Machine-learning computation utilizing spin waves

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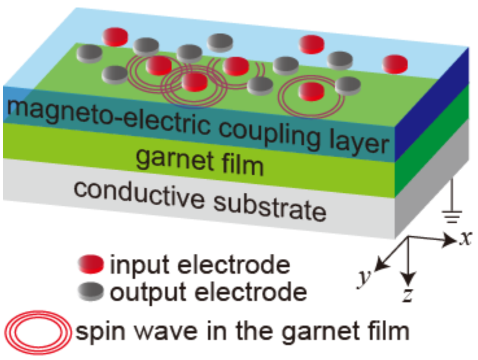
In next-generation internet of things (IoT) era, information processing near/at terminal devices, so-called "edge computing", is necessary to receive the merits of big data by constructing a load distribution network. Since such information processing contains information extraction, compression, and disposal from time-sequential data detected by sensors, it requires machine-learning devices. The most effective edge computing system can be realized if each terminal has an on-chip machine-learning device with high performance and extremely low power consumption.

Reservoir computing is a computational framework which is originally based on recurrent neural networks [1, 2]. A reservoir computing system is composed of a reservoir part and a readout part. In the reservoir part, input time-sequential data are nonlinearly transformed to high-dimensional spatiotemporal signals. In the readout part, the high-dimensional signals generated by the reservoir in response to input sequential data are used for pattern analysis of dynamical features of the input sequential data with a learning process. Notably, recent studies have demonstrated that reservoir computing is technically advantageous for on-chip machine-learning device [3]: Reservoir computing can be realized with nonlinear physical phenomena for the reservoir part and feasible numbers of weights for the readout part. For successful reservoir computing in pattern recognition tasks, it was found that a physical reservoir should satisfy several requirements, such as input history-dependent response, nonlinearity, and fading memory.

Spins in a magnetic material are intrinsically nonvolatile and history-dependent characteristics can be obtained in their distribution and dynamic motions. Thus, the spin system in a ferromagnetic material (or a ferrimagnetic material) has a potential capability for reservoir computing devices. There have been some successful reports on reservoir computing utilizing on-chip spin devices with one input node and one output node, in which time-sequential discrete values in the output were *virtually* used as multiple nodes for computing [4, 5]. However, feasible on-chip reservoir computing devices, which have many *real* inputs/outputs for advanced information processing, have not been proposed or demonstrated since there are some difficulties to overcome, particularly, the wiring explosion problem. To create such devices, on-chip wave-based computing devices are very promising since it requires a small number of wirings [6].

Motivated by these backgrounds, we proposed an on-chip spin-wave-based reservoir computing device with multiple inputs and outputs, as shown in Figure [7], where spin waves are locally excited by the input electrodes, then they transmit through the continuous magnetic garnet film, and finally the resultant spin waves are locally detected by the output electrodes. A notable feature is that nonlinear interference and history-dependent characteristics of spin waves are used as computation, which can be realized by moderately-unstable precession of spins with a vertical magnetic field below 500 Oe that is available in the matured magnetic bubble technology. Utilizing this device as the reservoir part, reservoir computing can be performed by the weighted sum of multiple outputs in the output part. From successful computation using a micromagnetics simulator based on Landau-Lifshits-Gilbert (LLG) equation, we demonstrated that this device works well as a reservoir showing good generalization characteristics applicable to machine-learning information processing.



Spin-wave-based reservoir computing device

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