Approaching a Question of Biologically Plausible Applications of Spiking Neural P Systems for an Explanation of Brain Cognitive Functions

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Summary. The approaches to the following question: *Do spiking neural P systems* cf. [9], [16] *provide biologically plausible mathematical models of brain cognitive functions?* are discussed.

1 Introduction

The (hierarchical) clustering (scene segmentation in particular) and binding (feature integration) problem solution in cortical neural network together with cortical subnetworks realizing Radial Basic Functions (briefly RBFs) represent among others cognitive functioning of brain. Recently various network models of clustering, binding problem solution, and realization of RBFs in cortical network have been proposed, where spiking neural networks are the most biologically plausible models, see [15], [17], [1], [2], [11], [13], [14], and [10] for a review. The main common feature of these models is Hebbian learning which provides their biological evidence. On the other hand, a transformation of an idea of Hebbian learning from a framework of spiking neural networks to a framework of spiking neural P systems has been proposed in [7]. Thus one formulates the following question:

> Do spiking neural P systems provide biologically plausible mathematical models of brain cognitive functions?

We approach the question and an answer to it in Section 2 by a brief review of state of art for spiking neural nets and spiking neural P systems, discussion of conjectures, and setting open problems.

2 State of art, conjectures and open problems

The papers [4], [8] contain promising applications of spiking neural P systems for solving topic problems related to some cognitive brain functions. But biological evidence of these applications seems problematic because Hebbian learning procedures approach is not considered for them.

On the other hand the Hebbian learning modelled by spiking neural P systems with only input neurons and one output neuron presented in [7] and solution of XOR problem by spiking neural networks equipped with a Hebbian learning procedure and with only three input neurons and one output neuron described in [3] gives rise to the following conjecture:

Conjecture. *There exists a learning problem, understood as in* [7], *whose output is a spiking neural P system solving XOR problem.*

If we compare precise timing of spikes approach for spiking neural networks to the number of spikes approach for spiking neural P systems, then the latter seems coarse and hence less biologically plausible than the spiking neural network approach.

On the other hand the precise timing of spikes approach for spiking neural networks is less biologically plausible than probabilistic spiking neural networks because a relevant amount of noise is contained in the behaviour of neurons (cf. [6]). Therefore it is worth to initiate a research of probabilistic spiking neural P systems.

The view that human mind is "massively modular" (cf. [5], [12]) argued by massively parallel functioning of brain neural network modules gives rise to a question of approaching these massive modularity and massive parallelism of mind and brain by application of a concept of a network of communicating spiking neural P systems equipped with Hebbian learning procedures, respectively. The spiking neural P systems constituting that network could correspond to brain network modules realizing simultaneously various cognitive functions, respectively.

On the other hand, since spiking neural P systems seem more coarse with respect to an approach to time than spiking neural networks with precise timing of spikes, like e.g. in [1], we propose the following conjecture.

Conjecture. *A biologically plausible modularity of brain could be represented* (*modelled*) *by the following hybrid constructs*:

- *a two-level construct of a* spiking super-neural P system *which is a spiking neural P system whose neurons are superneurons, i.e. multi-layer spiking neural networks with a precise timing of spikes like e.g. in* [1],
- *a three-level construct of a* spiking sub-super-neural P system *which is a spiking super-neural P system as above, where the neurons of superneurons are P systems approaching neurons as cells which produce and transport copies of molecules between electrically charged membranes.*

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