Circuits in the Brain Extract Information from Fluctuation of their Dynamics through Spike-Timing-Dependent Plasticity?

Takashi HAYAKAWA[1,2,4], Takeshi KANEKO[2], Toshio AOYAGI[3,4]
1. Department of Modeling, The Institute of Statistical Mathematics
2. Graduate School of Medicine, Kyoto University
3. Graduate School of Informatics, Kyoto University, 4. JST, CREST

In neuroscience, it is a fundamental problem to understand how neural networks learn to yield a high behavioral performance. Although a lot of experimental studies have been conducted for this goal with discoveries of characteristic activity profiles of the brain circuits, few single theoretical frameworks have succeeded in relating microscopic mechanisms of learning, activity profiles of circuits and macroscopic performances of the whole network altogether. In the present study, inspired by the fluctuation-dissipation relations in statistical physics, we constructed a theoretical framework for learning of stationary dynamics of neuronal networks, deriving a general form of biologically implementable learning rule from an arbitrary objective function. In this framework, neuronal networks compute gradients of an objective function through statistics of spike interactions in stationary dynamics. Furthermore, this spike interaction-based learning rule is similar to spike timing-dependent plasticity (STDP), which is an experimentally measured update rule of individual synaptic weights. So our theory suggests that STDP is machinery for extracting information from fluctuation of the system, although it would be fair to note that there was also a similar line of study in the fields of reinforcement learning [1].

In order to examine whether our theory works well and some properties of the brain circuits can be actually explained within our framework, we conducted numerical simulations. As the first example, we adopted mutual information between states at two successive time points as an objective function, and derived a biologically implementable learning rule according to the above framework. Then we could reproduce several firing profiles of the real brain circuits, that is, filter properties of visual neurons, repeated precise firing sequences and self-organized criticality called 'neuronal avalanche', as consequences of the learning. In the second example, we succeeded in deriving an efficient biological implementation of reinforcement learning. In this implementation, we simultaneously maximized two different objective functions on two systems and constructed a hybrid learning rule called 'actor-critic algorithm'. Interestingly, there are experimental evidences of this implementation in the real brain circuits, that is, thus constructed learning rule accounts for firing profiles of dopaminergic neurons and persistently firing cortical neurons.

From the above observation, we believe that our framework provides a useful tool for the unified understanding of different aspects of the brain circuits, and also a good example of biological systems which actively utilize information contained in fluctuation of their dynamics.

[1] Florian R. V., *Neural Computation* (2007), Vol.19, No.6, 1468-1502