Reservoir Computing with Spin Waves Propagating via a Continuous Magnetic Film on a Chip

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Summary. Numerical experiments on spin-wave-based reservoir computing (RC) are studied using our on-chip device with a continuous ferrimagnetic yttrium iron garnet (YIG) film. RC is performed with a reservoir output vector extracted from multiple device output signals in response to an input signal that is a time-series 1-GHz cosine carrier wave with 6- or 4-quantized amplitude modulation. In the 10th-order nonlinear autoregressive moving average task and channel equalization task, we achieve high prediction performance comparable to those obtained by RC with optical systems.

Toward drastic advances in Internet-of-Things (IoT) technology, increasing demand is to create on-chip machine-learning devices that allow energy-efficient information processing of time-series data near edges of information networks. Physical reservoir computing (RC) has a high potential for tackling this challenge because it is suitable for temporal data processing and feasible devices are applicable [1]. A successful RC can be achieved through a mechanism that a reservoir with rich physical dynamics nonlinearly transforms a time-series input data to a temporal higher-dimensional output state vector, i.e., a reservoir device generates diverse output signals in response to an input signal. Nonetheless, simple solutions for achieving such function can be hardly found for on-chip devices, since there are many difficulties, such as intractable technical problems in fabricating enormous internal wirings and unestablished device design for multiple output nodes up to a few hundreds. Using virtual nodes and a feedback loop can mitigate strict conditions, but it imposes large overheads, such as high-speed circuits for output signal sampling, as well as possibly causes an unstable operation under a high feedback gain. In addition, since robust, reproducible, and tolerant device characteristics are strongly required for long-term use in practical applications, it is desirable to use a fatigue-tolerant property, e.g., an electron-related quantity. Motivated by these backgrounds, we have studied spin-wave-based RC device and system [2–4].

A magnetic material has spontaneous magnetic moments originating from its electronic structure. Here, such a magnetic moment is called “spin” for simplicity. Spin waves indicate transmission of spin motions, and they have rich dynamical properties including emergent phenomena, such as linear / nonlinear propagation and interference, parametric oscillation, bifurcation, and chaotic behavior, which are caused by dynamical competitions between short-range parallel or antiparallel interactions (spin exchange interactions), common forces acting on each spin (magnetocrystalline anisotropic and external magnetic fields), and long-range antiparallel interactions (magnetic dipole interactions). We proposed an RC system with our spin-wave-based device, as shown in Fig. 1, where we eliminate a top magneto-electric coupling layer and topmost exciter input / detector output electrodes for a conceptual illustration. A notable feature is that a continuous ferrimagnetic yttrium iron garnet (YIG) used as an excitable media allows no interconnections, leading to a feasible structure with many output electrodes. The device operation is as follows. Spin waves are excited through an application of a time-series input voltage to the input electrode at the center of the plane and they propagate toward various directions. The resulting spin motions spatially distributed in the YIG are obtained as time-domain waveforms at output detectors outside the exciter. A key to high computational performance is how to realize diverse output signals through the spatial dynamics.

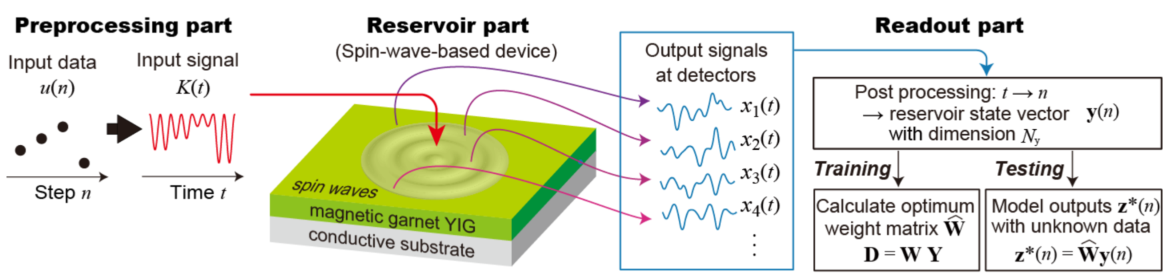

Figure 1． Spin-wave-based reservoir computing system

Numerical experiments on spin waves are performed using a micromagnetic simulator, where a YIG film is 12 μm × 12 μm × 320 nm in volume, material parameters estimated from actual experiments in literatures are adopted, an input exciter at the center of the *x*-*y* plane is 800 nm × 4 μm × 40 nm in volume, and 120 output detectors regularly arranged on the *x*-*y* plane are 200 nm × 200 nm × 40 nm in volume (Fig. 2(a)). To realize spatially-distributed rich dynamics, we used two approaches. The first approach is to use small external magnetic fields $\mu_0 H^{ex}$ = 2, 5, and 8 mT along the *y* direction, under which unstable spin motions leading to nonlinear phenomena are expected. In addition, such $\mu_0 H^{ex}$ values realize stripe magnetic domain structures, as shown in Fig. 2(b), which can enhance multiple reflections during spin-wave propagations. Dynamical properties of the entire YIG film are characterized by the ferromagnetic resonant frequency f_{FMR} and transient relaxation time τ: (in increasing $\mu_0 H^{ex}$ order) f_{FMR} = 0.98, 1.17, and 1.34 GHz and τ = 5.4, 5.3, and 10.7 ns. The second approach is to collect output signals under all the $\mu_0 H^{ex}$ values to construct a temporal reservoir state vector $\mathbf{y}$ with a N_y dimension (N_y = 120, 240, 360). From the $\mu_0 H^{ex}$-dependent properties, it is expected that computational performance is enhanced with increasing N_y.

We perform two time-series benchmark tasks: the 10th-order nonlinear autoregressive moving average (NARMA-10) task and nonlinear channel equalization (NCE) task with signal-to-noise ratio (SNR) 12 – 32 dB. In the preprocessing part, an input signal $K(t)$ corresponding to a time-series magnetic anisotropy in the exciter is prepared, where a sequential 6- or 4-quantized random values $u(n)$ with a time step n (= 1 – 8100) are linearly converted to the amplitude of a 1-GHz cosine carrier wave with the n duration of 2 ns. While $K(t)$ is applied, $x_i(t)$ at the ith detector (i = 1 – 120) is estimated from the averaged vertical z component of spins in each detector (Fig. 2(c)). Then, $\mathbf{y}(n)$ of dimension N_y is generated from $x_i(t)$ through postprocessing with envelope processing, low-pass filtering, and averaging over each time step duration. In a training phase, $\mathbf{y}(n)$ with n = 101 – 5098 are used to form a reservoir state collection matrix $\mathbf{Y}$. Next, an optimum weight matrix $\hat{\mathbf{W}}$ is calculated with a pseudo-inverse matrix of $\mathbf{Y}$ and a teacher collection matrix $\mathbf{D}$ for system outputs. In a testing phase, a system output vector $\mathbf{z}^*(n) = \hat{\mathbf{W}}\mathbf{y}(n)$ is calculated with unknown $u(n)$ in n = 5099 – 8098, and the computational performance is evaluated with normalized mean square error (NMSE) for NARMA-10 and symbol error rate (SER) for NCE.

We find that NMSE and SER decrease as N_y is increased. The results are clear evidence that the collection of diverse output signals efficiently increases the dimensionality of $\mathbf{y}(n)$ (i.e. reservoir-state richness) and thereby contributes to high computational performance. The lowest NMSE = 0.042 at N_y = 360 and SER = ~6×10^{-4} (under SNR = 24 dB) at N_y = 120 (Fig. 2(d)) are comparable to those obtained with optical RC systems and the computational performance is highest among emergent RC discrete devices on a chip. Our spin-wave-based RC system is promising for future practical applications in IoT technology.

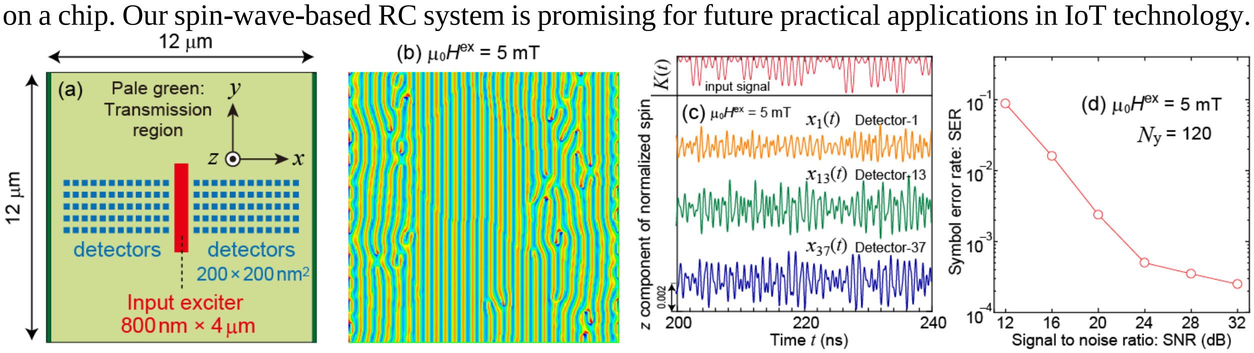

Figure 2. (a) Top-view schematic illustration of a 320-nm-thick YIG film with an input exciter and 120 detectors. (b) Domain structure (the *z* component of normalized spin). (c) Input signal and output signals at three different detectors. (d) Symbol error rate (SER) plotted against signal to noise ratio (SNR) in the nonlinear channel equalization task. (Figs. 2(a) and (b) are reproduced from [4], licensed under CC-BY 4.0.)

References

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