Liquid State Machine Built of Hodgkin-Huxley Neurons and Pattern Recognition

Grzegorz M. Wojcik, Wieslaw A. Kaminski

Department of Theoretical Physics
Maria Curie-Sklodowska University
Lublin, Poland
gmwojcik@neuron.umcs.lublin.pl

Neural networks built of Hodgkin-Huxley neurons were examined. The structure and behavior of these nets was intended to be similar to Liquid State Machines (LSM). They could effectively process different input signals (i.e. geometrical patterns shown to artificial eye). The analysis of output responses was performed in two ways: by means of Artificial Neural Network and by calculating informational entropy.

Key Words: informational entropy, pattern recognition, LSM.

1. Introduction

The new idea for treating the brain as a whole was suggested by Maass and since then it has been called Liquid State Machine (LSM) [4,5] . In general, the brain (or a fragment of it) is treated as a liquid. Neural microcircuits appear to be very good “liquids” for computing on perturbations because of the large diversity of their elements, neurons and synapses [2], and the large variety of mechanisms and time constants characterising their interactions, involving recurrent connections on multiple spatial scales [5]. Like Turing machine [4], the model of LSM is based on strict mathematical framework that guarantees, under ideal conditions, universal computational power as proved in [5].

Idea of the Maass' LSM is shown in Fig. 1. The liquid is represented by the column L^M consisting of some integrate and fire neurons. Input signals u's are stimulating randomly chosen neurons of the liquid. There is a mapping function $X^M(t)$ which transforms the input into the readout layer giving the output signals y's.

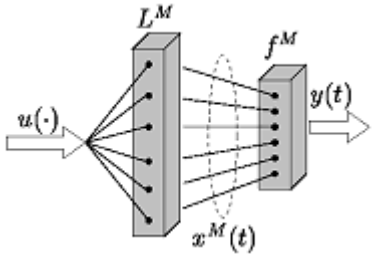

Fig. 1. Scheme of the Maass' LSM [5].

We simulated some biological visual system using group of neuronal columns like in the LSM model. We will show that fundamental microcircuits built of Hodgkin-Huxley neurons may be applied to different computational functions. We will make the analysis of such structures by means of artificial neural network (ANN) and we will show some changes of informational entropy for the investigated system.

2. Concept of neural computations and results

It has been found that neocortex of mammals is built of microcircuits. Microcircuits are organized in columns. Even though microcircuits are identical and the structure of columns is similar, their function may be different depending on the part of brain in which the column or group of columns is situated. As a fundamental microcircuit we used 4 Hodgkin-Huxley neurons

(see. Fig.2). All of the microcircuit's neurons were interconnected with some randomly chosen weights and there were no auto-connections. We used multicompartmental neurons with a dendrite compartment, a soma, and an axon. The dendrite contained a synaptically activated channel and the soma contained voltage activated Hodgkin-Huxley sodium and potassium channels. For more details see [1,3].

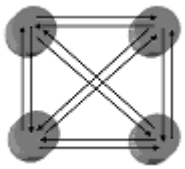

Fig.2. Hodgkin-Huxley fundamental microcircuit. Arrows represent randomly chosen weights of connections.

Having the fundamental microcircuit we built single column units (see Fig. 3) with connections similar to the structure of the neocortex layers.

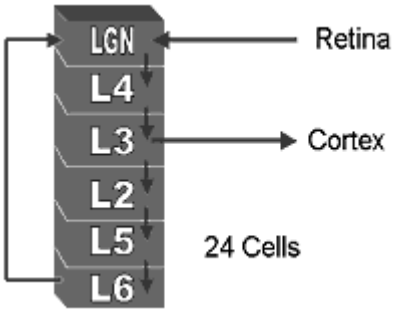

Fig. 3. Structure of single column.

Each column consisted of 6 microcircuits with one microcircuit for every layer (24 neurons). It is of course possible to build columns consisting more neural cells but because of the large CPU time consumption we chose small units. Such a column can be considered (when we take its structure into consideration) as singular Hodgkin-Huxley Liquid State Machine (HHLSM).

In order to build simple visual system we decided to simulate a part of primary visual cortex. Then we created an Input Device (ID) as an "artificial retina" built of 100 neurons which were put on the square 10×10. The ID was divided into 25 patches with 4 neurons in each (note that each patch was a fundamental microcircuit, nevertheless, its function in the eye was different then i.e. in the cortex or readout system). The main structure, cortex, was an ensemble of 25 HHLSMs (600 cells). As an output we use the so-called readout which was similar to the ID and also consisted of 25 microcircuits. Randomly chosen patches of the ID were connected with randomly chosen columns. Output connections from the cortex to the readout were realized in the same way. All of the structures described above were simulated in GENESIS [1].

For the analysis of readout responses we built an ANN in Stuttgart Neural Network Simulator (SNNS) [8]. The network had 100 inputs, two hidden layers and 100 outputs (see Fig. 4). In each hidden layer there were 12 units. Full connection was arranged in the system. As a training function we chose RPROP algorithm with learning parameters: 0.1, 30, 40 and 400 training cycles.

Our aim was to create an artificial structure ready to decrypt the operations of abovementioned biological system as closely as possible. In our simulations we stimulated the neurons of ID by series of spikes with amplitude of A=0.2 mV. The signals went through the "cortex" and as a result we obtained

the readout responses, treated as ANN inputs. We collected readout responses to 9 different input patterns i.e. stimulation of the cells on the diagonal of ID or group of cells forming a square shown to ID. We trained the ANN and after learning process we showed to our "visual system" some patterns slightly different then presented before (i.e. position of the diagonal was moved a bit, or the shape of the square was "not ideal"). In all cases we obtained such a responses (see. Fig. 5 and Fig. 6) of the visual system that the ANN could generalize and classify the noisy ID input patterns correctly. It turned out that ANN could classify effectively given patterns even though it had not experienced them before.

Note that simple ANN similar to the single biological column (HHLSM) may have much better qualification skills. It does the job equal to signal processing carried by 25 HHLSMs. Something similar was also shown in De Schutter's and Steuber's work [7] when they were comparing Purkinje cells abilities with ANNs. One could wonder why such effective structures like ANNs were not created in evolutional way. The answer nowadays may be that there are so many neurons in mammalian brains that such extravagance of the nature is quite understandable.

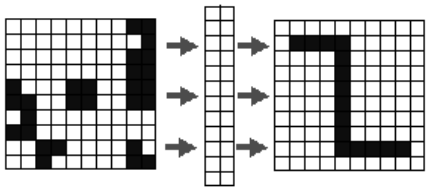

Fig.4. Structure of ANN. Readout responses from "visual system" are given to the ANN input (in the left) and the ANN is trained. Input is transformed by two hidden layers and as the response (in the right) there is an information about ID's patterns.

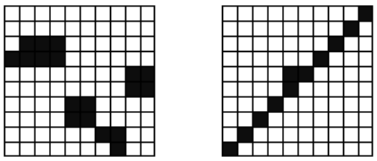

Fig. 5. Input and output of ANN for “diagonal” pattern.

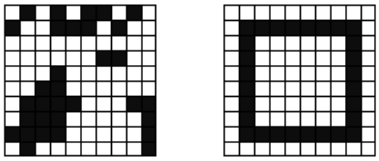

Fig. 6. Input and output of ANN for “square” pattern.

In order to investigate thermodynamics of the system we apply a version of entropy based on the classical definition of Shannon’s informational entropy [6]. Simulating the T=50 ms of biological system’s work N spike potentials on the readout were obtained for each of 9 patterns shown to ID. Of course, number of spikes is different for each defined pattern shown to ID. Thus one can introduce probability of observation of n_i spikes occurred during a period t_i=0.1 ms:

$$p_i = \frac{n_i}{N}. \tag{1}$$

Such a probability can be interpreted as a chance of giving the whole information in i^{th} part of time T. Using probability p_i one can introduce individual entropy as follows:

$$S_0^i = -p_i \cdot \ln(p_i). \tag{2}$$

More general global entropy reads:

$$S = \sum_i S_0^i = -\sum p_i \ln(p_i). \tag{3}$$

Fig. 7. shows the changes of the readout entropy for 2 patterns shown to ID. For each of 9 patterns, the changes of entropy are slightly different. Basing on such thermodynamical analysis one can, in principle, differentiate with satisfying accuracy pattern shown to the ID. However, in our opinion, there have to be used some more sophisticated statistical methods like i.e. mutual information in order to improve recognition abilities of the system.

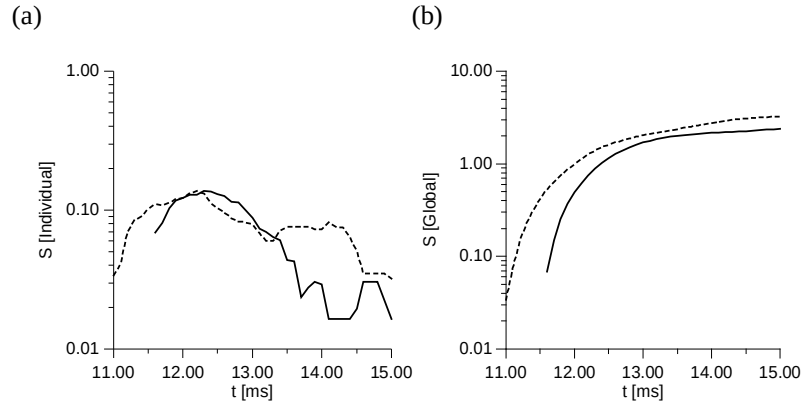

Fig.7. Changes of the individual entropy S_0 (a) and global entropy S (b) for two different patterns shown to ID. Solid lines represent the entropy changes for the "diagonal" pattern and dashed lines the "square" pattern.

3. Summary

In conclusion, we simulated some biological-like visual system using the LSM model. Fundamental microcircuits built of Hodgkin-Huxley neurons can be applied to different functions such as "input patches", parts of HHLSMs or

readout elements. We showed that signal processing abilities of such a system are good enough for the ANN to be correctly classified. However, the structure of ANN may be much simpler than in the LSM model. Estimating computational power of such systems requires further experiments. The analysis of system's thermodynamics shed some light on the recognition process in the visual system. However, understanding this process in detail requires further and more precise research.

This is only initial stage of our project. In further experiments we will implement dynamic synapses to the system and improve on the series of changing in time input patterns shown to ID. This should help to investigate the temporal integration abilities of such systems more precise.

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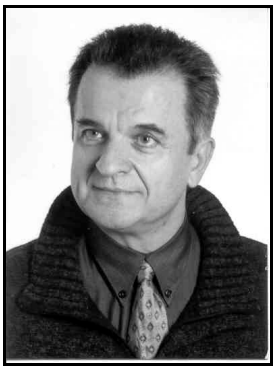
Grzegorz M. Wojcik was awarded the Master of Science degree at the Maria Curie-Sklodowska University in 2000. He is PhD student at the Mathematics, Physics and Informatics Faculty of this University. He is interested in computational artificial intelligence.



Wieslaw A. Kaminski was awarded the Master of Science degree at the Maria Curie-Sklodowska University in 1972, PhD in Physics in 1977 and Habilitation in 1992. He also received the professor title in 1996. At present he is a full professor at the Maria Curie-Sklodowska University. His main research interests include the computational artificial intelligence, neurocomputations and description of learning processes and other properties of neural networks using field theory and statistical physics methods. He is a head of the Complex System Physics Division at the Maria Curie-Sklodowska University, Lublin, Poland.