

# Encoding Multiple Temporal Waveforms by Neural Population with Spike-time-dependent Plasticity

**Naoki Masuda**

masuda@brain.riken.jp

Laboratory for Mathematical Neuroscience, RIKEN Brain Science Institute,  
Saitama, Japan,

**Kazuyuki Aihara**

aihara@sat.t.u-tokyo.ac.jp

Institute of Industrial Science, University of Tokyo, Tokyo, Japan,  
ERATO Aihara Complexity Modelling Project, Japan Science and Technology  
Agency, Tokyo, Japan

## Extended Abstract

Experimental and theoretical results on synchrony and precise spike timing suggest importance of the functions provided by spatiotemporal spike patterns rather than mere firing rates. Many theoretical investigations of this issue have focused mainly on global synchrony in more or less homogeneous networks. However, neuronal assemblies identified by synchrony or correlated activities of neurons may actually coexist in the brain. Such assemblies may underlie segregation of distinct information sources or objects and are concerned to the binding problem and the superposition catastrophe. Multiple assemblies of neurons may also interact to enable even more information processing.

Recently, spike-time-dependent plasticity (STDP) was found in experiments. In the asymmetric case [4, 9], synapses are potentiated when a presynaptic spike arrives about 20 ms or less before a postsynaptic spike, whereas they are depressed if the order of firing is reversed. In symmetric case, which was found more recently for excitatory [6] and inhibitory [8] synapses, synapses are potentiated only when the pre- and postsynaptic spikes occur in near coincidence regardless of the order. STDP supports the importance of spike timing for brain function and provides a mechanism for cluster formation via the STDP learning. In feedback neural network models, STDP generally promotes self-organization of the coupling to result in clustered firing, which can serve as a mechanism for memory retrieval [3], synfire chains [2], and cognitive map reformation [7]. In feedforward architecture, STDP induces synaptic competition in which only the synapses encoding more synchronous, precise, or early inputs are more likely to survive [7].

In our recent work, we analyzed formation of clusters via STDP when multiple inputs are presented in feedforward neural networks with possible recurrent connection [5]. Using the Fokker-Planck equations and numerical simulations, we examined how synaptic competition occurs, especially when multiple inputs with equal or different degrees of synchrony are presented. However, we considered only excitatory neurons, in spite of recent extensive work regarding the importance of inhibitory spiking neurons and inhibitory gap junctions [1]. A very recent experimental finding of symmetric STDP learning in inhibitory synapses is also in favor of functional roles of inhibitory synapses [8]. Therefore, in this presentation, we present numerical results on a feedforward network with learnable recurrent excitatory and inhibitory connection. We show that only symmetric learning windows can be led to clustered synchrony.

We use a neural network with two layers. The upstream layer contains  $n_1 = 240$  excitatory neurons. Firing time of the  $i$ th neuron in this layer is determined by an inhomogeneous Poisson process with rate function  $\nu_i(t)$ . The downstream layer comprises  $n_2 = 50$  leaky integrate-and-fire neurons, which receive spike inputs from the upstream layer. The feedforward synaptic weight is assumed to change via STDP with an asymmetric window. Intralayer coupling is also assumed within the downstream layer. We apply two input sources, each covering a half of the upstream layer in a complementary way:

$$\nu_i(t) = \begin{cases} 10.0 + 5.0\nu_a(t), & 1 \leq i \leq n_1/2, \\ 10.0 + 5.0\nu_b(t), & n_1/2 + 1 \leq i \leq n_1. \end{cases} \quad (1)$$

where  $\nu_a(t)$  and  $\nu_b(t)$  are Ornstein–Uhlenbeck processes with the correlation time equal to  $\tau_c = 14$  ms. A neuron in the downstream layer is assumed to receive synapses from 100 neurons in the upstream layer according to the following rule. When a neuron is connected to more (or fewer) presynaptic neurons in assembly  $\{1, 2, \dots, n_1/2\}$  than in assembly  $\{n_1/2 + 1, \dots, n_1\}$ , this neuron will prefer  $\nu_a(t)$  (or  $\nu_b(t)$ ) after learning [7]. Here we consider nontrivial situations in which each downstream neuron receives a synapse from an upstream neuron belonging to either assembly with equal probability. The STDP learning makes each downstream neuron encode  $\nu_a(t)$  or  $\nu_b(t)$ , and those encoding the same input are expected to form clusters identified by correlated firing.

When feedback coupling is absent, each downstream neuron learns to encode  $\nu_a(t)$  or  $\nu_b(t)$  independently with equal probability [5, 7]. As a result, weak synchrony is established among the neurons encoding the same stimulus. In this situation, the downstream layer represents  $\nu_a(t)$  and  $\nu_b(t)$  by population rate codes with asynchrony, or weak synchrony, with two segregated subpopulations.

With a fixed strength of uniform positive or negative feedback coupling, global synchrony is naturally induced. The downstream layer operates in a full synchronous

mode, where the information on  $\nu_a(t)$  and that on  $\nu_b(t)$  are mixed. Either  $\nu_a(t)$  or  $\nu_b(t)$ , which is chosen randomly, is eventually encoded by the whole downstream layer.

The downstream layer can encode  $\nu_a(t)$  and  $\nu_b(t)$  by two exclusively synchronous clusters with uniform coupling only for a small range of parameter values. A more reliable mechanism is to apply the symmetric STDP learning rule in which the synaptic strength is increased only when the corresponding pair of neurons fire almost synchronously and is decreased otherwise [6, 8]. The simple learning window that we use is defined as follows:

$$\overline{G}(t) = \begin{cases} 0.0009 \epsilon_{max}, & (0 \leq |t| \leq \Delta t_1 \text{ ms}) \\ -0.0006 \epsilon_{max}, & (2\Delta t_1 \leq |t| \leq \Delta t_2 \text{ ms}) \end{cases} \quad (2)$$

where  $\epsilon_{max}$  is the maximum value of the absolute synaptic strength, and  $\Delta t_1$  and  $\Delta t_2$  specify the temporal precision of the learning window. The numerical results show that two synchronous clusters stably coexist for a range of  $\Delta t_1$  and  $\Delta t_2$ . This observation holds when the downstream layers are assumed to be either a population of excitatory neurons or one of inhibitory neurons. Feedback coupling eventually formed, separating two clusters and enhancing intracluster synchrony.

On the other hand, synchronous clusters do not emerge via STDP with asymmetric learning windows. This is because, within the downstream layer, synaptic potentiation in one direction means synaptic depression in the other direction. The asymmetric STDP learning enables neurons to respond fast, to be precise, and to be relational or sequential [1], but not synchronous. In more or less synchronous situations, jitter may cause the next near-synchronous firing event to occur with the converse order of firing. Finally, the coupling strengths between these two neurons decay to the minimum in both directions. In other words, a dynamical state in which the synapses are bidirectionally strong is unstable. In sum, no feedback structure is formed with the asymmetric learning window if the neuronal activity is mainly driven by the feedforward inputs. The dynamics is the same as that in the uncoupled situation.

We have shown the existence of the asynchronous mode, the clustered synchronous mode, and the global synchronous mode. One or another mode appears depending on whether the synapses are plastic or not and whether the learning window is symmetric or asymmetric. Our results suggest different functional roles of symmetric and asymmetric STDP learning. The cases with more complicated input paradigms and mixture of excitatory and inhibitory spiking neurons and inhibitory interneurons with gap junctions are our future problem.

## References

- [1] W. Gerstner, W. M. Kistler. *Spiking neuron models*. (Cambridge, Cambridge University Press, 2002).
- [2] D. Horn, N. Levy, I. Meilijson, E. Ruppin. *Advances in Neural Information Processing Systems 12*, 129–135 (2000).
- [3] N. Levy, D. Horn, I. Meilijson, E. Ruppin. *Neural Networks 14*, 815–824 (2001).
- [4] H. Markram, J. Lübke, M. Frotscher, B. Sakmann. *Science*, *275*, 213–215 (1997).
- [5] N. Masuda, K. Aihara. *Neural Computation*, *16*, in press (2004).
- [6] M. Nishiyama, K. Hong, K. Mikoshiba, M. Poo, K. Kato. *Nature* *408*, 584–588 (2000).
- [7] S. Song, L. F. Abbott, *Neuron*, *32*, 339–350 (2001).
- [8] M. A. Woodin, K. Ganguly, M.-M. Poo. *Neuron* *39*, 807–820 (2003).
- [9] L. I. Zhang, H. W. Tao, C. E. Holt, W. A. Harris, M. Poo. *Nature* *395*, 37–44 (1998).