



Neuronal synchrony detection on single-electron neural networks

Takahide Oya ^{*}, Tetsuya Asai, Ryo Kagaya, Tetsuya Hirose, Yoshihito Amemiya

Department of Electrical Engineering, Hokkaido University, Kita 13, Nishi 8, Sapporo 060-8628, Japan

Accepted 1 April 2005

Abstract

Synchrony detection between burst and non-burst spikes is known to be one functional example of depressing synapses. Kanazawa et al. demonstrated synchrony detection with MOS depressing synapse circuits. They found that the performance of a network with depressing synapses that discriminates between burst and random input spikes increases non-monotonically as the static device mismatch is increased. We designed a single-electron depressing synapse and constructed the same network as in Kanazawa's study to develop noise-tolerant single-electron circuits. We examined the temperature characteristics and explored possible architecture that enables single-electron circuits to operate at $T > 0$ K.

© 2005 Elsevier Ltd. All rights reserved.

1. Introduction

Single-electron integrated circuits should be an important candidate of next generation integrated circuits because of their ultra-lowpower consumption and high integration density. Moreover, their intrinsic quantum behaviors give us insight in developing modern computing paradigms including nature-inspired computing and quantum computing. However, single-electron circuits are very sensitive to thermal fluctuations in a practical environment. Therefore, if we use conventional (deterministic) computing, we need a fully worked-out plan for both computing and circuit architectures; e.g., see [1–5]. Thermal-noise tolerance is an importance characteristic of single-electron computers because the rate of random electron tunneling increases exponentially as the temperature increases. Several practical circuits have been developed by improving the process for fabricating ultra-low capacitance of tunneling junctions [4] and by using an error-compensation algorithm in the architecture [5].

We can now easily observe robust, fault- and noise-tolerant systems in nature. How can we incorporate such robust properties into single-electron circuits? One possible way is by learning from our central nervous systems. Neurons are fluctuated by thermal noises, as well as single-electron circuits. They utilize thermal noise to detect weak neuronal signals buried under the noise. Furthermore, the reappearance of neuronal behaviors and matching properties between neurons are really poor compared with semiconductor neural devices. Actually, a huge number of neurons die every

^{*} Corresponding author.

E-mail address: oya@sapiens-ei.eng.hokudai.ac.jp (T. Oya).

day in our brains. Moreover, they are often exposed to electromagnetic waves, and they even experience physical shocks sometimes; nevertheless, our brains work robustly.

Even traditional neural networks, such as feed-forward and Hopfield neural nets, have strong robustness for both removing neurons and synapses. On the other hand, Shimozawa showed that thermal noise is not only annoying for insects, but they utilize the energy and stochastic properties of the noise [6]. Furthermore, Fukai showed that a stochastic recurrent neural network, where each connection strength was randomly selected, exhibited good synchrony (within a few milliseconds) between spiking neurons when external noise was given [7]. He assumed excitatory connections between the neurons, and he assumed that they were about to diverge. Because the external noise acts as the onset of the divergence, the network is suddenly activated by the positive feedback. Such properties; i.e., precise operation on noisy devices, are very interesting for single-electron developers because if the information is represented by this kind of synchrony, one can construct robust single-electron computers by mimicking the structure of such a neural network. Moreover, Asai et al. showed a network-level noise tolerance on a hardware competitive neural network based on population coding [8]. In the circuit, a cluster (population) of neurons was defined, and information was given to the cluster (not a neuron). The cluster (average of the neurons) also represented the results of the competition. One neuron in each cluster is not totally responsible for the final results. The important thing here is the use of winners-share-all competitive neural nets because if conventional winner-takes-all networks were used, a single winner must be responsible for the final results.

Recently, Kanazawa et al. designed a CMOS depressing synapse circuit and demonstrated its application to contrast invariant pattern classification and synchrony detection [9,10]. They found that the performance of a network with depressing synapses that discriminates between burst and random input spikes increased non-monotonically as the static device mismatch increased [10]. Namely, the static noise helps the network to increase the discrimination performance. Thus, in this paper, we report on our design of a single-electron depressing synapse and our construction of the network. We examine the temperature characteristics and explore possible architecture that enables the single-electron circuits to operate at high temperature. What we wanted was to examine the quantitative difference between the original model [10] and the single-electron circuit so as to optimize the performance. If we can receive some benefits from the original network, we may develop robust information processing elements on single-electron devices, although the processing will be limited to a dedicated network.

2. Single-electron depressing synapse circuit

We proposed neuromorphic single-electron circuits for fundamental neural components in modern spiking neural networks [11]. Our aim was to implement artificial neural networks on a single or multi-layer nano-dot array. A unit circuit consists of a pair of single-electron oscillators. Using these unit circuits with coupling capacitors, we designed a single-electron neuron circuit that consists of excitable axons and dendrites, excitatory and inhibitory synapses, and a soma. We demonstrated an application of the neuron circuit in an inhibitory competitive neural network, where the neurons compete with each other in the temporal domain. However, we observed expected neural competition at a very low temperature (≤ 0.1 K). Therefore, in this paper, we explore a possible solution to improve the performance in another application, i.e., neuronal synchrony detection, by using the proposed single-electron depressing synapse.

To design a depressing synapse circuit, we used a pair of single-electron oscillators [Fig. 1(a)] that were proposed for a spiking neuron circuit [11] and an excitable media [12]. The oscillator consists of a tunneling junction (C_j), a conductive device (g), and a bias voltage source (V_{dd}). The oscillator has an island node n_i where excess electrons are stored. Fig. 1(b) is a nominal phase diagram of this circuit for positive V_{dd} . The vertical and horizontal axes represent node

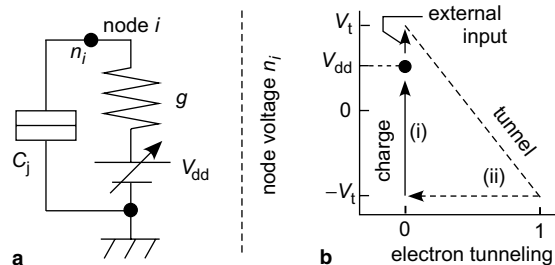


Fig. 1. Single-electron oscillator and phase diagram.

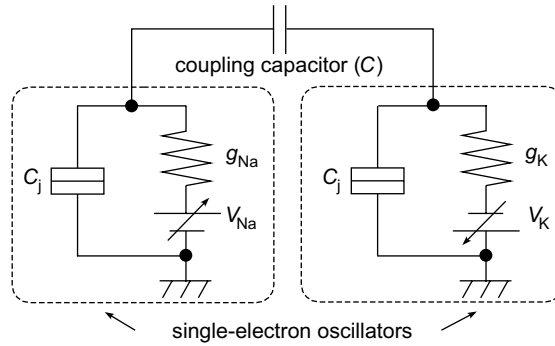


Fig. 2. Depressing synapse circuit with single-electron oscillator.

voltage n_i and a tunneling phenomenon [= 1 (when an electron tunnels), 0 (else)] at C_j . Note that trajectories between the tunneling phenomenon (0 and 1) in the figure do not have any quantitative physical meaning, but they have been used only to explain this circuit’s operation. We assumed that $V_{dd} < e/2C_j$ ($\equiv V_T$: tunneling threshold voltage of junction C_j). Because tunneling junction C_j is charged by V_{dd} [(i) in Fig. 1(b)], the circuit is stable when $n_i = V_{dd}$. Under this resting condition, if n_i is further increased by an external input and exceeds V_T , an electron tunnels from the ground to node i through junction C_j , which results in a sudden decrease in n_i from V_T to $-V_T$ [(ii) in Fig. 1(b)]. Then, V_{dd} starts charging C_j , and the circuit becomes stable again [(i) in Fig. 1(b)].

Note that there is a time lag from when the junction voltage exceeds V_T to when tunneling actually occurs. We utilized this “monostable” (excitable) oscillatory property to produce the depressing characteristics of the synapses; i.e., we regard an array of oscillators as a depressing synapse because input spike trains are depressed by each neuron operating in its refractory period. Therefore, we can use an array of single-electron oscillators to construct the single-electron depressing synapse (SEDS) as shown in Fig. 2. It should be noted that the term of the refractory period increases as the values of g_{Na} and g_K increase [12].

A neuromorphic relationship exists between the proposed SEDS and electronic Hodgkin–Huxley (H–H) models: (i) a tunneling junction (C_j) corresponds to a membrane capacitance and voltage-controlled gates in the H–H models, (ii) non-linear chemical reactions between Na^+ and K^+ can be mediated by a coupling capacitance (C) because of the neuron’s dielectric inside the soma.

3. Results

First, we examined the depressing properties of a single SEDS by numerical simulations. We used typical parameter values for the single-electron circuit [12], except for g_{Na} ($=g_K$) = 5, 2.5, and 1 μS . Fig. 3 shows synaptic conductivities (\sim the number of postsynaptic spikes) for interspike intervals (ISIs) of input spike trains. As the ISIs increase, the

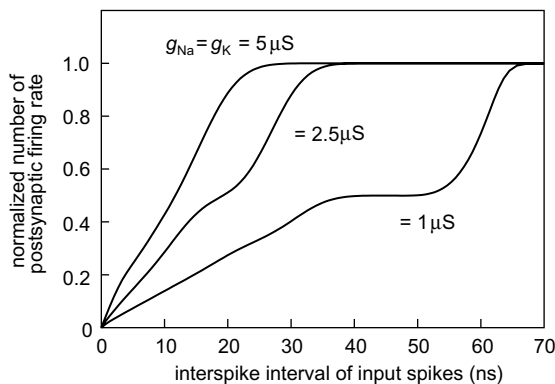


Fig. 3. Changes in postsynaptic firing rate of depressing synapse circuit against interspike interval of input spikes.

conductivity increases because each SEDS can easily be recovered from its depressed (refractory) period as the ISIs increase. Because the depressed period increases as g_{Na} and g_K increase, the SEDS's conductivity for increasing ISIs decreases significantly.

Next, we demonstrate a network of the SEDSs. We used a typical functional example of depressing synapses proposed by Senn [13]. He showed that an easy way to extract coherence information between cortical neurons is by projecting spike trains through depressing synapses onto a postsynaptic neuron [13]. We demonstrate it here by using our synapse circuits.

Let us assume a simple circuit, as shown in Fig. 4. The circuit is designed based on the construction of Senn's neural network. The right part represents a postsynaptic neuron and the left part represents its dendrite with our synapse circuits. The postsynaptic neuron consists of a membrane capacitance (C_m) and a leak conductance (g_m). In this study, we omitted including a threshold (V_{th}) detector from our postsynaptic neuron circuit; i.e., our postsynaptic neuron circuit never fires. The postsynaptic neuron accepts spike inputs from excitatory neurons through depressing synapses. If the postsynaptic neuron circuit has a firing function, it outputs a spike when its EPSP $< V_{th}$, and resets the EPSP after the firing. In this setup, the average values of the EPSP increase in proportion to the number of presynaptic active neurons. Therefore, it can detect the number of presynaptic active neurons by setting the appropriate threshold V_{th} corresponding to the number of active neurons. On the other hand, the EPSP also increases in proportion to the firing rate of spiking neurons. Therefore, the performance needed to discriminate the number of presynaptic active neurons largely deteriorates if the firing rate is not a constant value. During a burst input, the output current of the depressing synapse circuit that flows via a conductance (g') rapidly decreases for successive spikes due to the refractory properties of the single-electron oscillator. But during a non-bursting period, the oscillator has time to be in a resting period, and these results in a strong EPSP at the onset of the next burst. If we compare this dynamic response with that for a non-depressed synapse evoking the same EPSP on average, the depressed synapse will have a larger response at the burst onset and a smaller response toward the end of the burst.

Fig. 5 show the response of the EPSP with bursting inputs for (a) a non-depressed synapse (b) and a depressed synapse circuit (c). The results ensure that the EPSP caused by the depressed synapse circuit has a larger response at the burst onset, as compared with a non-depressed synapse circuit.

In this paper, we demonstrate that the depressing synapse circuit can detect the synchrony in the burst times. We used two bursting neurons as the input of the postsynaptic neuron that receives the burst inputs through depressed or non-depressed synapses. Figs. 6 and 7 show the results. When the input bursts were not synchronized [Fig. 6(a) and (b)], the peak EPSPs evoked by non-depressed [Fig. 6(c)] and depressed synapses [Fig. 6(d)] were both around 3 mV. But, when the input bursts were synchronized [Fig. 7(a) and (b)], the peak EPSPs evoked by depressed synapses [Fig. 7(d)] were significantly larger than the non-depressed synapses [Fig. 7(c)]. Therefore, after defining an appropriate threshold V_{th} of the postsynaptic neuron, e.g., $V_{th} = 1.5$ mV in the experiments, the postsynaptic neuron with the depressing synapse circuit can fire when the burst inputs are synchronized.

Next, we simulated the output of 100 neurons by random spike trains [Fig. 8(a)]. According to Senn's report [13], there is experimental evidence to assume that before and during the tone, auditory cortical neurons fire in short bursts with bursts of three to four spikes at 40–50 ms, repeated every 200–250 ms. During the tone, the burst onsets are as-

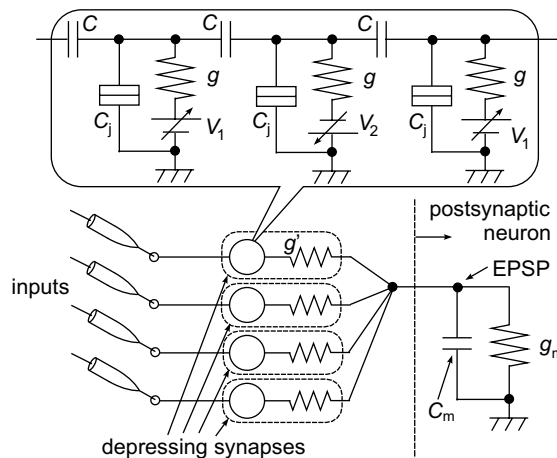


Fig. 4. Circuit configuration of depressing synapses with postsynaptic neuron circuit.

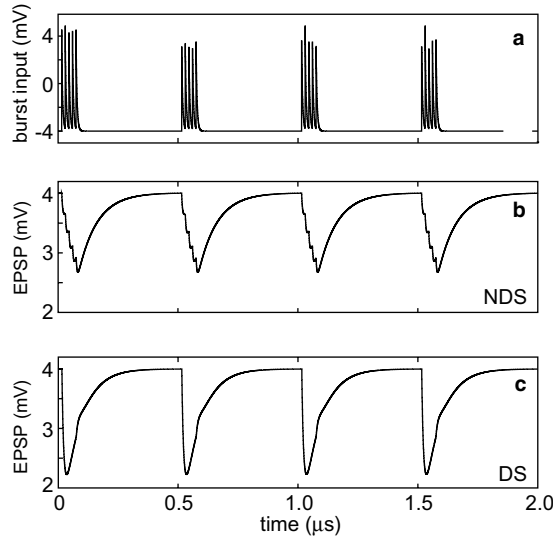


Fig. 5. Responses of EPSP for single burst input (a) via non-depressed (b) and depressed synapse circuit (c).

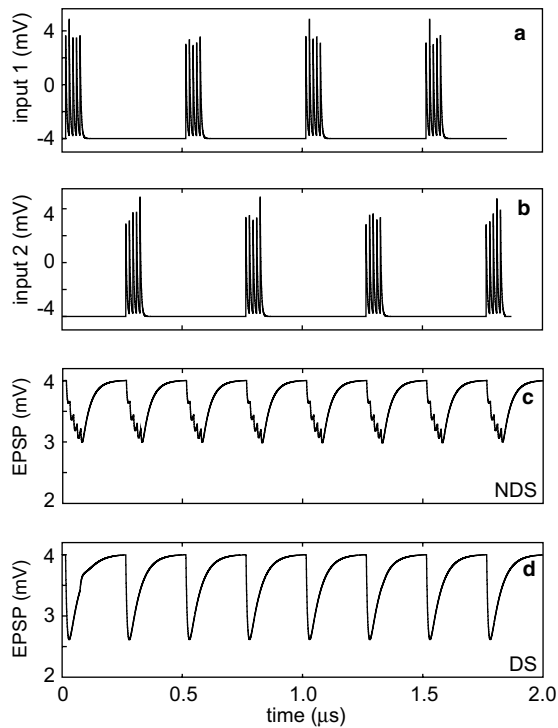


Fig. 6. Responses of EPSP for asynchronous burst input [(a) and (b)] via non-depressed (c) and depressed synapse circuit (d).

sumed to be synchronized within groups of 70 neurons that are randomly assembled anew for each burst. In our simulation, the overall firing rate of the population remains constant, apart from the short onset and offset of the tone when most cells burst together. This is because the bursting times of the groups alternate during the on-going tone (see Fig. 8(b)).

The neurons respond at the onset and offset by applying a tone stimulus (1.5–4.0 μ s in Fig. 8). They correlate their bursts only between randomly assembled subgroups during the stimulus. Because the mean firing rate is on the

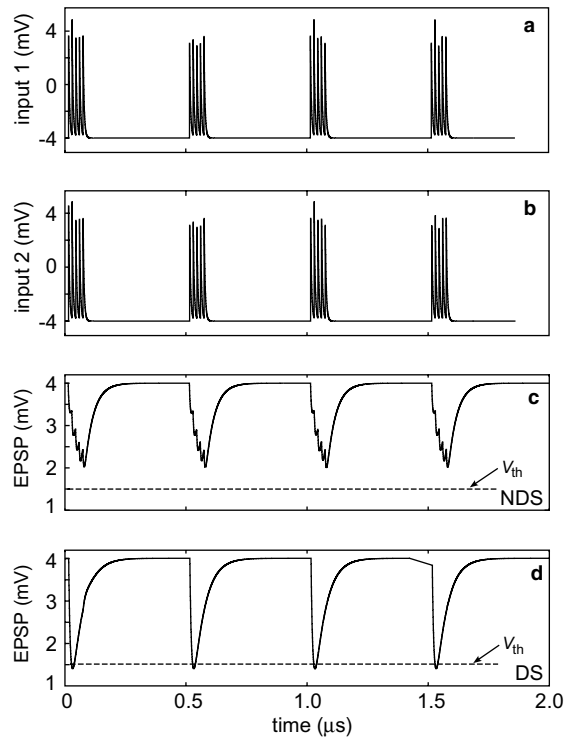


Fig. 7. Responses of EPSP for synchronous burst input [(a) and (b)] via non-depressed (c) and depressed synapse circuit (d).

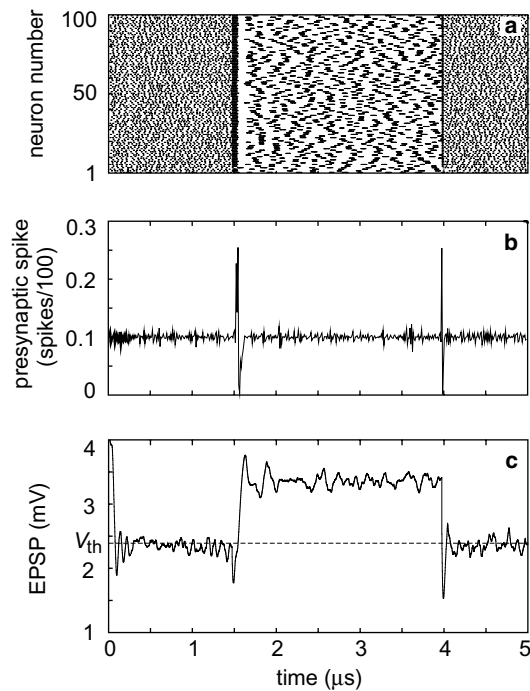


Fig. 8. Simulation results of 100-neuron network simulated by random spike trains through our depressing synapses.

background level during the tone [Fig. 8(b)], a postsynaptic neuron gathering the input spike trains through non-depressed synapses responds only at the stimulus onset and offset. With a depressing synapse, however, the postsynaptic neuron detects the correlated bursts, and then it fires as well [Fig. 8(c)], as shown in Senn's original work.

The difference in EPSP between burst and non-burst inputs represents the network's signal-to-noise (SN) ratio when the task is to discriminate burst spikes from non-burst ones. The results in Fig. 8(c) showed it was around 1 mV. Note that parameters of depressing synapse circuits were not optimized well. So what is the most important parameter to increase the difference? Apparently, it is the time constant of the depression because it determines the maximum EPSP, as shown in Fig. 7(d). The constant is proportional to the junction capacitance and the channel conductance. The other important parameter is the ISIs of the input bursting spikes. In the aforementioned simulations, we used typical bursting inputs that can easily be generated by external spike generators.

To consider the noise tolerance, we examined Monte-Carlo simulations for the network circuit with typical parameter sets. What we wanted here was to examine the quantitative difference between the original model [10] and the proposed single-electron circuit to optimize the performance. As described, the performance of the discrimination strongly depends on the SN ratio between the burst and non-burst spike inputs. Increasing temperature results in an increase in the averaged EPSP. Our interest here is whether the SN ratio is constant or not for increasing the temperature. Of course, we need to re-calculate an appropriate threshold for the discrimination. We show the performance is definitely increased by increasing the temperature. However, all of the parameter sets are not optimized.

To investigate the noise tolerance of Senn's network with our circuits, we simulated the 100-neuron network. To evaluate the noise tolerance, we calculated the difference between the averaged EPSP for the bursting and non-bursting periods and the threshold V_{th} that was defined as 2.4 mV in Fig. 8(c), as shown in Fig. 9. Ideally, the postsynaptic neuron must not fire during the non-bursting period but rather during the bursting period for the task of synchrony detection. The difference between the numbers thus represents the performance of this task. The difference between the averaged EPSP and V_{th} increased as the temperature increased during the non-bursting period. On the other hand, when $T > 0.5$ K, the difference started increasing. Namely, the performance of the synchrony detection did not change significantly due to an increase in T as long as $T < 0.5$ K. Remarkably, the difference (\sim performance of synchrony detection) changed non-monotonically as T increased, as shown in Fig. 10.

Our postsynaptic neuron circuit does not yet have any firing mechanism because the circuit is a feed-forward neural network and because the important value for discriminating the burst spikes from the non-burst spikes is whether the EPSP is lower than the threshold or not. However, for the visualization alone, a significant difference is evident between the original model [10] and our circuit in Fig. 8(c), where the EPSP is oppositely represented due to the lack of firing (discharging the membrane capacitance). The results shown in Fig. 10 indicated that the performance increased up to 0.5 K in the simulations when the temperature was increased. In our previous work [11], the maximum temperature for desired competitive operation was 0.1 K. Needless to say, the temperature is not enough to operate at room temperature. However, the phenomena where the performance increases monotonically as the temperature increases have different physical meanings for conventional stochastic resonance. We are currently optimizing the device and environmental parameters to make the phenomena clear and to optimize these parameters.

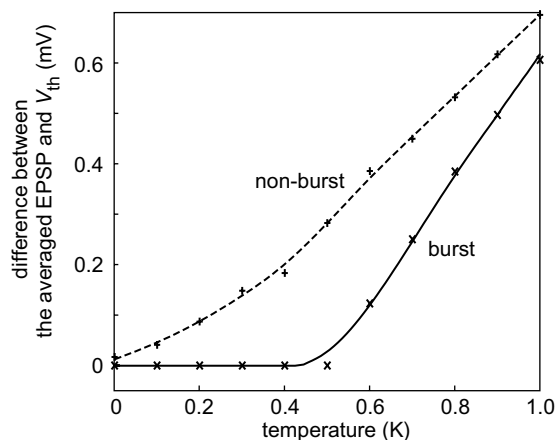


Fig. 9. Changes in the difference between the averaged EPSP and the threshold V_{th} during bursting and non-bursting period as a function of temperature.

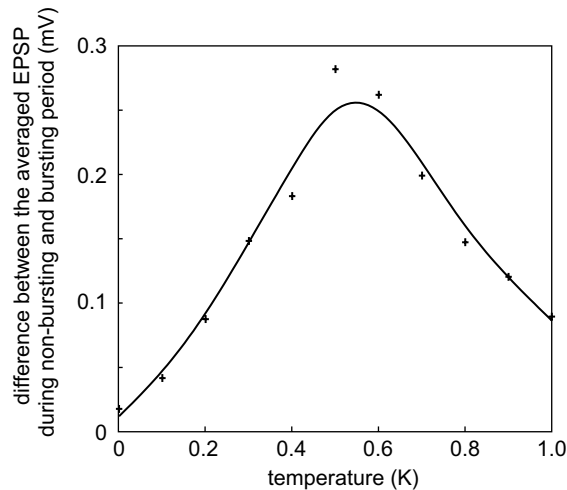


Fig. 10. Changes in the difference between the averaged EPSP during bursting period and during non-bursting period as a function of temperature.

4. Conclusions

We designed single-electron depressing synapses and constructed a simple network to demonstrate a typical functional example of the synapse; i.e., neuronal synchrony detection. Previous works on CMOS VLSI showed that the network had great noise-tolerant ability for static noise embedded as device (threshold) mismatches of MOSFETs. We expanded this notion to dynamic ones that are usually a common problem in the area of single-electron circuits. The results showed that the performance is greatly increased by increasing the temperature until $T < 0.5$ K. However, all of the parameter sets are not optimized. The performance is apparently sensitive to the time constant of a single-electron oscillator and interspike intervals of input burst spikes. Our next goal is an appropriate theory for the emergence of the noise tolerance and optimization of these parameters to explore the possible development of fault- and noise-tolerant single-electron computing devices.

References

- [1] Benioff P. Quantum mechanical models of turing machines that dissipate no energy. *Phys Rev Lett* 1982;48:1581–5.
- [2] Tucker JR. Complementary digital logic based on the Coulomb Blockade. *J Appl Phys* 1992;72:4399–413.
- [3] Gershenfeld NA. Bulk spin-resonance quantum computation. *Science* 1997;275:350–6.
- [4] Takahashi Y, Nagase M, Namatsu H, Kurihara K, Iwadata K, Nakajima K, et al. Fabrication technique for Si single-electron transistor operating at room-temperature. *Electron Lett* 1995;31:136–7.
- [5] Shor PW. Scheme for reducing decoherence in quantum computer memory. *Phys Rev A* 1995;52:2493–6.
- [6] Shimozawa T, Murakami J, Kumagai T. Cricket wind receptors: thermal noise for the highest sensitivity known. In: *Sensors and sensing in biology and engineering*. Wien New York: Springer; 2003. p. 145–57.
- [7] Fukai T, Kanemura S. Noise-tolerant stimulus discrimination by synchronization with depressing synapses. *Biol Cybern* 2001;85:107–16.
- [8] Asai T, Ohtani M, Yonezu H. Analog integrated circuits for the Lotka–Volterra competitive neural networks. *IEEE Trans Neural Networks* 1999;10:1222–31.
- [9] Kanazawa Y, Asai T, Ikebe M, Amemiya Y. A novel CMOS circuit for depressing synapse and its application to contrast-invariant pattern classification and synchrony detection. *Int J Robot Automat* 2004;19:206–12.
- [10] Asai T, Kanazawa Y, Hirose T, Amemiya Y. A MOS circuit for depressing synapse and its application to contrast-invariant pattern classification and synchrony detection. In: *International joint conference on neural networks, W107*, 2004.
- [11] Oya T, Asai T, Kagaya R, Hirose T, Amemiya Y. Neuromorphic single-electron circuit and its application to temporal-domain neural competition. In: *Proceedings of 2004 international symposium on nonlinear theory and its application (NOLTA)*. p. 235–9.
- [12] Oya T, Asai T, Fukui T, Amemiya Y. Reaction–diffusion systems consisting of single-electron circuits. *Int J Unconven Comput* 2005;1:177–94.
- [13] Senn W, Segev I, Tsodyks M. Reading neuronal synchrony with depressing synapses. *Neural Comput* 1998;10:815–9.