Anticipative Tracking with the Short-Term Synaptic Plasticity of Spintronic Devices

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Real-time tracking of high-speed objects in cognitive tasks is challenging in the present artificial intelligence techniques because the data processing and computation are time-consuming resulting in impulsive time delays. A brain-inspired continuous attractor neural network (CANN) can be used to track quickly moving targets, where the time delays are intrinsically compensated if the dynamical synapses in the network have the short-term plasticity. Here, we show that synapses with short-term depression can be realized by a magnetic tunnel junction, which perfectly reproduces the dynamics of the synaptic weight in a widely applied mathematical model. Then, these dynamical synapses are incorporated into one-dimensional and two-dimensional CANNs, which are demonstrated to have the ability to predict a moving object via micromagnetic simulations. This portable spintronics-based hardware for neuromorphic computing needs no training and is therefore very promising for the tracking technology for moving targets.

I. INTRODUCTION

Neuromorphic computing using artificial neural networks has shown tremendous efficiency in applications, such as pattern recognition [1, 2] and natural language programming [3–5]. These computations usually require a finite processing time and hence bring challenges to those tasks involving a time limit, e.g., tracking objects that are quickly moving. Object tracking has been performed with various algorithms including the correlation filter [6–8] and artificial neural networks [9–11]. Visual object tracking is a basic cognitive ability of animals and human beings. Some particular mechanisms are intrinsically adopted in biological brains [12, 13] to compensate the finite processing time in neural systems. A brain-inspired algorithm is developed to incorporate the delay compensation into a tracking scheme and allow it to predict fast moving objects. It has been implemented based on a special neural network called a continuous attractor neural network (CANN) [14–16], which has been experimentally observed in animals’ brains [17, 18]. Anticipative tracking can be achieved using CANNs with short-term depression (STD) of synaptic efficacy [16], spike frequency adaptation of neurons [19] or negative feedback from a neighboring layer [20].

STD is one of the typical properties of short-term synaptic plasticity and naturally exists in biological neural systems [21]. Because of the depletion of the neurotransmitter at the end of the presynaptic neuron consumed during spikes, the synaptic efficacy becomes weaker than its normal amplitude shortly after spikes and recovers with a time constant τ [22, 23]. This special property of synapses intrinsically introduces a negative feedback into a CANN, which therefore sustains spontaneous traveling waves. If the CANN with negative feedback is driven by a continuously moving input, the resulting network state can lead the external drive at an intrinsic speed of traveling waves larger than that of the external input. Anticipative tracking is therefore achieved [16].

Tracking and predicting a moving object using CANNs does not require the prior identification of the object, indicating that the network captures any moving elements, in contrast to other algorithms such as the correlation filter. The key parameter is the speed of the spontaneous traveling waves, which depends on the decay time of the STD and network parameters and is tunable in practice. In the mean time, the time delay due to signal propagation and information processing can be naturally compensated [16, 24]. Another advantage of CANNs is that training is not needed and the anticipative tracking occurs for a broad range of speeds with the appropriate network parameters. Nevertheless, concerning the realization of high-speed object tracking and portable terminal devices, obstacles arise from the separate storage and computing units in the conventional von Neumann computers. A specialized neuromorphic hardware with an inherent compatibility with CANNs is highly necessary. The recently developed Tianjic chips have integrated many CANNs into their architecture and show the ability to track objects in the application [25]. Unfortunately, there are no dynamical synapses with short-term plasticity: thus, predicting the trajectory of a moving object is not yet possible.

There have already been many attempts to implement
synapses and neurons for some desired functionalities of artificial neural networks with hardware devices including CMOS \cite{26, 27}, memristive \cite{28–31}, spintronic \cite{32–35} and other functional materials \cite{36–44}. The recently developed high-speed cameras can capture up to a million frames per second \cite{45} and therefore require very quick device responses for real-time tracking. The magnetization dynamics in the gigahertz regime and the small time constant $\tau$ of the STD in spintronic devices fulfill these conditions. Moreover, the STD constant $\tau$ can be flexibly tuned by choosing different devices, such as magnetic tunnel junctions (MTJs)\cite{46, 47} or magnetic skyrmions \cite{48}, and/or by applying appropriate external conditions such as an electric current and a magnetic field. In addition, the nonvolatile memory and large endurance ($>10^{15}$) of spintronic devices make them highly suitable for the hardware implementation of artificial neural networks \cite{35, 49}.

In this article, we use the magnetization dynamics of MTJs to realize short-term synaptic plasticity. These dynamical synapses are then plugged into a CANN to achieve anticipative tracking, which is illustrated by micromagnetic simulations. As a proof of concept, we first demonstrate a prediction for a moving signal inside a chain of neurons, the firing rate $r(t)$ of neurons is determined by the external input and the signal received from other neurons. The light-green line is the unidirectional connection, which allows the output of the ith neuron to be transmitted to the jth neuron, as indicated by Eq. (2). (b) The hardware implementation of a synapse consisting of a constant component and a dynamical one with STD. The constant weight $J_{ij}$ is modeled by an electric resistor, and the dynamical synapse $p_i$ is simulated by an MTJ.

\section{II. The Structure of a CANN}

A CANN is a special type of recurrent neural network that has translational invariance. We first use a 1D model as an example to illustrate the structure and functionality of a CANN. As shown in Fig. 1(a), a number of neurons are connected to form a closed chain. We use an angular coordinate $\theta_i$ to describe the neuron positions $x_i = (\cos \theta_i, \sin \theta_i)$, which are uniformly distributed on the unit circle. The ith neuron follows the dynamical equation

$$\tau_s \dot{U}_i(t) = -U_i(t) + I_i(t), \quad (1)$$

where $U_i$ denotes the population-averaged synaptic current to the ith neuron. The second term on the right-hand side $I_i$ is the total input, including the external stimuli $I_i^{ext}$ and the signals transmitted from other neurons, i.e.,

$$I_i(t) = I_i^{ext}(t) + \sum_j J_{ji}p_j(t)r_j(t). \quad (2)$$

The external input has a Gaussian profile, and its center moves inside the network. To avoid the divergence of the network, it is essential to have a global inhibition; here, we consider a normalization of $U_i$ for convenience in the implementation. Specifically, we define

$$u_i(t) = \frac{U_i(t) - \min[U_i(t)]}{\max[U_i(t)] - \min[U_i(t)]}, \quad (3)$$

and the firing rate of the ith neuron is given by $r_i(t) \equiv u_i^2(t)/k$ in Eq. (2). Here, the parameter $k$ denotes the inhibition strength.

The key characteristic of the CANN that we propose is the dynamical synapses; every synapse connects a pair of neurons, as illustrated by the green lines in Fig. 1(a). In Eq. (2), the synaptic efficacy contains two factors, i.e., a constant weight $J_{ji}$ that is only a function of the distance between the ith and jth neurons and a dynamical weight $p_j$ that depends on the neuron dynamics in the recent past. To implement the synapses, we propose the structure sketched in Fig. 1(b), where the constant weight $J_{ij}$ corresponds to a constant electric resistor. Usually, a dimensionless, normalized value is given by

$$J_{ji} = \frac{b}{a} \exp \left[ -\frac{(x_i - x_j)^2}{2a^2} \right], \quad (4)$$

with $b$ and $a$ being the parameters for controlling the strength and range of the synaptic connections, respectively. The dynamical synapses with STD can be realized.
by MTJs, and the driving current density injected into the MTJ depends on the firing rate of the neuron. In the end, the signals transmitted through the electric resistor and through the MTJ are multiplied as the input to the next neuron.

It is worth noting that we focus on synapses in this work and do not consider the particular hardware implementation of the neuron. This is because a CANN without dynamical synapses was realized based on a mixed digital and analogue silicon circuit [50] and in the Tianjic chip [25]. Moreover, as we have demonstrated in an independent work [51], Eq. (1) indicates a decayed dynamics, and this neuron can be replaced by a single MTJ. The precessional period of the MTJ determines the parameter $\tau_s$ in Eq. (1), which is usually required to be two orders of magnitude smaller than the STD time scale $\tau$. We take the limit of $\tau_s \rightarrow 0$ in this work for simplicity.

The eventual performance of the CANN is examined by comparing the instantaneous distributions of the external stimuli $I_i^{ext}(t)$ and the firing rate $r_i(t)$. Both $I_i^{ext}(t)$ and $r_i(t)$ form bump-like distributions and move in the CANN. If the center of $r_i(t)$ moves ahead of the external stimuli, anticipative tracking is achieved. Otherwise, one has delayed tracking.

III. SHORT-TERM PLASTICITY OF MTJS

The distinct feature of a dynamical synapse with STD is the temporarily reduced efficacy right after firing of the associated neuron, which can be gradually recovered over a longer time scale. This dynamical behavior can be found in an MTJ consisting of two thin ferromagnetic layers separated by an insulator. One of the ferromagnetic layers has a fixed magnetization, which is usually pinned by a neighboring antiferromagnetic material via the so-called exchange bias. The magnetization of the other (free) layer can be excited to precess by an electric current via the spin-transfer torque. The precession will not stop immediately after the end of the injected current but will gradually decay due to Gilbert damping. The electrical resistance of the MTJ, which depends on the relative magnetization orientation of the two ferromagnetic layers, therefore exhibits a temporary variation after the excitation. Then, we can implement the STD with the dynamics of MTJs by taking the injected electric current and electric resistance as the input and output, respectively.

Here, we consider a cylindrical CoFeB/MgO/CoFeB MTJ with a radius of 20 nm [52], as schematically shown in Fig. 2(a), where the free layer, insulating layer and fixed layer are stacked from top to bottom. The thicknesses of the free and insulating layers are 2 nm and 1.1 nm, respectively [52]. The fixed layer has a perpendicular magnetization along $+z$, and the free layer has a spin vortex, with the magnetization of the vortex core oriented along the $+z$ direction. For CoFeB, we choose the following material parameters: the saturation magnetization $M_s = 10^6$ A/m, exchange stiffness $A = 2 \times 10^{-11}$ J/m [53], and Gilbert damping $\alpha = 3 \times 10^{-4}$.

In the presence of an electric current density $j$ through the MTJ, the magnetization of the free layer is excited to precess following the generalized Landau-Lifshitz-Gilbert equation [54–56].

$$\dot{m} = -\gamma m \times H_{eff} + \alpha m \times \dot{m} + \tau_i m \times m_p \times m - \beta \tau m \times m_p.$$  

(5)

Here, $m$ is the local magnetization direction in the free layer, and $H_{eff}$ is the effective magnetic field, including the exchange, anisotropy and demagnetization fields, as well as an external magnetic field $B_{ext} = 0.5$ T along the $+z$ axis to stabilize the precession. The last two terms in Eq. (5) are the adiabatic and nonadiabatic spin-transfer torques, respectively, where $m_p$ denotes the magnetization direction of the fixed magnetic layer and the magnitude of the torque $\tau = (\gamma hP/\mu_0eM_s) j$ depends on the current polarization $P$, the current density $j$, the saturation magnetization $M_s$ and the free-layer thickness $t$. The Slonczewski parameter $\epsilon = \Lambda^2/((\Lambda^2+1)+\Lambda^2-1)m \cdot m_p$ characterizes the angular dependence of the torque with the dimensionless parameter $0 \leq \Lambda \leq 1$. $\beta$ is the nonadiabaticity of the spin-transfer torque and is usually much smaller than one. The dynamic equation (5) is solved numerically using the micromagnetic simulation program MuMax3 [57], and the free magnetic layer is discretized into a $10 \times 10 \times 1$ grid.
We apply the Julliere formula to estimate the tunneling magnetoresistance ratio
\[ \text{TMR} = \frac{2P_{\text{free}}P_{\text{fixed}}}{1 - P_{\text{free}}P_{\text{fixed}}}, \]
where \( P_{\text{free}} \) and \( P_{\text{fixed}} \), representing the spin polarization of the free and fixed layers, respectively, are both set to 0.6 for CoFeB. The resistance \( R \) of the MTJ is determined by the instantaneous magnetization \( \mathbf{m} \) of the free layer [58]:
\[ R(\mathbf{m}) = \frac{R_p}{2} \left[ 1 + \text{TMR} - \text{TMR}(\mathbf{m} \cdot \mathbf{m}_p) \right], \]
and the resistance of the MTJ for the parallel configuration \( R_p = 71.6 \text{ k}\Omega \) [59].

Note that \( R \) depends not only on the instantaneous current density but also on its historically recent dynamics. As plotted in Fig. 2(b), a steady oscillatory state is found for a current density \( 4 \times 10^7 \text{ A/m}^2 \) at \( t \leq 20 \text{ ns} \). Then, the current density is increased to \( 8 \times 10^7 \text{ A/m}^2 \) for the next 10 ns and returns to \( 4 \times 10^7 \text{ A/m}^2 \) afterwards. It can be seen that the electric resistance of the MTJ gradually increases or decreases in an oscillatory way due to the change in \( j \) before reaching the corresponding steady state. Here, we take the average resistance \( \bar{R} \) as the weight of the dynamical synapses, while the high-frequency oscillations can technically be filtered. \( \bar{R} \) at the steady states is plotted in Fig. 2(c) as a function of input current density \( j \), and we restrict \( j \) in this work to the range from \( j_{\text{min}} = 4 \times 10^7 \text{ A/m}^2 \) to \( j_{\text{max}} = 8 \times 10^7 \text{ A/m}^2 \), resulting in \( \bar{R}_{\text{min}} = 92.5 \text{ k}\Omega \) and \( \bar{R}_{\text{max}} = 93.1 \text{ k}\Omega \).

To explicitly examine the STD behavior, we artificially apply a time-dependent current density, as shown in Fig. 3(a), to mimic a piecewise firing rate of a single neuron that has influence on the variable weight of the dynamic synapse. Then, the calculated \( \bar{R} \) of the MTJ is plotted in Fig. 3(b), which shows the short-term memory effect. As the current density changes, the resistance gradually varies towards the value for the steady state. Then, we define a dimensionless synaptic efficacy that is associated with a specific neuron as
\[ p(t) \equiv \frac{[\bar{R}_{\text{max}} - \bar{R}(t)]/[\bar{R}_{\text{max}} - \bar{R}_{\text{min}}]} \]
and show \( p \) in Fig. 3(c) as a function of time. When the current density changes, indicating a differing firing rate, the synaptic efficacy \( p \) exhibits an exponential variation corresponding to a short-term memory effect.

Usually, the dynamical synapse with STD is described by the following differential equation:
\[ \tau \dot{p}(t) = 1 - p(t) - \tilde{\eta}\dot{p}(t)r(t), \]
where \( \tau \) is the time scale of the STD and the parameter \( \tilde{\eta} \) determines the strength of the STD in the synaptic efficacy. For the piecewise firing rate shown by the blue dashed line in Fig. 3(c), one can solve Eq. (9) analytically and obtain \( p(t) \), plotted as the empty circles. Here, we take the parameters \( \tau = 25 \text{ ns} \) and \( \tilde{\eta} = 0.79 \). The perfect agreement between the efficacy with the MTJ and the solution of Eq. (9) demonstrates that the dynamic synapses with STD can be realized very well using MTJs.

**IV. ANTICIPATIVE TRACKING WITH DYNAMICAL SYNAPSES**

Since we have demonstrated that dynamic synapses with STD can be realized by MTJs, it is possible to implement hardware CANNs to perform the anticipative tracking of moving objects. In this section, two examples are illustrated to show the capability of CANNs with MTJs as the functional dynamic synapses. We first consider a 1D model system with twenty neurons forming a closed chain, as shown in Fig. 1(a), where a signal with a Gaussian distribution is moving around. In this model system, we show how anticipative tracking is achieved and discuss the influence of network parameters. Then, we consider a moving tennis ball in a video and use a 2D CANN with arrays of MTJs to predict the motion of the ball.
The current density injected into the MTJs depends on the firing rate of the corresponding neuron $r_i$ and is explicitly computed by

$$j_i(t) = j_{\text{max}} - \frac{2}{\pi} \arctan(\eta r_i(t)) (j_{\text{max}} - j_{\text{min}}).$$

Here, $j_{\text{max}} = 2j_{\text{min}} = 8 \times 10^7$ A/m$^2$ is defined, and the parameter $\eta = 0.8$ for controlling the STD strength. Then, we apply an external stimuli with a Gaussian distribution in the 1D CANN to simulate the received signal of a moving object:

$$I_{\text{ext}}(t) = A \exp \left[ -\frac{(\theta_1 - \omega_{\text{ext}} t)^2}{a^2} \right],$$

where $A = 0.5$ is the amplitude of the external pulse and $\omega_{\text{ext}} = 0.003$ rad/ns is the angular velocity of the external signal.

Owing to the STD effect, the CANN sustains traveling waves that are propagating in the network. As a consequence, the bump of the firing rate moves ahead of the external signal, indicating that anticipative tracking is achieved. Figure 4 shows the firing rate of the 1D CANN as a response to a moving external signal. At the initial stage, e.g., $t = 40$ ns, the firing rate of the neurons already forms a bump-like response to the external stimuli, and the firing rate (blue line) is slightly delayed compared with the right-going external signal (red line). At $t = 440$ ns, the firing-rate distribution is already ahead of the external signal. Afterward, the firing rate is always in the lead and remains steady. The anticipative tracking can be clearly seen in Fig. 4(f), where the central positions of the firing rate and the external signal are plotted as a function of time. The central position of the external signal is a straight line due to the constant $\omega_{\text{ext}}$. The firing rate exhibits a slight delay in the first 0.07 $\mu$s but catches up with the external signal within the first 0.1 $\mu$s. The leading distance has a minor oscillation in the initial stage and becomes steady after 0.5 $\mu$s. If we artificially remove the MTJs from the network, i.e., the STD effect does not exist and $p \equiv 1$, the firing rate of the 1D CANN will be as plotted by the green dashed line in Fig. 4(a)–(e). Then, the bump of the firing rate always has a finite delay relative to the external signal. We note that the external signal moves only towards the right (counterclockwise) in Fig. 4. If the signal abruptly changes its moving direction, the response of the CANN can follow the updated moving direction and quickly achieve anticipative tracking again. The dynamic process is explicitly shown in the Supplemental Material [60].

The global inhibition strength $k$ and the STD strength $\eta$ are two key parameters that influence the performance of the 1D CANN. In the above computation, we use fixed values $k = 1$ and $\eta = 0.8$. We now examine the prediction functionality of the 1D CANN for a constant $\omega_{\text{ext}} = 0.005$ rad/ns and vary the two parameters in a broad range from $0.2 \leq k \leq 1.8$ to $5 \leq \eta \leq 50$. The phase diagram of the CANN is shown in Fig. 5.

### 1D model

We first construct a 1D CANN consisting of twenty neurons that are uniformly distributed in the unit circle, as shown in Fig. 1(a). Then, the constant connection Eq. (4) is simplified as $J_{ji} = \frac{(b/a) \exp(2 \cos(|\theta_j - \theta_i|/2)/a^2)}{2}$, with $a = 0.5$ and $b = 1.27$. The current density injected into the MTJs depends on the firing rate of the corresponding neuron $r_i$ and is explicitly computed by

$$j_i(t) = j_{\text{max}} - \frac{2}{\pi} \arctan(\eta r_i(t)) (j_{\text{max}} - j_{\text{min}}).$$

Here, $j_{\text{max}} = 2j_{\text{min}} = 8 \times 10^7$ A/m$^2$ is defined, and the parameter $\eta = 0.8$ for controlling the STD strength. Then, we apply an external stimuli with a Gaussian distribution in the 1D CANN to simulate the received signal of a moving object:

$$I_{\text{ext}}(t) = A \exp \left[ -\frac{(\theta_1 - \omega_{\text{ext}} t)^2}{a^2} \right],$$

where $A = 0.5$ is the amplitude of the external pulse and $\omega_{\text{ext}} = 0.003$ rad/ns is the angular velocity of the external signal.

Owing to the STD effect, the CANN sustains traveling waves that are propagating in the network. As a consequence, the bump of the firing rate moves ahead of the external signal, indicating that anticipative tracking is achieved. Figure 4 shows the firing rate of the 1D CANN as a response to a moving external signal. At the initial stage, e.g., $t = 40$ ns, the firing rate of the neurons already forms a bump-like response to the external stimuli, and the firing rate (blue line) is slightly delayed compared with the right-going external signal (red line). At $t = 440$ ns, the firing-rate distribution is already ahead of the external signal. Afterward, the firing rate is always in the lead and remains steady. The anticipative tracking can be clearly seen in Fig. 4(f), where the central positions of the firing rate and the external signal are plotted as a function of time. The central position of the external signal is a straight line due to the constant $\omega_{\text{ext}}$. The firing rate exhibits a slight delay in the first 0.07 $\mu$s but catches up with the external signal within the first 0.1 $\mu$s. The leading distance has a minor oscillation in the initial stage and becomes steady after 0.5 $\mu$s. If we artificially remove the MTJs from the network, i.e., the STD effect does not exist and $p \equiv 1$, the firing rate of the 1D CANN will be as plotted by the green dashed line in Fig. 4(a)–(e). Then, the bump of the firing rate always has a finite delay relative to the external signal. We note that the external signal moves only towards the right (counterclockwise) in Fig. 4. If the signal abruptly changes its moving direction, the response of the CANN can follow the updated moving direction and quickly achieve anticipative tracking again. The dynamic process is explicitly shown in the Supplemental Material [60].

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FIG. 5. The phase diagram of the 1D CANN. The graph shows the tracking performance of the network achieved by varying the STD strength $\eta$ and the inhibition strength $k$. It is examined by comparing the central positions of the firing rate bump and the external signal at $t = 80$ ns. The external signal moves with a constant angular velocity $\omega_{\text{ext}} = 0.005$ rad/ns.

every $k$, there is a boundary for $\eta$, below which anticipative tracking can be realized. This is because a smaller $\eta$ in Eq. (10) results in a larger current density $j$ and hence a stronger STD. The boundary of the delayed and anticipative tracking exhibits a weak, nonmonotonic dependence on $k$, indicating the presence of a wide range of parameters to realize anticipative tracking.

B. Tracking a moving ball in a video

The 1D CANN presented above is only a simplified model for demonstrating how a CANN combined with STD works in the prediction of a moving object. Here, we switch to a realistic case, where a moving object is recorded in a video. A 2D CANN is then considered, with arrays of neurons associated with MTJs in a square lattice. The particular process is schematically shown in Fig. 6(a)–(c). A video is taken by a cell phone, in which a table tennis ball is rolling on the ground and 60 frames are extracted to examine the prediction of the ball motion using the 2D CANN. The resolution of the original video is $N_{GW} \times N_{GH} = 544 \times 960$ pixels, as shown in Fig. 6(a). We first integrate every $32 \times 32$ pixels of the video as one element of the external signal, and every frame is therefore converted into an $N_{W} \times N_{H} = 17 \times 30$ matrix; see Fig. 6(b). To avoid artifacts due to the boundary, we apply 5 additional rows or columns of neurons to every side of the frame until the number of neurons in the 2D CANN $N_{NW} \times N_{NH} = 27 \times 40$. The constant connection is given in Eq. (4), with $a = 35$ and $b = 0.24$, and the global inhibition strength $k$ is set as 0.11. The dynamical synapses are realized by the same MTJs used in the 1D CANN and for $\eta = 5$. Without involving complex signal processing, we simply define the external signal using its color in the corresponding pixels. Specifically, the external input is set as 0.8 for the position of the orange ball and 0 otherwise. Then, the input for every frame is transferred into the 2D CANN for a period of 4 ns, which is an unrealistically fast speed of the moving target. This is done to match the short time scale of the STD using the particular MTJs because of the limited computational power for the micromagnetic simulations in practice. The predicted moving direction is determined by the maximum firing-rate location of the 1128 neurons, which is marked
by a red circle in every frame. We take the predicted position for a few frames and plot the red circles in Fig. 6(d). These circles closely follow the white dashed line, which denotes the real rolling trajectory of the table tennis ball. The successful tracking result is shown in an animation in graphics interchange format in the Supplemental Material [60].

V. CONCLUSIONS

We have demonstrated using a micromagnetic simulation that magnetic tunnel junctions can be used as the hardware of dynamic synapses, which have short-term synaptic plasticity. Continuous attractor neural networks with MTJ-based dynamical synapses are shown to have the ability to anticipatively track high-speed moving objects. A 1D CANN consisting of twenty neuron is used to illustrate in detail how the dynamical synapses are implemented and contribute to the modulation of the firing rates of neurons. The latter is used to predict the position of a moving signal. In a realistic example, we show that a rolling table tennis ball in a video can be tracked and its motion predicted using a 2D CANN including 27 × 40 neurons, where every neuron is associated with an MTJ.

The demonstration of the MTJ-based dynamical synapses significantly expands the promising and powerful functionality of spintronic devices for neuromorphic computing [35, 61] to process high-speed dynamical information. Moreover, the simple implementation with no need for training makes this proposal very attractive in application. In addition, this work can be used to guide the hardware implementation of neuromorphic chips using other materials. For example, the short-term synaptic plasticity has been discovered in resistive, ferroelectric and even 2D van der Waals layered materials [38–44], which can be equally good candidates for developing CANN hardware with the capability of anticipative tracking.

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