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Biologically-inspired stochastic vector matching for noise-robust information processing

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Abstract

"End of Moore's Law" has recently become a topic. Keeping the signal-to-noise ratio (SNR) at the same level in the future will surely increase the energy density of smaller-sized transistors. Lowering the operating voltage will prevent this, but the SNR would inevitably degrade. Meanwhile, biological systems such as cells and brains possess robustness against noise in their information processing in spite of the strong influence of stochastic thermal noise. Inspired by the information processing of organisms, we propose a stochastic computing model to acquire information from noisy signals. Our model is based on vector matching, in which the similarities between the input vector carrying external noisy signals and the reference vectors prepared in advance as memorized templates are evaluated in a stochastic manner. This model exhibited robustness against the noise strength and its performance was improved by addition of noise with an appropriate strength, which is similar to a phenomenon observed in stochastic resonance. Because the stochastic vector matching we propose here has robustness against noise, it is a candidate for noisy information processing that is driven by stochastically-operating devices with low energy consumption in future. Moreover, the stochastic vector matching may be applied to memory-based information processing like that of the brain.

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1. Introduction

Moore's Law, first stated in 1965, predicts that the number of transistors on a chip will double about every two years [1] and LSIs [2] have developed actually according to this law and have brought us immeasurable contribution. However, the "End of Moore's Law" has recently become a topic of increased discussion [3]. So far, greater levels

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of operating energy have allowed digital devices to maintain their signal-to-noise ratio (SNR) and thus the accuracy of their logics. However, attempting to keep the SNR at the same level in the future, since a transistor's energy consumption cannot be suppressed, will surely increase the energy density of smaller-sized transistors. This would lead to an extreme increase in the surface temperature of chips. The most effective way to prevent this would be to lower the operating voltage, but this would inevitably degrade the SNR due to noises. Under this condition, a conventional computing principle, such as Boolean logic, will not stand up, and it will become critical to establish a novel noise-robust calculation method. Meanwhile, the molecular machines of organisms operate at low energy level, not far from the average thermal noise energy ($k_B T$), where k_B and T are Boltzmann constant and absolute temperature, respectively. The biological molecular machines are thus strongly influenced by thermal agitations and hence their operations are stochastic [4,5]. Such stochastic biomolecular computation would have a major weakness in calculation accuracy. However, actual organisms manage successfully to acquire noise-robust characteristics and flexibility in their information processing. Inspired by biological processing, we propose the following stochastic calculation method based on the concept of stochastic computing [6–10]. This will provide a complementary approach to conventional computing principles.

2. Stochastic processing model

To handle signals mixed with unavoidable noises, we consider a stochastic comparator in which the basic calculation is a comparison between two signals (Fig. 1(a)). When an input signal ($S = s + \xi$) is compared with a reference signal ($R = r + \eta$), since R acts as a threshold value, the output of the comparator is "High" when $S \geq R$ and "Low" when $S < R$ (Fig. 1(b)). Here, s and r are the net values of input and reference signals, respectively. ξ and η are independent noises. The rising edge detector generates spikes when comparator's output switches from "Low" to "High".

The generated spikes become stochastic due to the noise mixed into both signals. The firing rates of spikes become larger when the values of s and r are closer with each other, indicating that the firing rates of spikes reflect on the similarity between the net value of input and reference signals (Fig. 1(c)). With increasing calculation steps, the spike counts become larger leading to improvements of accuracy of firing rates. This stochastic comparator is the elementary module for stochastic vector matching as described below.

By arranging the stochastic comparators in parallel, the similarities between two numerical series, called as input vector and reference vector, can be evaluated as the firing rates of spikes calculated by the summation of firing counts (Fig. 2(a)) [9,10]. This calculation resembles the general calculation method known as vector matching (VM), which is now frequently utilized for such as motion compensation in video compression [11]. Since each calculation process is stochastic in our model, we call it stochastic vector matching (ScVM). The input vector carries external signals to be processed, while the reference vectors are prepared in advance as memorized templates. When the similarities between the input and the reference vectors are higher, the firing rates of spikes become larger. By calculating multiple reference vectors, we can stochastically select one reference vector most similar to the input vector. For example, when we vectorize two-dimensional images as numerical series representing brightness of each pixel, the most similar image to the input image can be chosen stochastically among the memorized reference images.

3. Performance

To evaluate the performance of ScVM, we compared it with the exact result obtained by VM (see Appendix). The best performance was defined as 100 points, and the worst was around 50 points. As shown in Fig. 2(b), ScVM shows good performance with increasing calculation steps, which is a characteristic feature of stochastic computing. From the viewpoint of calculation power consumption, it is desirable to achieve relatively high performance with a smaller number of calculation steps. In some cases, only 10 calculation steps were enough to attain the performance as high as 90 points (Fig. 2(b)). The performance of ScVM also depended on the noise strength (standard deviation; σ_N).

Maximum performance was attained at an appropriate strength of noise (Fig. 2(c)). This means that this calculation method can be improved by addition of noise, which is similar to phenomena observed in stochastic resonance (SR) [12–15]. As shown in Fig. 1(c), when the difference of the signals ($s - r$) is constant, the expected firing rate of each elementary module has no suitable σ_N and just increase up to 0.25 as σ_N becomes large. However, ScVM system composed of these elementary modules shows SR-like phenomenon. In contrast to SR, which can improve SNR of a faint signal by benefits of noise, ScVM does not improve SNR of noisy signals. Instead, ScVM utilizes noise for