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Hebbian encoding in the biological visual system

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Abstract

We examined neural networks built of several hundred Hodgkin-Huxley neurons. The main aim of the research described below was to simulate memory processes occurring in *hippocampus* and biological visual system. In our model we chose the ancient Chinese I-Ching Oracle as a set of input patterns. Maps of Hebbian weights appearing on the output device of the model can be analysed by artificial neural networks playing a role of some kind of visual consciousness.

1. Introduction and problem statement

The idea of synaptic plasticity was proposed by Hebb [1]. Hebb's postulate describes how the connection from presynaptic neuron A to a postsynaptic neuron B should be modified (see Fig. 1). When an axon of cell *A* is near enough to excite cell *B* or repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such as *A*'s efficiency, as one of the cells firing *B*, is increased [1].

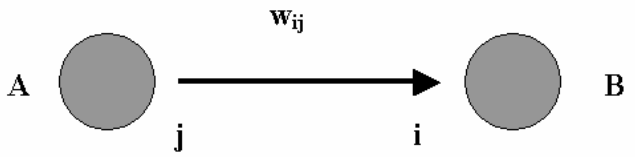

Fig. 1. The change on synapse w_{ij} depends on the state of presynaptic neuron j, the postsynaptic neuron i and the current efficacy w_{ij}

Hebb formulated his principle on purely theoretical grounds. He realized that such a mechanism would help to stabilize specific neuronal activity patterns in

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the brain. If neuronal activity patterns correspond to behaviour, then stabilization of specific patterns implies learning of specific types of behaviours.

In the formal theory of neural networks the weight w_{ij} of a connection from the neuron j to the neuron i is considered as a parameter that can be adjusted so as to optimise the performance of a network for a given task. The rule for changing weights in the numerical model reads:

$$\frac{d}{dt}w_{ij} = \gamma_1(w_{ij}^{\max} - w_{ij})y_i y_j - \gamma_0 w_{ij}\,, \tag{1}$$

where y_i and y_j represent activities of the presynaptic and postsynaptic neurons. The parameter γ_1 characterises the speed of learning, and $w_{ij}^{\max}$ limits increasing of the weights values to infinite value. There is also the parameter γ_0 responsible for the so-called "weight decay". Owing to this mechanism, after some time of simulation, the values of weights on some not used synapses will be sufficiently small.

Synaptic plasticity was found in mammalian brains, especially in *neocortex* and the brain structure called *hippocampus* [2-4]. Even though we generally know the structure of *hippocampus*, we cannot precisely define its functions. However, it was proved that hippocampal encoding is necessary to transfer information from the short-term memory to the long-term memory in brain [2-4].

The aim of research discussed in this paper was to implement Hebbian plasticity to the model of mammalian visual system. Simulation of simple hippocampal structures provided us with the memory unit and allowed to improve modeling of complex neural systems.

2. Concept of neural computations and results

Mammalian brains are built of microcircuits. Microcircuits are organized in columns, and the function of particular microcircuit can be different depending on the part of brain in which it is situated. We want to model simple biologically based visual system using the Liquid State Machine (LSM) theory [5]. Simulations of visual system based on LSMs and analysis of its informational entropy were discussed in [6].

In our model we used 4-neuron microcircuits. An input device (ID) representing the retina was built of 25 microcircuits. As a part of primary visual cortex we built a set of 25 Hodgkin-Huxley Liquid State Machines (HHLSMs). There were 24 neurons in each HHLSM. Randomly chosen microcircuits of ID were connected with randomly chosen HHLSMs. The same architecture of connections was arranged between the cortex and the "readout" device (for details see Fig. 2). The readout consisted of 100 neurons. Its architecture is the same as ID, but in order to implement memory mechanism to the model we used here dynamic Hebbian synapses as the synaptic plasticity allows some learning

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processes to take place in the model. There were also some random connections among HHLSMs, however, their number is not very large (just like in reality)[1].

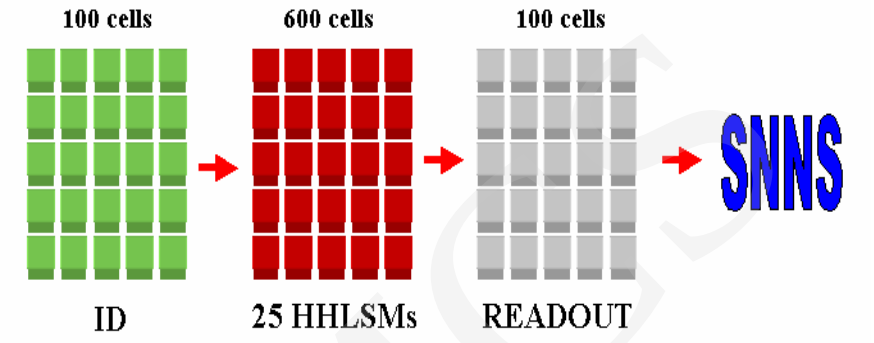

Fig. 2. Scheme of simulated biological-like visual system

We chose the ancient Chinese I-Ching Oracle as a set of input patterns. We stimulated the retina of simulated visual system with a sequence[2] of 2 input patterns chosen out of the group of 8 (see Fig. 3). Such an approach allowed us to conduct 64 different time varying stimulations. The activity was transformed through the group of HHLSMs and then reached the Hebbian readout representing *hippocampus*. We collected the values of weights of connections coming to particular neurons of the readout. The maps of weights for chosen stimulations are presented in Fig. 4.

It turned out that for each pattern sequence we obtain different weight representation on the generated map (see Fig. 4). This implies that some trained device would be able to assess which pattern was stimulating the retina earlier and which one later. Thus the neural network with Hebbian synapses can remember its previous state and stimulations.

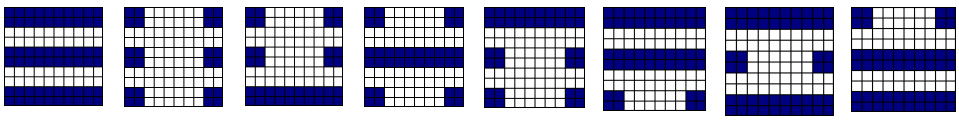

Fig. 3. I-Ching patterns used as ID inputs. A pattern chosen out of the set of 8 was shown for 25ms. For the next 25 ms we stimulated the ID of visual system again with a pattern chosen from the same set. Such choice gives us 64 possible stimulation sequences

[1] All of the structures described above were simulated using the GEneral NEural SImulation System (GENESIS) [7]. GENESIS (also described in [6]) can be run on almost all UNIX systems, including Linux.

[2] Each pattern stimulated the retina for 25 ms what gives 50 ms for each simulation.

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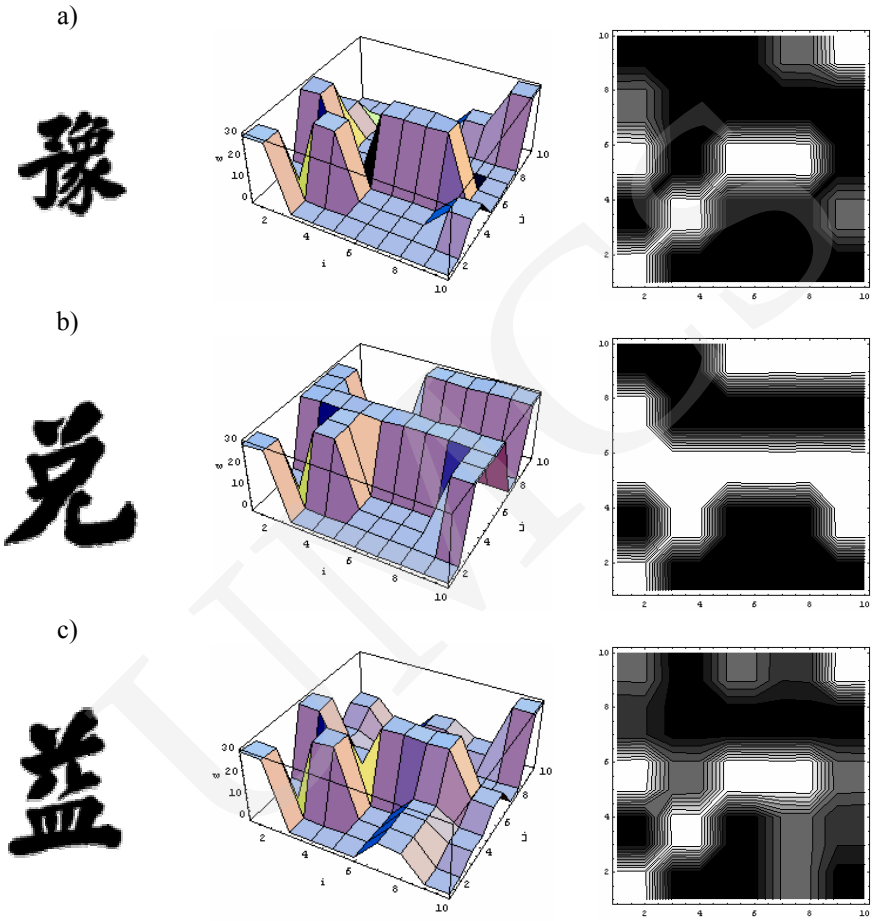

Fig. 4. Representation of Hebbian weights on the readout (3D in the left and 2D in the right) for the ENTHUSIASM (a), PLEASURE (b) and INCREASE (c) input sequences

Analysis of weight maps was performed using Artificial Neural Network (ANN) simulated within the Stuttgart Neural Network Simulator (SNNS) [8]. The network had 100 inputs, 2 hidden layers and 64 outputs[3] (see Fig. 5). In each hidden layer there were 12 units. The idea of using ANN in order to analyse biological responses comes from Maass' works [5] and in our model SNNS plays a role of "visual consciousness" – the device that is able to decode the information encoded in *hippocampus*.

[3] Full connections were arranged in the system. As a training function we choose RPROP (Resilient Backpropagation) algorithm with learning parameters: 0.1, 30, 40 and 400 training cycles [5].

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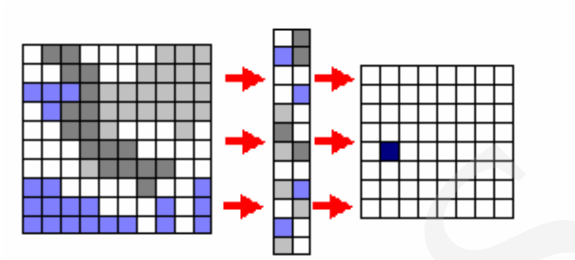

Fig. 5. The ANN used to decode hippocampal information. As an input to ANN (in the left) we give the output of visual system (in this case the map of weights). On the right there is ANN's response adequate to one of 64 possible pattern sequences

We trained ANN with "biological responses" of the readout which were treated as ANN's inputs. In the next step we stimulated ID of visual system with some noisy I-Ching patterns i.e. the time of stimulation was different from 25 ms or the shape of lines in the pattern was diffused.

In all cases we obtained correct ANN responses thus ANN could generalize and classify even noisy patterns correctly. It turned out that ANN was able to classify effectively given patterns even though it did not process them before. In other words the biological system transforms the diffused inputs in such a way that the responses of its readout in weight representation are sufficient to be ANN inputs. Information about the current and previous stimulations is then encoded on Hebbian synapses and can be decoded with appropriately trained neural device.

3. Summary

In conclusion, it is possible to implement biologically realistic memory model to the simulated visual system. Numerical experiments show that some encoding on Hebbian synapses takes place. In future this may help to understand similar processes occurring in the real *hippocampus*. We also hope that such an approach will help to construct a visual system of intelligent robots. However, more precise analysis of visual system models requires machines with higher computational power. That is why we are going to investigate similar structures on meta-clusters.

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