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

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Neural networks built of Hodgkin-Huxley neurons were examined. These structures behaved like Liquid State Machines (LSM). They could effectively process different input signals (i.e. geometrical patterns shown to artificial eye). The SNNS analysis of responses to such patterns was conducted.

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) [1,2] . 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 [3], and the large variety of mechanisms and time constants characterising their interactions, involving recurrent connections on multiple spatial scales [1]. Like Turing machine [5], the model of LSM is based on strict mathematical framework that guarantees, under ideal conditions, universal computational power as proved in [1].

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.

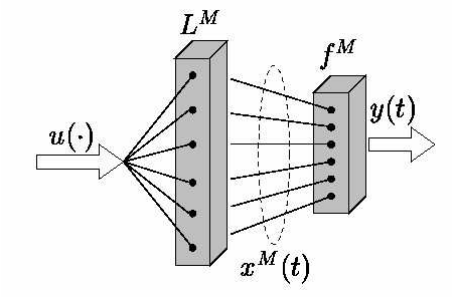

Fig. 1. Scheme of the Maass' LSM [1].

We simulated some biological visual system using the LSM model. We will show that fundamental microcircuits built of Hodgkin-Huxley neurons can be applied to different computational functions. We will also make the analysis of such structures by means of artificial neural network (ANN). It will be proved that some operations performed by ANNs can be done by biological systems as well.

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 weight and there were no auto-connections. More details concerning the Hodgkin-Huxley parameters of these neurons can be found in Appendix A.

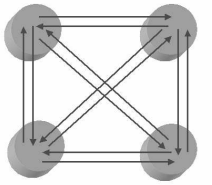

Fig.2. Hodgkin-Huxley fundamental microcircuit. Arrows represent randomly chosen weights of connections.

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

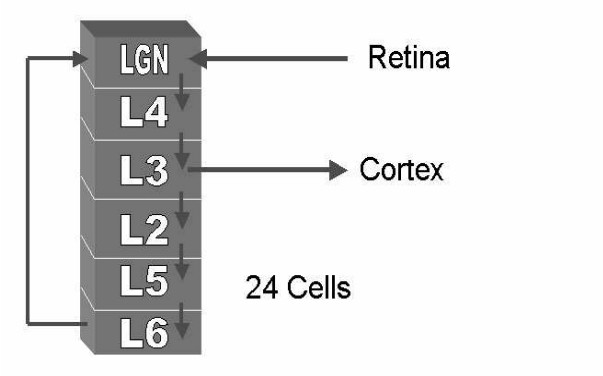

Fig. 3. Structure of single column.

Each column consisted of 6 microcircuits with one microcircuit for every layer (24 neurons)[1]. Such a column can be considered 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[2]. 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 [4].

For the analysis of readout responses we built an ANN in Stuttgart Neural Network Simulator (SNNS) [7]. The network had 100 inputs, two hidden layers and 100 outputs[3] (see Fig. 4). In each hidden layer there were 12 units.

Our aim was to create an artificial structure ready to simulate 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 correct responses (see. Fig. 5 and Fig. 6) of the visual system thus the ANN could generalize and classify noisy patterns correctly. It turned out that ANN could classify effectively given patterns even though it had not seen them before.

Note that simple ANN similar to the single biological column (HHLSM) has much better qualification skills. It does the job equal to 25 HHLSMs. Something similar was also shown in De Schutter's and Steuber's work [6] 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.

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[1] It is of course possible to build columns consisting more neural cells but because of the large CPU time consumption we chose small units.

[2] 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.

[3] 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.

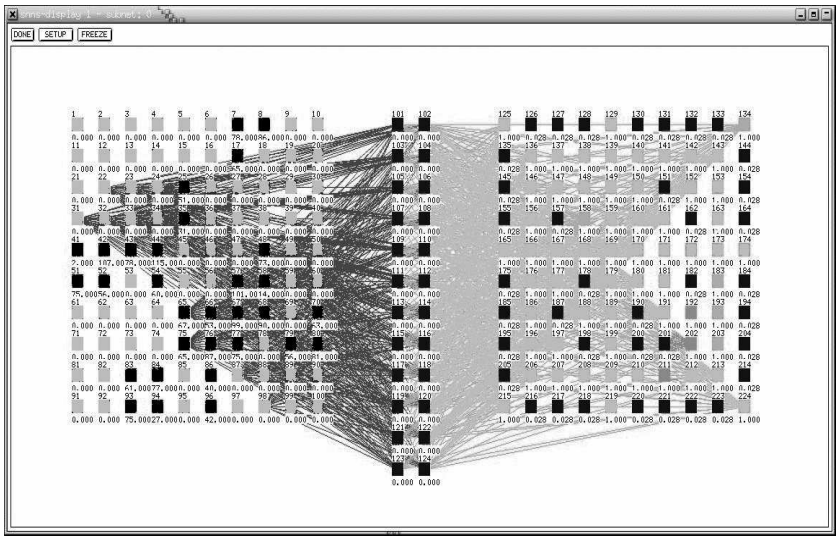

Fig.4. Structure of ANN. Readout responses from “visual system” are given to the ANN input (in the left) and the ANN is trained. Input is transformed by two hidden layers and as the response (in the right) there is an information about ID’s patterns. (Screenshot from SNNS for Red Hat Linux).

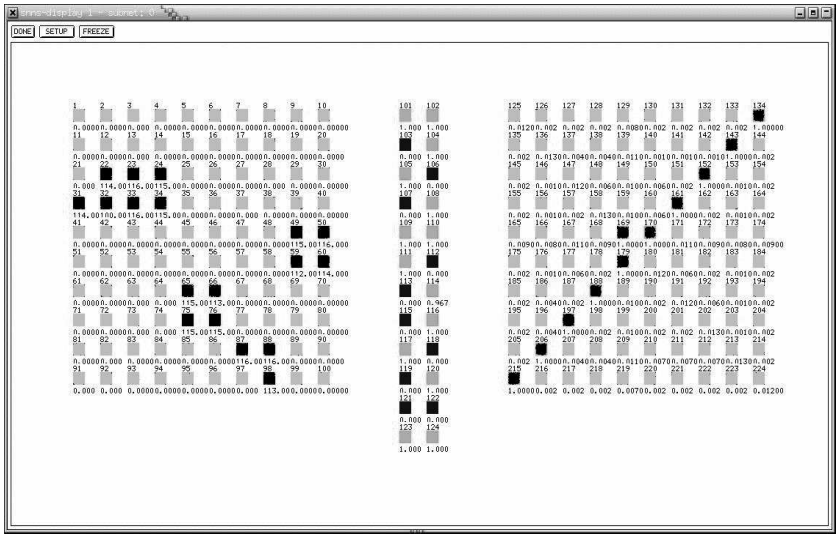

Fig. 5. Input and output of ANN for “diagonal” pattern. (Screenshot from SNNS for Red Hat Linux).

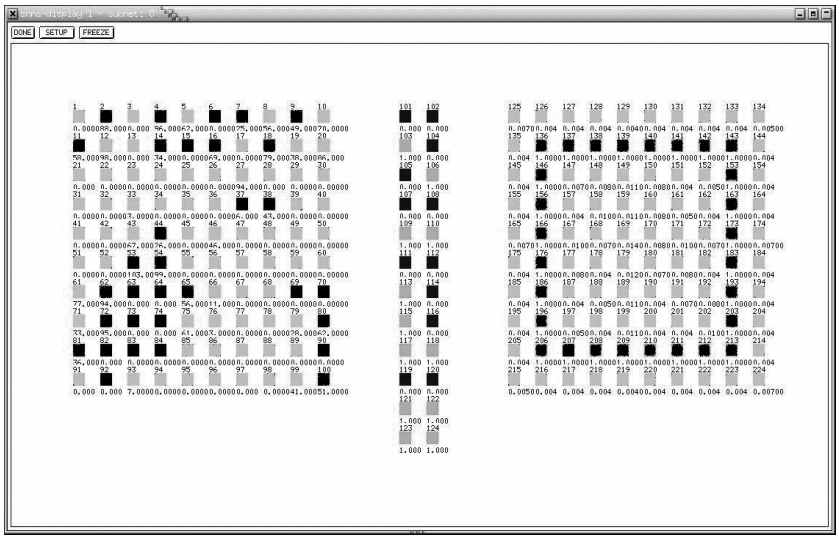

Fig. 6. Input and output of ANN for "square" pattern. (Screenshot from SNNS for Red Hat Linux).

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 such system can be as effective as ANNs, however, the structure of ANN may be much simpler. Estimating computational power of such systems requires further experiments.

Appendix A – Details of Hodgkin-Huxley Neurons

Our HHLSMs consisted of 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. The behaviour of each compartment followed :

$$C_m \frac{dV_m}{dt} = \frac{(E_m - V_m)}{R_m} + \sum_k [(E_k - V_m)G_k] + \frac{(V_m^{'} - V_m)}{R_a^{'}} + \frac{(V_m^{''} - V_m)}{R_a} + I_{inject} \cdot \quad (1)$$

Each sub-circuit was characterised by a group of parameters: R_a=0.3 Ω, R_m=0.333333 Ω, C_m=0.01 F, E_m=-0.07 V. For the soma compartment E_k=-0.0594 V whilst for the dendrite E_k=-0.07 V. Conductance for each type of ionic channels was chosen: G_K=360 Ω^{-1} and G_{Na}=1200 Ω^{-1}. The soma had

a circular shape with the diameter of 30 μm, the dendrite and axon were cable like with the length of 100 μm. The weights of connections in the biological part of the system were fixed. All other parameters were chosen as default and suggested by GENESIS authors as best for simulations [4]. More details concerning Hodgkin-Huxley model one can find in [5].

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