huxley-type dynamics and the computational efficiency of integrate-and-fire neurons. Using this model, one can simulate tens of thousands of spiking cortical neurons in real time (1ms resolution) using a desktop PC.

Telecommunication Innovation Lab(TIL):

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About:
TIL is part of the school of Electrical and Computer Engineering (ECE) at University of Tehran. This lab concentrates on interdisciplinary research centered around telecommunications.

At TIL, we are committed to sustain world class research on areas related to telecommunications. To achieve this goal, we make strong partnership with industry and set our strategic priorities based on industrial needs and cutting edge technologies.

THE RESEARCH AREAS IN TIL INCLUDES:

- **5G and beyond cellular systems**
- **Neural Communications**
- **Telecommunications applications in Artificial Intelligence (AI)**

AT A GLANCE ON ACHIEVEMENTS:

In this stage we want to take a brief look on tasks which done by our research group:

During this 320 hours' internship I was part of a research group working on spiking neuron models how it is related to telecommunications and also how it can be formulated which provide basic knowledge to understand information transmission by neurons.

our research position is organized into Three interleaved parts:

- First, I started to learn about basics of mathematics and theory behind the Neural coding which has similar concept to telecommunication systems by reading abundance number of related papers. We leveraged this method to reach an expected point which had let us start learning about the next stage of research basically related to simulate and formulate spiking neuron models.

- Model-based analysis of izhikevich model in MATLAB mostly relevant to reproduce spiking and bursting behaviour of known types of cortical neurons.

- In the end, we used simulation results and knowledge-based results provided by izhikevich to justify membrane voltage equations through a numerical-based method in MATLAB.

A SINGLE NEURON IN COMMUNICATING WITH OTHER NEURONS:

Neurons (also called neurones or nerve cells) are the fundamental units of the brain and nervous system, the cells responsible for receiving sensory input from the external world, for sending motor commands to our muscles, and for transforming and relaying the electrical signals at every step in between. More than that, their interactions define who we are as people. Having said that, our roughly 100 billion neurons do interact closely with other cell types, broadly classified as glia (these may actually outnumber neurons, although it’s not really known).

The creation of new neurons in the brain is called neurogenesis, and this can happen even in adults.

CONCEPTS AND DEFINITIONS:

Axon – The long, thin structure in which action potentials are generated; the transmitting part of the neuron. After initiation, action potentials travel down axons to cause release of neurotransmitter.

Dendrite – The receiving part of the neuron. Dendrites receive synaptic inputs from axons, with the sum total of dendritic inputs determining whether the neuron will fire an action potential.

Spine – The small protrusions found on dendrites that are, for many synapses, the postsynaptic contact site.

Action potential – Brief electrical event typically generated in the axon that signals the neuron as 'active'. An action potential travels the length of the axon and causes release of neurotransmitter into the synapse. The action potential and consequent transmitter release allow the neuron to communicate with other neurons.

WHAT DOES A NEURON LOOK LIKE?

A useful analogy is to think of a neuron as a tree. A neuron has three main parts: dendrites, an **axon**, and a cell body or soma (see image below), which can be represented as the branches, roots and trunk of a tree, respectively. A dendrite (tree branch) is where a neuron receives input from other cells. Dendrites branch as they move towards their tips, just like tree branches do, and they even have leaf-like structures on them called spines.

The axon (tree roots) is the output structure of the neuron; when a neuron wants to talk to another neuron, it sends an electrical message called an **action potential** throughout the entire axon. The soma (tree trunk) is where the nucleus lies, where the neuron's DNA is housed, and where proteins are made to be transported throughout the axon and dendrites.

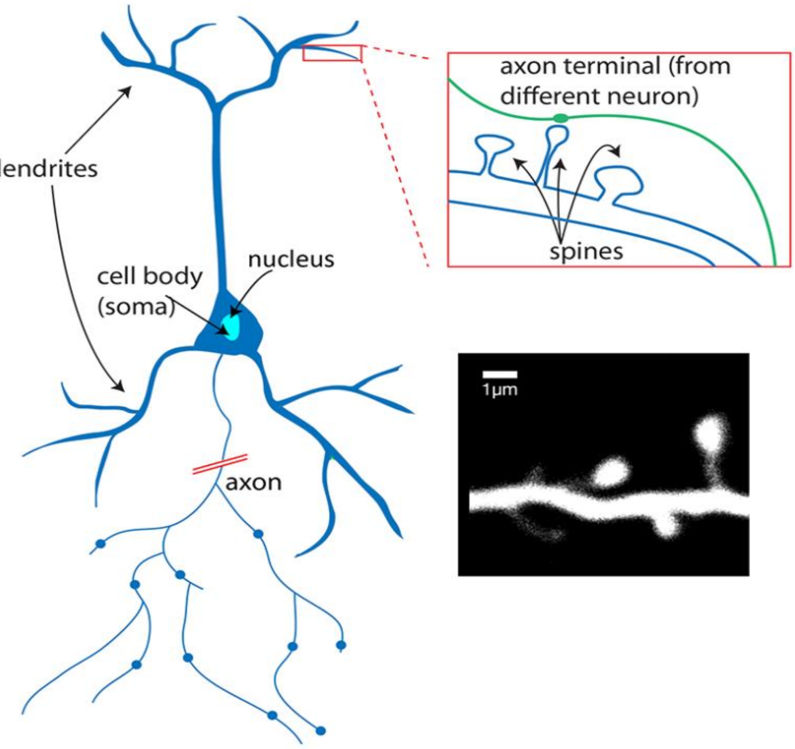

FIGURE 1: THE TREE-LIKE STRUCTURE OF A NEURON

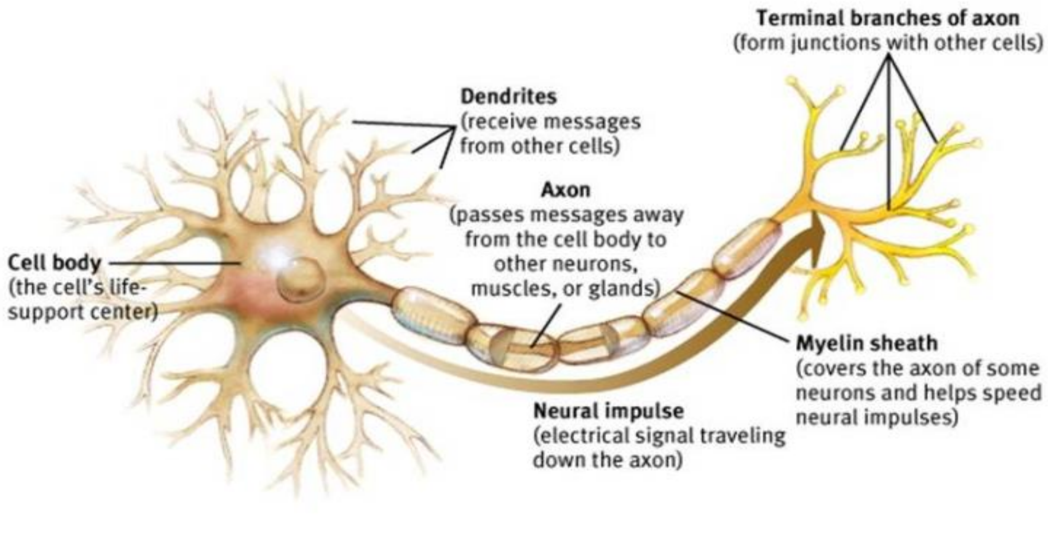

FIGURE 2. ANATOMY OF A MULTIPOLAR NEURON

NEURAL CODING:

Neural coding describes the study of information processing by neurons. Such studies seek to learn what information is used, and how information is transformed as it passes from one processing stage to another. The field of neural coding seeks to synthesize information arising from many levels of analysis and to explain how integrated behaviour arises from the cooperative activity of the neurons in the brain.

INFORMATION THEORY AND NEURAL CODING:

- Information theory quantifies how much information a neural response carries about the stimulus.

- This can be compared to the information transferred in particular models of the stimulus–response function and to maximum possible information transfer.

- Such comparisons are crucial because they validate assumptions present in any neurophysiological analysis.

- Because these models require specification of spike timing precision, they can reveal which time scales contain information in neural coding. This approach shows that dynamic stimuli can be encoded efficiently by single neurons and that each spike contributes to information transmission.

- If stimulus A yields a mean response r_A and stimulus B yields r_B, information in the response could be measured as the difference between r_A and r_B. However, two neurons with the same differential response ($r_A - r_B$) may have different variability in their individual trial responses.

- Information theory allows one to consider not only response variance, but exact conditional probability distributions.

- A second advantage is that information theory can be used to calculate maximal rates of information transfer. This measure, which is estimated from the set of all possible neuronal responses, is used to evaluate neuronal precision.

Box 1. Information theory and significance of neuronal encoding.

$p(r_i)$	Probability that neural response takes the value r_i
$p(s_j)$	Probability that stimulus condition takes the value s_j
$p(r_i \vert s_j)$	Probability that neural response takes the value r_i when stimulus condition s_j is presented (conditional probability)

Information about stimulus condition s_x:

$$I\,(R, s_x) = \sum_i p(r_i|s_x) \log_2 \frac{p(r_i|s_x)}{p(r_i)}$$

Average information obtained from all stimulus conditions:

$$I\,(R, S) = \sum_i \sum_j p(s_j) p(r_i|s_j) \log_2 \frac{p(r_i|s_j)}{p(r_i)}$$

FIGURE 3. INFORMATION THEORY AND SIGNIFICANCE OF NEURONAL ENCODING.

ENCODING AND DECODING:

Neural encoding is the study of how neurons represent information with electrical activity (action potentials) at the level of individual cells or in networks of neurons. Studies of neural encoding aim to characterize the relationship between sensory stimuli or behavioral output and neural signals.

Neural decoding refers to finding the stimulus that causes a determined response (from response to stimulus); the challenge is to reconstruct a stimulus, or certain aspects of it, from the spike sequences it evokes.

A sequence, or ‘train’, of spikes may contain information based on different coding schemes. A traditional coding scheme is Rate Coding, stating that as the intensity of a stimulus increases, the frequency or rate of action potentials, or “spike firing”, increases. Rate coding is sometimes called frequency coding. In rate coding, learning is based on activity-dependent synaptic weight modifications.

The spike-count rate, also referred to as temporal average, is obtained by counting the number of spikes that appear during a trial and dividing by the duration of trial. The spike-count rate can be determined from a single trial, but at the expense of losing all temporal resolution about variations in neural response during the course of the trial.

When precise spike timing or high-frequency firing-rate fluctuations are found to carry information, the neural code is often identified as a temporal code. A number of studies have found that the temporal resolution of the neural code is on a millisecond time scale, indicating that precise spike timing is a significant element in neural coding.

Such codes, that communicate vi the time between spikes are also referred to as interpulse interval codes, and have been supported by recent studies.

Neurons exhibit high-frequency fluctuations of firing-rates which could be noise or could carry information. Rate coding models suggest that these irregularities are noise, while temporal coding models suggest that they encode information. Temporal coding supplies an alternative explanation for the “noise,” suggesting that it actually encodes information and affects neural processing.

The temporal structure of a spike train or firing rate evoked by a stimulus is determined both by the dynamics of the stimulus and by the nature of the neural encoding process. Stimuli that change rapidly tend to generate precisely timed spikes no mtter what neural strategy is being used.

SIMPLE MODEL OF SPIKING NEURONS (BASED ON IZHIKEVICH MODEL):

A model is presented that reproduces spiking and bursting behaviour of known types of cortical neurons. The model combines the biologically plausibility of Hodgkin–Huxley-type dynamics and the computational efficiency of integrate-and-fire neurons. Using this model, one can simulate tens of thousands of spiking cortical neurons in real time (1 ms resolution) using a desktop PC.

To understand how the brain works, we need to combine experimental studies of animal and human nervous systems with numerical simulation of large-scale brain models. As we develop such large-scale brain models consisting of spiking neurons, we must find compromises between two seemingly mutually exclusive requirements: The model for a single neuron must be: 1) computationally simple, yet 2) capable of producing rich firing patterns exhibited by real biological neurons. Using biophysically accurate Hodgkin–Huxley-type models is computationally prohibitive, since we can simulate only a handful of neurons in real time. In contrast, using an integrate-and-fire model is computationally effective, but the model is unrealistically simple and incapable of producing rich spiking and bursting dynamics exhibited by cortical neurons.

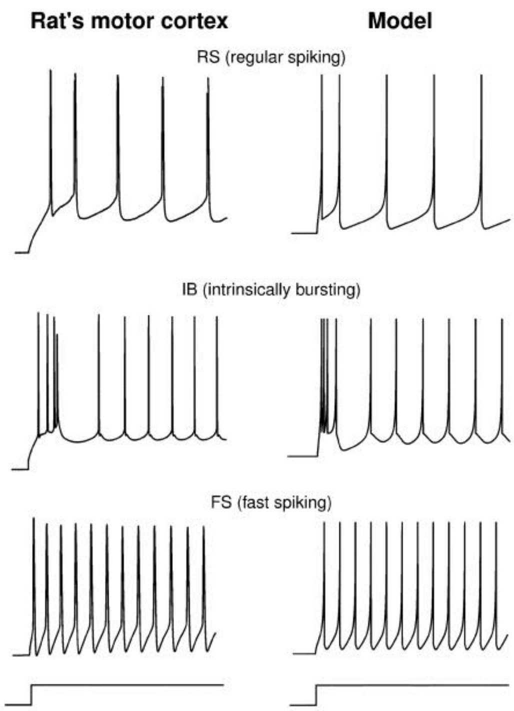

FIG. 4. THE SIMPLE MODEL (1), (2) CAN REPRODUCE FIRING PATTERS OF NEURONS RECORDED FROM THE RAT'S MOTOR CORTEX.

THE IZHIKEVICH MODEL:

Bifurcation methodologies enable us to reduce many biophysically accurate Hodgkin–Huxley-type neuronal models to a two-dimensional (2-D) system of ordinary differential equations of the form

$$v' = 0.04v^2 + 5v + 140 - u + I \qquad (1)$$

$$u' = a(bv - u) \qquad (2)$$

with the auxiliary after-spike resetting

$$if\ v \geq 30\text{mv}\text{, then } |x| = \begin{cases} v \leftarrow c, \\ u \leftarrow u + d, \end{cases} \qquad (3)$$

Here, v and u are dimensionless variables, and a, b, c, and d are dimensionless parameters, and 0 = d=dt, where t is the time. The variabl v represents the membrane potential of the neuron and u represents a membrane recovery variable, which accounts for the activation of K+ ionic currents and inactivation of Na+ ionic currents, and it provides negative feedback to v. After the spike reaches its apex (+30 mV), the membrane voltage and the recovery variable are reset according to the (3). Synaptic currents or injected dc-currents are delivered via the variable I.

The part $0.04v^2 + 5v + 140$ was obtained by fitting the spike initiation dynamics of a cortical neuron (other choices also feasible) so that the membrane potential v has mV scale and the time t has ms scale. The resting potential in the model is between -60 and -70 mV depending on the value of b. As most real neurons, the model does not have a fixed threshold; Depending on the history of the membrane potential prior to the spike, the threshold potential can be as low as -55mV or as high as -40 mV.

- The parameter a describes the time scale of the recovery variable u. Smaller values result in slower recovery. A typical value is a = 0.02.
- The parameter b describes the sensitivity of the recovery variable u to the subthreshold fluctuations of the membrane potential v. Greater values couple v and u more strongly resulting in possible subthreshold oscillations and low-threshold spiking dynamics. A typical value is b = 0.2. The case b<a (b>a) corresponds to saddle-node (Andronov–Hopf) bifurcation of the resting state.
- The parameter c describes the after-spike reset value of the membrane potential v caused by the fast high-threshold K+ conductances. A typical value is c = -65mV.
- The parameter d describes after-spike reset of the recovery variable u caused by slow high-threshold Na+ and K+ conductances. A typical value is d = 2.

Various choices of the parameters result in various intrinsic firing patterns.

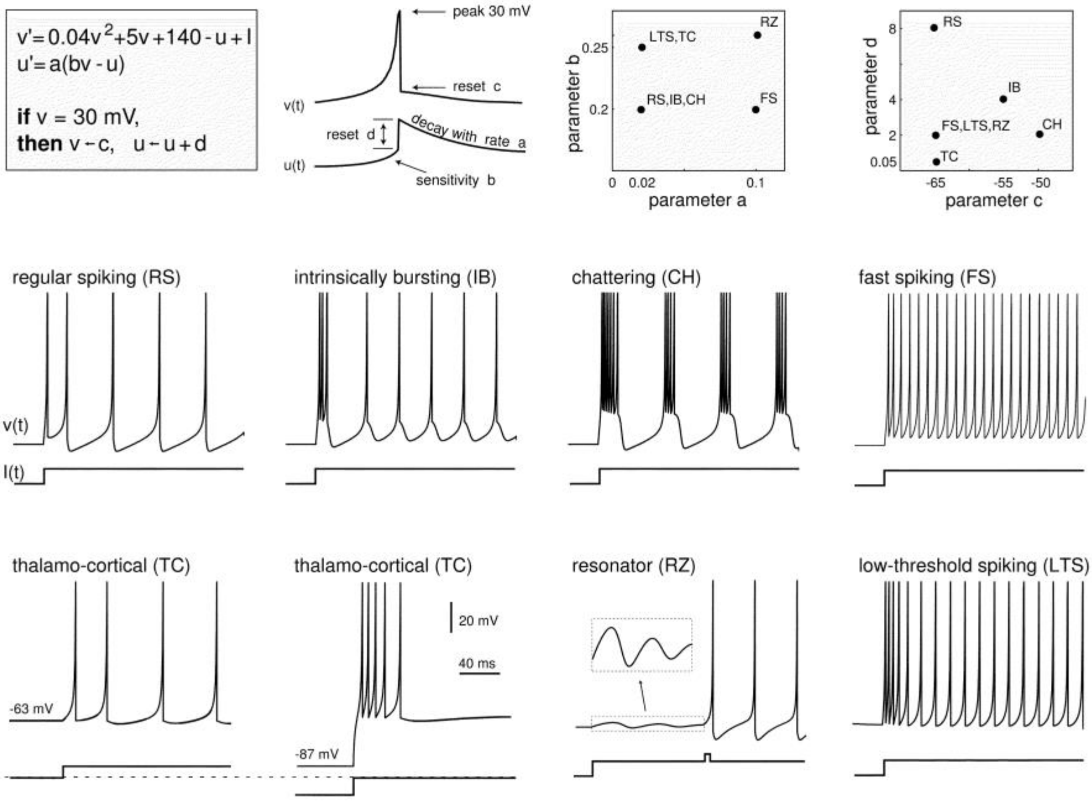

FIG5. KNOWN TYPES OF NEURONS CORRESPOND TO DIFFERENT VALUES OF THE PARAMETERS A, B, C, D IN THE MODEL DESCRIBED BY THE (1), (2). RS, IB, AND CH ARE CORTICAL EXCITATORY NEURONS. FS AND LTS ARE CORTICAL INHIBITORY INTERNEURONS. EACH INSET SHOWS A VOLTAGE RESPONSE OF THE MODEL NEURON TO A STEP OF DC-CURRENT I = 10 (BOTTOM). TIME RESOLUTION IS 0.1 MS.

JUSTIFY MEMBRANE VOLTAGE EQUATIONS VIA MATLAM IMPLEMENTATION:

```
Ne=800;                 Ni=200;
re=rand(Ne,1);          ri=rand(Ni,1);
a=[0.02*ones(Ne,1);     0.02+0.08*ri];
b=[0.2*ones(Ne,1);      0.25-0.05*ri];
c=[-65+15*re.^2;        -65*ones(Ni,1)];
d=[8-6*re.^2;           2*ones(Ni,1)];
S=[0.5*rand(Ne+Ni,Ne), -rand(Ne+Ni,Ni)];

v=-65*ones(Ne+Ni,1);    % Initial values of v
u=b.*v;                 % Initial values of u
firings=[];             % spike timings

for t=1:1000            % simulation of 1000 ms
  I=[5*randn(Ne,1);2*randn(Ni,1)]; % thalamic input
  fired=find(v>=30);    % indices of spikes
  firings=[firings; t+0*fired,fired];
  v(fired)=c(fired);
  u(fired)=u(fired)+d(fired);
  I=I+sum(S(:,fired),2);
  v=v+0.5*(0.04*v.^2+5*v+140-u+I); % step 0.5 ms
  v=v+0.5*(0.04*v.^2+5*v+140-u+I); % for numerical
  u=u+a.*(b.*v-u);                 % stability
end;
plot(firings(:,1),firings(:,2),'.');
```

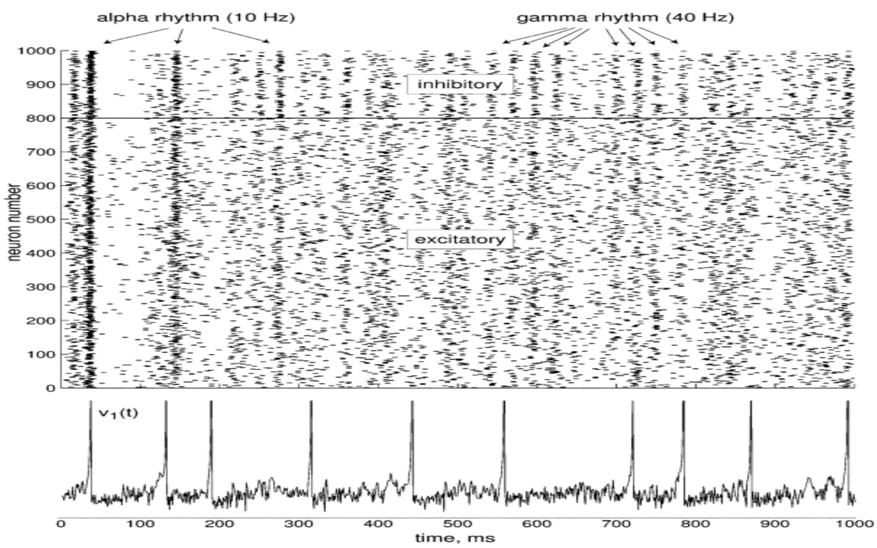

Fig. 6. Simulation of a network of 1000 randomly coupled spiking neurons. Top: spike raster shows episodes of alpha and gamma band rhythms (vertical lines). Bottom: typical spiking activity of an excitatory neuron. All spikes were equalized at +30 mV by resetting v first to +30 mV and then to c.

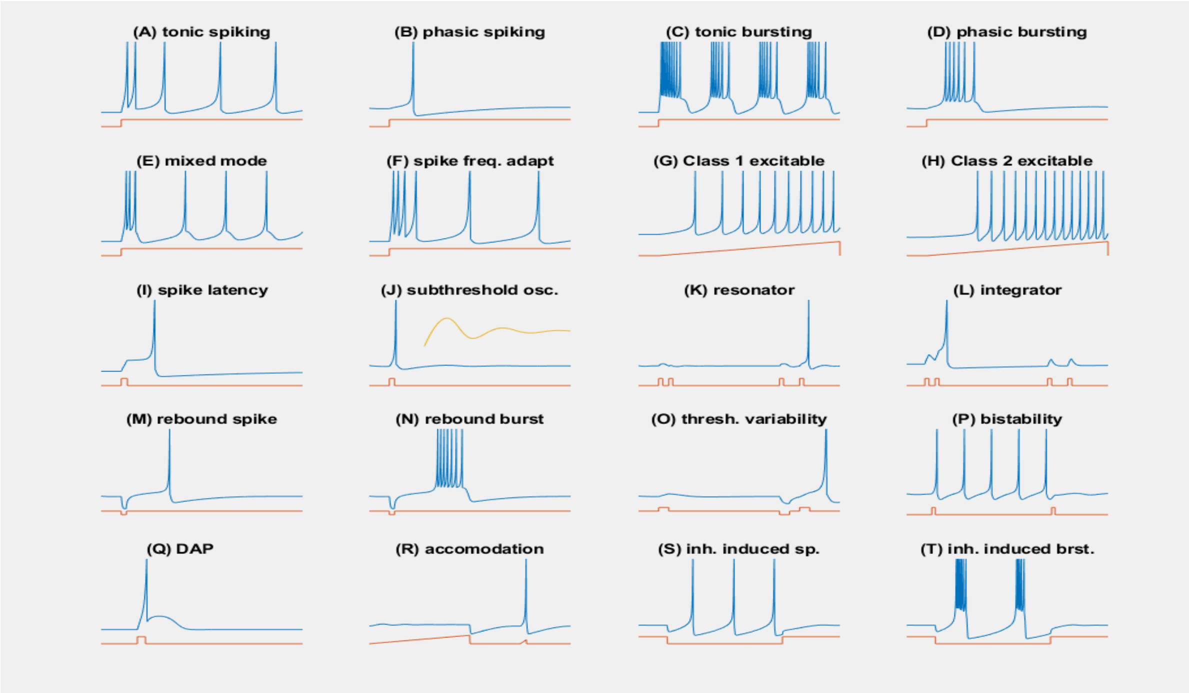

Figure 7. Different spike patterns simulated in Matlab

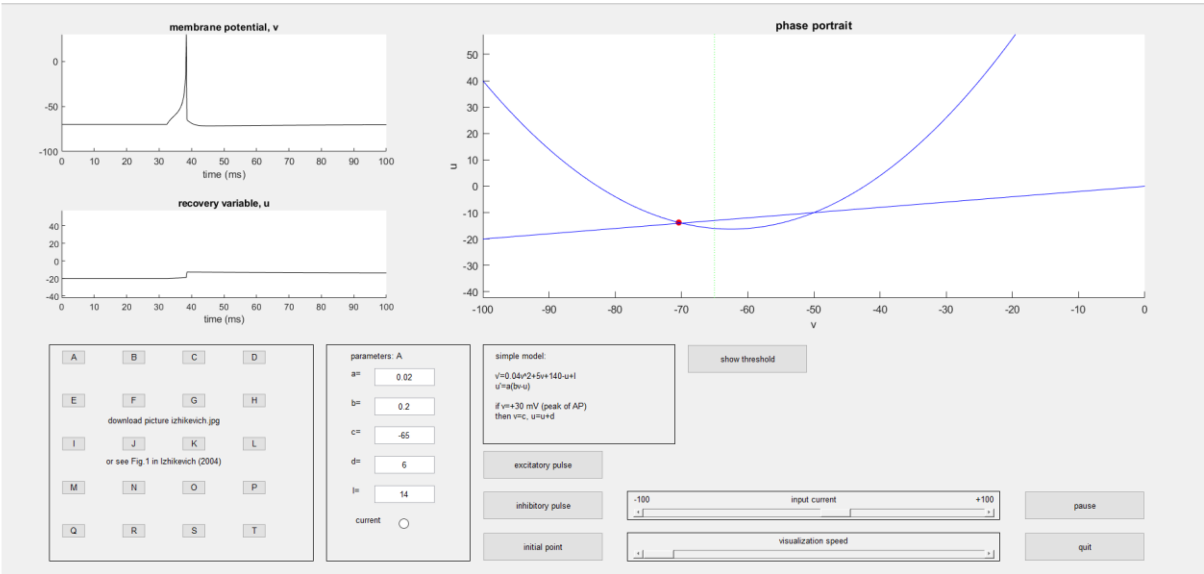

FIGURE 8. GRAPHICAL IMPLEMENTATION

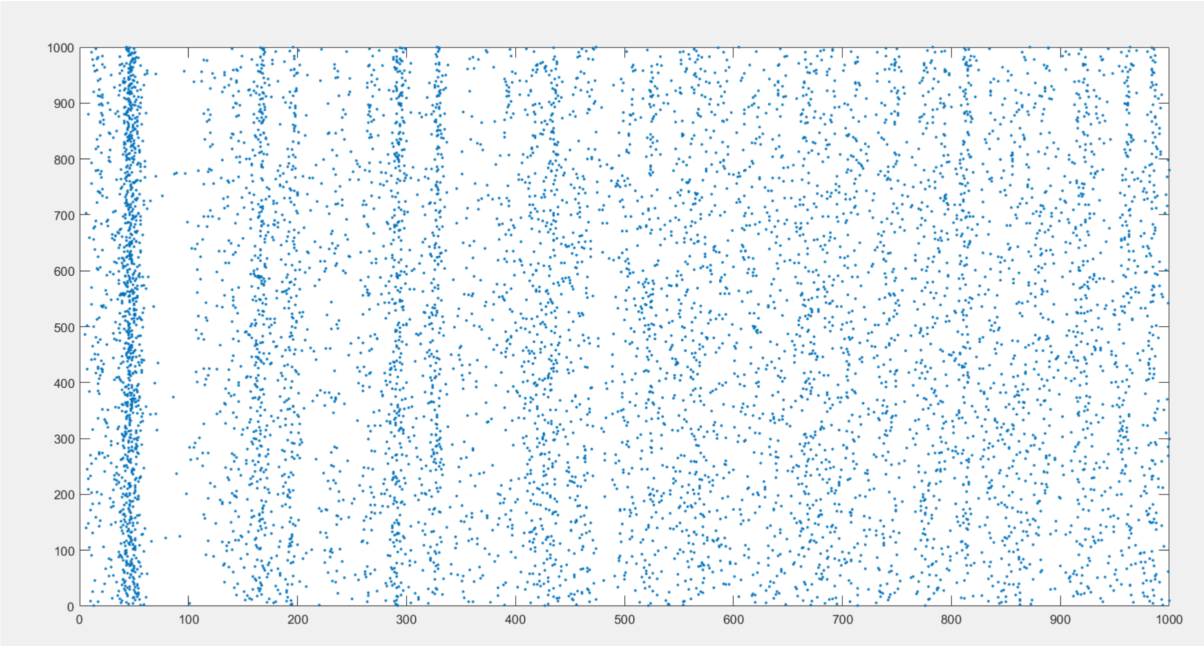

Fig. 9. Simulation of a network of 1000 randomly coupled spiking neurons.

7 ACKNOWLEDGEMENT

I am really grateful for Dr. Maryam Sabbaghian’s spirit, energy, and supervision. It was a great pleasure to work as a member of his laboratory. In addition, I also thank University of Tehran for accessing the articles and other resources.

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