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Desynchronization induced by highly heterogeneous strengths of inhibitory current on electronic neuron

Hisashi Kada† and Isao T. Tokuda†

†Department of Mechanical Engineering, Ritsumeikan University
1-1-1 Noji-higashi, Kusatsu-shi, Shiga 525-8577, Japan,
Email: {rt001084@ed,isao@fc}.ritsumei.ac.jp

Abstract—In neural networks research, neural information is assumed to be generally represented by a spatio-temporal firing pattern of neurons. When the neurons generate synchronized spike trains with each other, their capability of information representation is severely limited, because all the neurons represent merely a single temporal pattern. On the other hand, when the neuronal activities become desynchronization, the network may exhibit much more variations of their firing patterns, increasing the information processing capability. The aim of the our study is to consider a way how to avoid such synchronized neuronal firings that degrade the information processing capability. First, as a typical situation to induce neuronal synchrony, we introduce common inputs to a feed-forward neural network. Then, to suppress the synchrony, heterogeneity is introduced to inhibitory inputs. Using an electric circuit, we verify that the heterogeneous inputs indeed give rise to asynchronous firings among the electronic neurons.

1. Introduction

The asynchronous irregular activity of the neurons in cortical networks can be spontaneously maintained ongoing firings without external stimuli, which is observed in vitro [1] and in vivo [2]. The various information processing, as a asynchronous irregular state of the cortex, including sensory perception [3], memory [4], signal processing [5] and transmissions [6] in neural networks is reported. To elucidate the underlying mechanism for the cortical network to sustain the spontaneous asynchronous state, the random network with balanced excitatory and inhibitory inputs realizes the asynchronous firing in theoretical studies [7]. In the experiment, entropy is maximum under the asynchronous irregular firings by the balanced inputs [8]. Moreover, the asynchronous firings generate variously spatio-temporal patterns of a neural activity in the network [9]. The spatio-temporal patterns are brain operations that generate adaptive external inputs. We consider that the asynchronous firing takes information processing capability. When the neural activities synchronized with each other, their capability of information representation is severely limited, because all the neurons represent merely a single temporal pattern.

To avoid such neural activities that degrade the information processing capability, we firstly explore underlying mechanism of neural synchronization. The synchronous firings were observed when the neurons were injected by common inputs with each other [10, 11]. The our study showned that inhibitory common inputs give rise to synchronous firings a feed-forward model with leaky integrate-and-fire neurons based on the physiological experiments [12]. In addition, highly heterogeneous inhibitory post-synaptic potentials (IPSPs) was proposed to suppress their strong synchronization [12]. The introduction of heterogeneous IPSP amplitudes can generate uncorrelated inputs and then the firing pattern can be desynchronized [12].

This paper is to implement a electronic circuit that gives rise to asynchronous firings to avoid synchronous firings induced by inhibitory common inputs. First, using electronic circuit with common inputs, we reproduce a typical situation to induce neuronal synchrony. Next, to suppress the synchrony, we adjust inhibitory inputs to heterogeneity from homogeneity. We verify that asynchronous firings among the electronic neurons can be induced by the heterogeneous inputs.

2. Method

2.1. Electronic neuron circuit

The axon-Hillok circuit in the electronic neuron circuit is an analog circuit originally proposed by Mead (Fig.1) [13]. The axon-Hillok circuit imitates the simple dynamic of neuron with leaky integrate-and-fire model. The input current $I_i(t)$ is stored linearly into the membrane potential $v_i(t)$ of i th electronic neuron on the capacitor (C_1, $1\mu F$) until the membrane potential exceeds threshold V_{thr}. The stored membrane potential $v_i(t)$ is released by n-MOS transistor (M_1) and the voltage V_{lk} [14]. The voltage V_{lk} is set to 1.2 V. When the membrane potential $v_i(t)$ reaches threshold V_{thr}, the output voltage V_{out} quickly change from 0 to V_{dd} and the electronic neuron generate the spike. The spike can be detected by the sigmoid function, which consists of n- and p-MOS transistors (M_2-M_5) and capacitor (C_2, $47\mu F$). Then a gate voltage of n-MOS transistor (M_6) is high by the on-state of the output voltage V_{out}. The n-MOS transistor (M_6) comes into an on-state from an off-state by the high gate voltage, and then the membrane potential $v(t)$ with a full charge is released to ground and the output voltage V_{out} swings back to 0 V. When the membrane potential $v(t)$ is the reset potential, the n-MOS transistor (M_6) return to an off-state from an on-state and the cycle repeats.

The membrane potential in neurons ($v_i(t)$) is measured by the oscilloscope (Keysight: DSOX2104A). The function generator of arbitrary current (Keysight: N6784A) can inject into the electronic neurons.

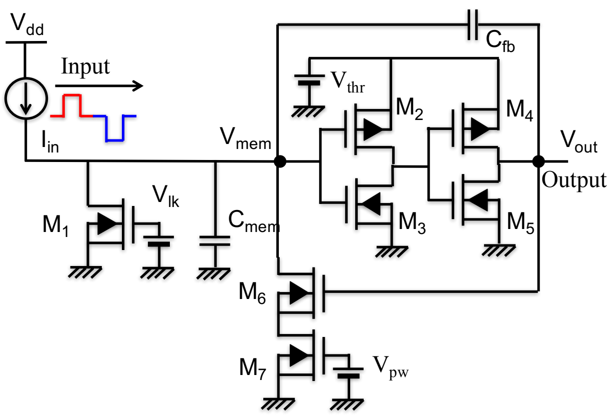

Figure 1: Circuit diagram of electronic neuron: The parameters on electronic neuron are set to $C_1 = 1\mu F$, $C_2 = 47\mu F$, $V_{pw} = 1.6V$, $V_{lk} = 1.2V$, and $V_{th} = 5V$, respectively.

2.2. Input current on electronic neuron

In neural network, it is a generally considered that recurrent networks are composed of two types neurons (excitatory and inhibitory neurons). To simplify recurrent network, we set a feed-forward network that has excitatory and inhibitory neurons in a first layer and 10 neurons in a second layer (Fig. 2A). The neurons in the second layer generate synchronous firings by the input current $I_i(t)$ including inhibitory common inputs [11]. The common input current depends on the spikes and synaptic weights of excitatory and inhibitory neurons in first layer.

The input currents $I_i(t)$ on the electronic circuit are hard to set, because we adjust a number of coupling strengths more than neurons and we prepare many electronic neurons in first layer. Here, the input current is set to the ensembles of synaptic weights and spikes generated by all neurons in the first layer (Fig. 2B). Concretely, the current is combined with positive and negative pulse waves with a width of 0.01 sec for excitatory and inhibitory inputs, respectively. The input current $I_i(t)$ injected into output neurons is given by

$$I_i(t) = W_{i,E}\sum_k \delta(t-t_{E,k}) + W_{i,I}(t)\Big(\sum_s \delta(t-t_{I,s}) + \sum_c \delta(t-t_{I,c})\Big), \quad (1)$$

where the indices E and I are for excitatory and inhibitory neurons, respectively. $\delta(t)$ represents the delta function, $W_{i,n}$ and $t_{n,b}$ are the strengths of excitatory and inhibitory inputs and b-th spike from the neurons in first layer, respectively. Excitatory inputs generate independent Poisson spike trains (red in Fig.2), whereas inhibitory inputs in the first layer generate independent Poisson spike trains (blue in Fig.2) and shared Poisson spike trains (green in Fig.2). We conduct experiments for 20 sec using the 10 electronic neurons and the 10 kinds of input currents.

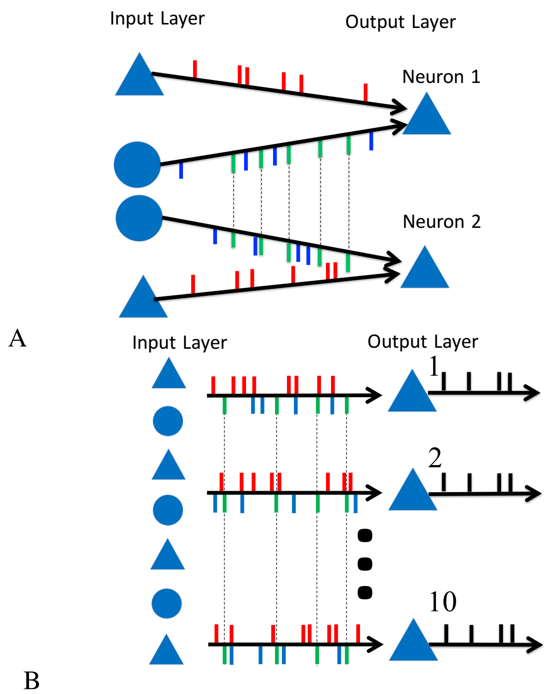

Figure 2: Schematic imagination of input currents on the electronic neuron. (A) Imagination of a feed-forward network with two layers. In the network, Excitatory (triangle) and inhibitory neurons (circle) in the first layer are connected to 10 neurons in a second layer. Excitatory neurons in the first layer generate independent Poisson spike trains (red), whereas inhibitory neurons in the first layer generate independent Poisson spike trains (blue) and shared Poisson spike trains (green). (B) Input current implemented on the electronic neuron corresponding to (A).

2.3. Description of synchronous firing

The level of synchronous firing in the output neurons, we evaluate the Cross-correlogram (CCG). We calculate CCG as a histogram of inter-spike intervals for all pairs among electronic neurons. The time lag was set to the range between -5 sec and 5 sec with an increment of 1 sec. If the neural activity can be synchronized with each other, the CCG appears with a sharp peak at zero time lag, whereas asynchronous firings indicate the existence of the CCG with a flat structure.

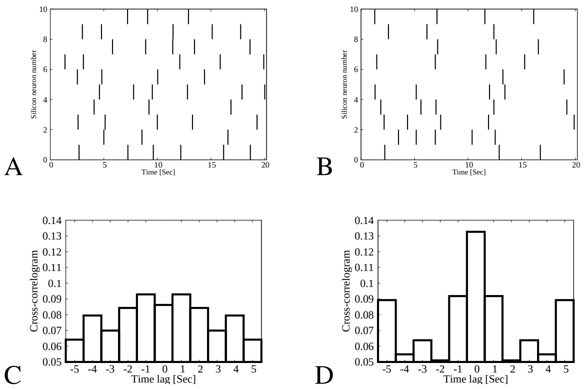

Figure 3: Effect of inhibitory common inputs on synchronous firings of the electronic neuron: (A) Raster plots corresponding to the case that no common inputs (c = 0) were injected. Spikes of electronic neurons are indicated. (B) Raster plots corresponding to case that the ratio to shared inputs c is set to 0.77. (C,D) The CCG histograms corresponding to (A,B), respectively.

3. Results

3.1. Experiment with synchronization induced by common inputs of inhibitory current

For the desynchronization, we first set synchronous firings on the electronic neurons by inhibitory common inputs. Then, we introduce a network mechanism that reduces the correlated inhibitory inputs.

The parameters of input current $I_i(t)$ are defined as strengths and frequencies of excitatory and inhibitory inputs. The mean strengths of excitatory and inhibitory inputs are constant for $W_{i,E}$ = W_E = 1 mA and $W_{i,I}(t)$ = W_I = -1.25 mA, respectively. Moreover, R_E = 8 Hz indicate the frequency of independent Poisson spike trains for excitatory inputs, whereas inhibitory inputs are classified into independent Poisson spike trains R_{II} and shared Poisson spike trains R_{cI}. The frequency of inhibitory inputs R_I is defined as the summation of each frequency R_{II} and R_{cI}, and R_I = 4 Hz is always constant in all experiments. To constrain correlated spike trains of inhibitory neurons, we introduce the ratio to shared spikes $c = R_{cI}/R_I$.

The raster plots under the two states with c = 0 and c = 0.77 are shown in Fig. 3. As comparing correlated inputs c = 0.77 (Fig. 3B) with uncorrelated inputs c = 0 (Fig. 3A), synchronous firing with c = 0.77 occurs than that with c = 0. As shown in CCG, the peak of CCG for uncorrelated inputs (Fig. 3C) is less than correlated inputs (Fig. 3D). The result is that the synchronous firings can be reproduced by the correlated inhibitory inputs on the electronic neurons.

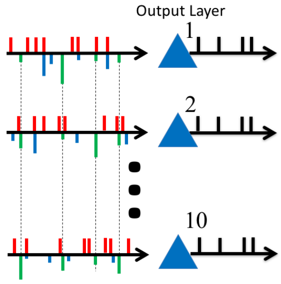

Figure 4: Schematic imagination of heterogenous input currents on the electronic neuron. Corresponding to Fig 2B, the strengths of inhibitory inputs are lognormally distributed.

3.2. Experiment with desynchronized firings induced by heterogeneous inputs of inhibitory current

In the previous subsection, we showed that synchronous firings are generated by high common inputs. We conduct the experiment with desynchronization under the c = 0.77, which induce synchronous firings in electronic neurons. To suppress the synchronous firings, the strengths of inhibitory inputs $W_{i,I}(t)$=w_i are distributed such that lognormal distribution has high heterogeneity (Fig. 4);

$$p(w_i) = \frac{\exp[-(\log w_i - \mu)^2/2\sigma^2]}{\sqrt{2\pi}\sigma w_i}, \tag{2}$$

where we set the mean of the distribution $\overline{W_i}$ and the value σ, respectively [15]. Once their parameters $\overline{W_i}$ and σ are decided, we can obtain the parameter $\mu = \log(\overline{W_i}) - \sigma^2/2$. The mean of the distribution $\overline{W_i}$ = -1.25 mA keeps the same value among experiments.

As shown in the raster plots with current strengths under the constant $\sigma = 0$ (Fig. 3B), the synchronous firings still remains, whereas the firing pattern is asynchronous under lognormal distribution with $\sigma = 3$ (Fig. 5A). We also understand that the peak of CCG exists under the constant (Fig. 3D), while the CCG disappears with a sharp peak under the lognormal distribution (Fig. 5B). The implies is that the highly heterogeneous strengths of inhibitory inputs have an impact on desynchronization.

4. Discussion

We implemented the electronic circuit that is mimics the neural activity proposed by Mead [13] and we introduced an input current injected into a neuron in output layer to the highly correlated inhibitory current. As increasing the ratio to shared inputs, we confirmed that the neurons in output layer are synchronized with each other. To break the highly correlated inhibitory current, we changed to heterogeneous strengths of inhibitory current. The input current can reduce the correlated inhibitory inputs and then the asynchronous firings can be observed on the electronic circuit.

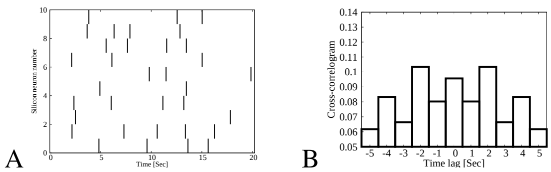

Figure 5: Effect of standard deviation of inhibitory strengths on the electronic neuron. The proportion to shared inputs c is set to 0.77. (A) Raster plot represents spikes of electronic neurons under he inhibitory inputs distributed as lognormal distribution with $\sigma = 3$. (B) The CCG histograms corresponding to (A).

We consider that the asynchronous firings on the electronic neuron are more information capacity than the synchronous firings. It is reported that the spontaneous asynchronous firing activity gives rise to the maximum information capacity in the physiological experiments [8]. The pathological synchronous firings that may relate to epileptic seizare [16] reduce information capacity because all the neurons represent merely a single neural activity. In the our future, we discuss the relationship between the pathological synchronous firings and information capacity on electronic neurons.

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