Brain-inspired computing with spintronics devices

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Abstract— **Neural networks and artificial intelligence utilizing artificial neurons and synapses are attracting much attention. Spintronic devices are considered to be suitable for mimicking artificial synapses and artificial neurons because of nonvolatility of information and rich nonlinearity of spin dynamics. We focused on the nonlinearity of spin dynamics and formed a virtual artificial neural network by using the time multiplexing method. By using reservoir computing for learning rules, we succeeded in speech recognition with a high recognition rate of 99.6%. These results pave the way for hardware implementation of artificial intelligence.**

Keywords-spintronics, oscillator network, reservoir computing

I. INTRODUCTION

Machine learning using digital processors consisting of CPU, GPU, memory and storage, and artificial intelligence using deep learning technology are considered to be very useful for the next information society.[1] These computational models have been developed from mimicking the neural circuits in the human brain.[2] The activity in neural circuits consists of neurons and synapses. They are performed through interactions in a network formed by an enormous number of neurons and synapses. An approach to realize the neural circuits with artificial functional devices and implement the brain function or calculation model (neural network) by hardware is so called brain-inspired computing. In recent years, several researches aimed at realizing this new approach are vigorously carried out in various fields.[3,4] In this approach, it is important that artificial synapses have the function of controlling the coupling (weight) between neurons, and artificial neurons realize the function of interacting with one another and outputting signals.

II. SPINTRONICS FOR BRAIN-INSPIED COMPUTING

Researches aiming at realizing brain-inspired computing, in particular, the neural network with functional devices have been carried out in Spintronics.[5] To mimic neurons and synapses, magnetoresistive devices based on the structure as shown in Fig. 1 are used. The magnetoresistive device consists of multilayer of ferromagnetic materials. It has a function of converting the magnetization motion of the ferromagnetic material into an electric signal through the magnetoresistance effect. Furthermore, it also has a function of electrically controlling the magnetization dynamics through spin transfer torque effect. Because the magnetoresistive device can be as small as down to about 10 × 10 × 10 nm^3, it is considered

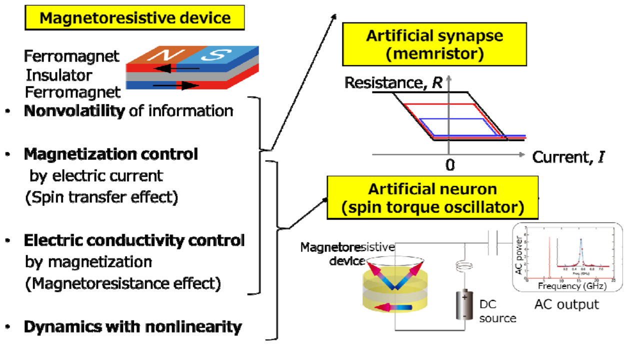

Figure 1 Features of the magnetoresistive device and use of it as an artificial synapse and neuron.

to be suitable for realizing the artificial neural network where the number of elements is enormously large. As shown in Fig. 1, by utilizing the two effects of the magnetoresistive device and the nonvolatility inherently possessed in the ferromagnetic material, the magnetoresistive device functions as a memristor [6], and thus can be used as an artificial synapse.[7,8] The advantage of the spin based memristor is its high writing endurance (> 10^{16}), and the disadvantage is its small dynamic range (about 200%).

For the reproduction of artificial synapses using spin based memristors, the nonvolatility of the ferromagnets, that is, the static nature of the device is utilized. On the other hand, ferromagnets also have dynamical nature. A spin torque oscillator (STO) shown in Fig. 1 takes advantage of this property.[9] The STO converts the steady precession of magnetization induced by the spin transfer torque effect into an electric signal through the magnetoresistive effect. Therefore, it is possible to generate an AC signal only by applying DC signal to the device. Since the STO does not require a resonator, the

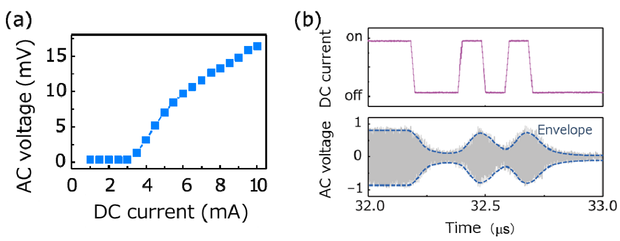

Figure 2 Nonlinearity of a STO. (a) DC current dependence of AC voltage generated by the STO. (b) Transient response of AC voltage when a pulse current is applied to the STO.

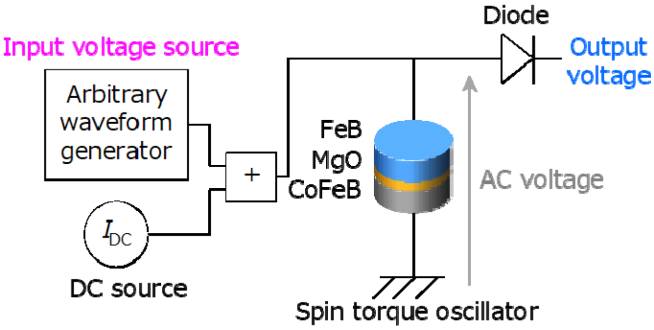

Figure 3 Experimental circuit of virtual network using a STO. From the arbitrary waveform generator, the digitally processed audio signal was input and the output signal was measured. The diode was used to convert the output signal to the envelope.

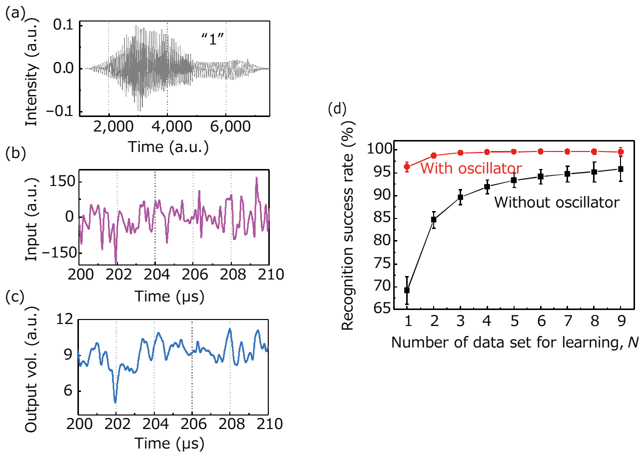

Figure 4 (a) Audio signal of utterance of "1". (b) Input signal to the STO that is the preprocessed audio signal. (c) output signal of the STO. (d) The dependencies of the success rate of speech recognition on the number of learnings.

device size can be reduced down to nanoscale. Furthermore, as shown in Fig. 2, the STO exhibits very rich nonlinearities.

III. Artifical Neural Network Using a Spin Torque Oscillator

In this work, we focused on the rich nonlinearity of the STO and formed echo state network [10], which is one of the recurrent neural networks by using the circuit as shown in Fig. 3.[11] Although only one oscillator was used, a network structure of 400 virtual neurons was formed by the time multiplexing method.[12] The process of learning rules used reservoir computing.[13] In this method, it is not necessary to have synapses inside the network, and thus the hardware implementation of the artificial neural network can be simplified.

Speech recognition was performed using this artificial neural network. FIG. 4 (a) shows an audio signal of "1". Pre-processing (filter and mask processing) was applied to the audio signal to obtain an input signal (FIG. 4 (b)). When this signal is input to the STO, an output voltage as shown in FIG. 4 (c) was obtained. The waveforms in Fig. 4 (b) and Fig. 4 (c)are different due to the nonlinearity of the STO. The audio data used for learning and recognition were composed of five speakers and ten digits "0" to "9" were used as one data set. 10 data sets with different utterances were prepared, of which N data sets were used for learning, and (10-N) data sets were used for recognition. Fig. 4 (d) shows the learning count N dependence of the speech recognition success rate. Here, "Without oscillator" means that the input signal (FIG. 4 (b)) was directly processed. By using the artificial neural network with the STO, the success rate of speech recognition was greatly improved even with a small number of learning. The success rate increased up to 99.6%, despite the use of a artificial neural network composed of a nanoscale device, achieving almost the same accuracy as done by a larger and more complicated optical system.

IV. Conclusion

We prepared a virtual neural network using dynamics of a STO with time multiplexing method. By using this virtual network and reservoir computing, speech recognition was successfully demonstrated with a recognition success rate of as high as 99.6%. These results open up the possibility of the implementation of artificial neural network with spin based functional devices.

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