Design of Spintronics-based Neuronal and Synaptic Devices for Spiking Neural Network Circuits

(Invited Paper)

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Abstract—Topologically stable magnetic skyrmion has a much lower depinning current density that may be useful for memory as well as neuromorphic computing. However, skyrmion-based devices suffer from the Magnus force originating from the skyrmion Hall effect, which may result in unwanted skyrmion annihilation if the magnitude of the driving current gets too large. A design of an artificial neuron and a synapse using a synthetic antiferromagnetically coupled bilayer device, which nullifies the Magnus force, is demonstrated in this work. The leak term in the artificial leaky integrate-and-fire neuron is achieved by engineering the uniaxial anisotropy profile of the neuronal device. The synaptic device has a similar structure as the neuronal device but has a constant uniaxial anisotropy. The synaptic device also has a linear and symmetric weight update, which is a highly desirable trait of an artificial synapse. Our simulation results show the energy required to perform such operation in DW or skyrmion-based devices is on the order of a few fJ.

Index Terms—spiking neuron, synapse, magnetic domain wall, magnetic skyrmion

I. INTRODUCTION

Brain-inspired neuromorphic computing has emerged as one of the promising approaches that can perform cognitive tasks [1], [2] with human-like accuracy. Neurons and synapses are the two key components in a biological spiking neural network (SNN) in which billions of neurons are interconnected via trillions of synapses. Information in an SNN propagates in the form of a spike that is transmitted from one neuron (pre-neuron) to the next neuron (post-neuron) connected via a synapse—the spikes get modified by the synaptic weight during this process. The schematic of a simple SNN consisting of two neurons that are connected by synapses is shown in Fig. 1. When the pre-neuron (Neuron1) fires a spike, the synapse modifies the spike with its synaptic weight before forwarding it to the post-neuron (Neuron2).

Among various emerging devices (e.g., resistive memory [3], [4] and phase-change memory [5], [6]), spintronics [7]–[10] is arguably the most promising technology due to its non-volatile nature, low power consumption, ultrafast dynamics, higher endurance, and stochastic nature [11]–[13]. Magnetic domain wall (DW) [14], [15] and skyrmion-based devices [16], [17] are the most popular among various other spintronics devices. Among these two, skyrmion-based devices are promising due to their topological stability (implies robustness against defects) and lower depinning current density (implies lower power consumption) compared to magnetic domain wall-based devices. However, skyrmion-based devices have limitations due to the Magnus force [18], [19], which acts perpendicular to the direction of the injected current. Consequently, the skyrmion moves along a resultant direction determined by spin-torque due to injection current and the Magnus force. The magnitude of the Magnus force is directly proportional to the velocity of the skyrmion, which is proportional to the magnitude of the injected current density. If the magnitude of the injected spin current is too large, the Magnus force may be large enough to annihilate the skyrmion at the nanotrack edge during its motion, which limits the utility of skyrmions for high-speed applications.

To drive the DW/skyrmion in a nanotrack, a spin current is needed, which can be injected either by (i) current-in-plane (CIP) or (ii) current-perpendicular-to-plane (CPP) scheme. CPP scheme stands out to be more
energy efficient compared to CIP, due to the lower current density needed to drive the DW/skyrmion. Elimination of the Magnus force in a skyrmion-based device was demonstrated using the CIP scheme in Ref. [20], through micromagnetic simulation, with the condition that the non-adiabatic spin-transfer-torque factor, $\beta$, needs to be exactly equal to the Gilbert damping constant, $\alpha$. Hence, this method is sensitive to the material parameter and any mismatch can introduce the undesired Magnus force.

Alternatively, a bilayer device where the magnetization of two ferromagnet (FM) layers are coupled via an antiferromagnetically (AFM) exchange coupling may be promising for eliminating the Magnus force. The Magnus force can be completely nullified if the coupling constant between the magnetic layers is sufficiently large [21]. In this work, we use micromagnetic simulations to demonstrate how this bilayer device can be designed to be neuronal and synaptic devices. The design of neuronal and synaptic devices using DW motion in a traditional monolayer structure is also presented and compared with the skyrmionic device.

II. DEVICE STRUCTURE

The bilayer system consists of a heavy metal (HM)/FM/insulator (I)/FM stack shown in Fig. 2(a). The FM layer adjacent to HM is the bottom layer (BL) whereas the topmost FM layer is the top layer (TL). Due to the spin-Hall effect, charge current injected through the HM layer generates a spin-current that is spin-polarized along the $-z$-direction and flows in the $z$-direction into the BL to drive the motion of any DW or skyrmion in it. The HM layer also gives rise to the Dzyaloshinskii-Moriya interaction (DMI) that stabilizes the skyrmion in the device. Both TL and BL are designed with perpendicular magnetic anisotropy (PMA) and their magnetizations are coupled by AFM exchange interaction. In the following, the initial magnetizations of TL and BL are assumed to be along $+z$ and $-z$ direction, respectively.

Assume the size of both TL and BL layers in Fig. 2(a) is $260 \text{ nm} \times 50 \text{ nm} \times 1 \text{ nm}$ in the following discussion. The membrane potential in the leaky integrate-and-fire (LIF) neuron device implemented using the bilayer structure in Fig. 2(a) is represented by the position of a skyrmion-pair along the length of the device. Local injection of a $5 \times 10^{14} \text{ A/m}^2$ current pulse that is spin-polarized along the $-z$-direction can nucleate a skyrmion at the desired location of TL. The magnetization of the core of the nucleated skyrmion points in the $-z$-direction. As shown in Fig. 2(b), another skyrmion with opposite magnetization to that in TL is simultaneously nucleated in BL simultaneously due to the AFM coupling. Input spikes that are integrated by the device are in the form of current pulses that are injected along the length of the device, which moves the skyrmion-pair.

The leak term in the neuron device may be achieved by implementing a gradient in the uniaxial anisotropy constant, $K_u$, along the length of the BL. On the other hand, the TL has a uniform $K_u$ as shown in Fig. 3(a). To validate the integration and leak functionalities, we test the device in the following way. A skyrmion-pair in the TL and BL is initially nucleated at $x=50 \text{ nm}$. A uniform $30 \times 10^{10} \text{ A/m}^2$ charge current density is next applied in the HM along the $+x$-direction, which moves the skyrmions in TL and BL in unison. The position of the skyrmion center in the TL versus time is plotted as the green curve in Fig. 3(b). The skyrmion in the BL has the same behavior due to the AFM coupling. Thus, the position of the skyrmion appears as the time-integral of the injected current and the integration functionality of the proposed neuron device is verified.

Next, consider when the skyrmion-pair is initially at $x=215 \text{ nm}$ and no charge current flows through the device. Notice that, as shown by the red color plot in Fig. 3(b), the skyrmion in BL moves gradually along the $-x$-direction due to the $K_u$ gradient. Due to AFM coupling, the skyrmion in TL moves in unison with that in BL. After 23 ns, the skyrmion stops at $x=25 \text{ nm}$ due to the edge repulsion. This behavior of the skyrmion resembles the leak functionality of neuron.

On the other hand, synaptic devices should behave like a non-volatile memory devices. This can be achieved...
in the same bilayer device as the neuron if the $K_u$ is uniform along the device in both TL and BL. The synapse emulates different weight values to modulate the signal transmission from the pre-neuron to the post-neuron. Multiple values of the synaptic weight is achieved in a device having multiple conductance levels. These conductance levels can be achieved using multiple skyrmions in the device. With the application of different current pulses, the skyrmions can be moved between the two sides of the device, which changes the conductance of the detector arising from the magnetoresistance effect.

To demonstrate this, consider if three skyrmions are initially on the left half of a bilayer device and the detector is placed on the other half as can be seen from Fig. 4(a). When current pulses are applied, these skyrmions enter the detector area one by one, which changes the conductance of that area. The variation of the conductance in normalized scale, denoted by $G_{\text{norm}}$, with the number of skyrmions under the detector area is plotted in Fig. 4(b) that shows a linear relationship. Thus, the number of skyrmions under the detector area may be used to represent different weight values in the synapse to modulate the neuronal spikes.

A. Domain-wall (DW) based devices

Magnetic DW based devices do not suffer from the Magnus force issue and thus, a conventional monolayer structure may be used to implement these neuronal and synaptic devices. Consider the structure shown in Fig. 5, which consists of a single FM layer with PMA and is attached to a HM layer. In the neuron device, the membrane potential is represented by the position of the DW based skyrmion and domain wall-based neuron devices are described in Section I. Here, the performance of the skyrmion and domain wall-based neuron devices are explained.

First, consider the skyrmion-based neuron device. The membrane potential of the neuron is represented by the position of the skyrmion core in TL. The firing of the neuron occurs when the skyrmion reaches near the right end of the device, which may be sensed by a change of the local magnetoresistance measured using a detector based on the magnetic tunnel junction (MTJ). To achieve the leaky behavior, a $K_u$ gradient described by $K_u(x) = K_u + x\Delta K_u$ where $\Delta K_u=1.538 \text{ GJ/m}^3$, $K_u=0.6 \text{ MJ/m}^3$, and $x$ is the position along the length of the nanotrack, is engineered into BL. The $K_u$ of TL is at a constant value along its length.

Now, consider that the skyrmion was nucleated at $x=40 \text{ nm}$ and the detector is placed at $x=230 \text{ nm}$, as shown by the schematic in Fig. 6(a). A square current density pulse ($J=30 \times 10^{10} \text{ A/m}^2$) having 0.5 ns pulse width and 1 ns period is applied along the $+x$-direction to drive the skyrmion as shown by the green color plot in Fig. 6(b). During the high state of the applied pulse, the skyrmion moves in the $+x$-direction. During the low state, the skyrmion moves in the $-x$-direction due to the $K_u$ gradient. The motion of the skyrmion is demonstrated by the blue graph of the skyrmion position.

III. RESULTS AND DISCUSSION

Magnetization dynamics in FM layers is simulated in the Object Oriented MicroMagnetic Framework (OOMMF) [22] with the DMI extension module [23]. In all our simulations, the simulation volume is discretized into $2 \text{ nm} \times 2 \text{ nm} \times 1 \text{ nm}$ cells. The material parameters assumed are those for Co/Pt system [16], [21].

A. Demonstration of neuron device

The integration and leak functionality of a bilayer-based skyrmionic neuron device has already been described in Section I. Here, the performance of the skyrmion and domain wall-based neuron devices are explained.

To achieve the leaky behavior, a $K_u$ gradient described by $K_u(x) = K_u + x\Delta K_u$ where $\Delta K_u=1.538 \text{ GJ/m}^3$, $K_u=0.6 \text{ MJ/m}^3$, and $x$ is the position along the length of the nanotrack, is engineered into BL. The $K_u$ of TL is at a constant value along its length.

Now, consider that the skyrmion was nucleated at $x=40 \text{ nm}$ and the detector is placed at $x=230 \text{ nm}$, as shown by the schematic in Fig. 6(a). A square current density pulse ($J=30 \times 10^{10} \text{ A/m}^2$) having 0.5 ns pulse width and 1 ns period is applied along the $+x$-direction to drive the skyrmion as shown by the green color plot in Fig. 6(b). During the high state of the applied pulse, the skyrmion moves in the $+x$-direction. During the low state, the skyrmion moves in the $-x$-direction due to the $K_u$ gradient. The motion of the skyrmion is demonstrated by the blue graph of the skyrmion position.
versus time in Fig. 6(b). Once the skyrmion reaches under the detector (at 7 ns), the neuron fires and a reset circuitry (not shown) is triggered to activate a reset 60 $\times 10^{10}$ A/m$^2$ current pulse that resets the skyrmion to its initial position. This reset pulse is applied for 1 ns, shown in Fig. 6(a), which moves the skyrmion along $-x$-direction as shown in Fig. 6(b) (between 7 ns and 8 ns). The energy consumption to move the skyrmions in the nanotrack may be calculated as,

$$E = \rho_{HM} L_{HM} A_{HM} J^2 t_{\text{delay}}$$

where $\rho_{HM} = 100 \mu\Omega - \text{cm}$ is the resistivity of the HM [24]. $L_{HM}$, $A_{HM}$, $J$, and $t_{\text{delay}}$ are the length (along the $x$-axis), cross-sectional area (in the $yz$-plane) of the HM layer, current density, and time delay to move the skyrmion. The energy required for the rest-to-fire-to-reset operation of this neuron is 8.775 fJ.

Next, consider the neuron operation in a DW-based device shown in Fig. 5(a). Unlike the skyrmion-based device, the lateral dimension of the DW-based neuron device is 512 nm $\times$ 32 nm and the thickness of the FM layer is 1 nm. A similar $K_u$ gradient along the length of the device as shown in Fig. 7(a) is engineered into the FM to achieve the leak functionality. For driving the DW, a square charge current pulse ($J = 10 \times 10^{10}$ A/m$^2$) with a period of 1 ns and pulse width of 0.5 ns is injected into the HM as shown by the green plot in Fig. 7(a).

The plot of the current pulse train as the input stimulus is injected into the HM layer, along with the reset current after the neuron fires shown by the green plot, and variation of the DW position due to this current is shown in the blue curve.

B. Demonstration of synapse device

For the skyrmion-based synapse device, consider a bilayer device shown in Fig. 4(a) with lateral dimensions of 1000 nm $\times$ 50 nm, and the thicknesses of both TL and BL layers are 1 nm. As there is no need for the leaky behavior, both TL and BL have a constant $K_u$ value of 0.8 MJ/m$^3$. The TL nanotrack is further divided into two equal halves, where seven skyrmions are nucleated at equidistant on the left half. An MTJ-like detector is on the right half, we place an MTJ like a detector. The operation of the synaptic device is validated by applying a train of the square current pulse into the HM. The magnitude of the current pulse is $30 \times 10^{10}$ A/m$^2$, with a time-period of 1.5 ns and pulse width 0.75 ns.

The long term potentiation (LTP) operation is achieved by injecting the square current pulses in $+x$-direction whereas the long term depression (LTD) is achieved by reversing the direction of current flow. The applied current density ($J$) for the LTP and LTD operation is shown in Fig. 8(a). Individual $J$ pulse applied during the LTP operation moves the skyrmions one-by-one from the left half into the detector placed at the right half.

Fig. 6. (a) Schematic 3D-view of skyrmion-based neuron device. (b) Variation of the applied input current density (green) and corresponding skyrmion position (blue) along nanotrack length with time.

Fig. 7. (a) $K_u$ profile in the FM layer for the monolayer device. (b) The plot of the current pulse train as the input stimulus is injected into the HM layer, along with the reset current after the neuron fires shown by the green plot, and variation of the DW position due to this current is shown in the blue curve.

Fig. 8. (a) Plot for current density pulse train with time given as an input to a synaptic device. (b) The plot of $G_{\text{norm}}$ vs. pulse numbers during LTP and LTD.
of the device. As the skyrmions move into the detector area, the conductance of the detector starts to increase which is shown in Fig. 8(b) by the plot of the normalized conductance, $G_{\text{norm}}$ of the detector versus the number of pulses applied during the LTP operation. The eight discrete $G_{\text{norm}}$ values marked by black asterisks in Fig. 8(b) present the possible synaptic weight for the modulation of the neuron spikes. These eight weights represent different conductance values since the number of skyrmions in the detector area can vary from 0 to 7. When all seven skyrmions are in the detector area, the weight/conductance attains a maximum value of 1 (normalized scale). Further pulse current does not increase the conductance as can be seen from the same $G_{\text{norm}}$ value at pulse number 9 and 10 in Fig. 8(b).

During the LTD operation, the skyrmions in the detector area go back to the left half one-by-one in a similar fashion, which reduces the conductance of the detector area as can be seen from Fig. 8(b). Our simulation results show a total of 6 ns is required to complete the entire LTP or LTD operation. This generates highly linear and symmetric weight update characteristics (Fig. 8(b)), which is a highly desirable condition for an artificial synapse. Using Eq. (1), the energy required to fully change the synaptic weights of our proposed device from minimum to maximum is 0.36 fJ. Since there are a total of seven skyrmions in TL, the average energy required to adjust the synaptic weight is 3.587 fJ/unit.

Now consider the DW-based synaptic device shown in Fig. 5(b). Like the previous DW-based neuron device, the lateral size of the synaptic device is 512 nm $\times$ 32 nm, and the thickness of the FM layer is 1 nm. Unlike, the skyrmion-based synapse device, the detector spans from $x=40$ nm to the rest of the device along its length. A square current density pulse train with time-period, pulse width, and magnitude of 1 ns, 0.5 ns, and $5 \times 10^{10}$ A/m$^2$, respectively, is injected into HM. The current is injected for the first 18 ns along the $+x$-direction to perform the LTP operation and then in the reverse direction for another 18 ns for the LTD operation. The variation of the injected current density with time for the entire operation is plotted in Fig. 9(a). The initial position of the DW is just outside the detector area. With the injection of the current pulses during LTP, DW starts to move in the $+x$-direction. As the DW enters the detector area and moves farther in, the conductance of the detector increases as can be seen in the graph of the normalized conductance, $G_{\text{norm}}$ versus the current pulse number in Fig. 9(b). During LTD, the DW moves in the opposite direction and thus, the conductance of the detector starts to decrease as can be seen from Fig. 9(b). The results in Fig. 9(b) show that the weight update during LTP and LTD, is linear in nature and also highly symmetric. A total of 19 unique conductance states is achieved by different DW positions driven by the injected current. The energy consumed to fully change the synaptic weights of this device from minimum to maximum is 0.36 fJ, which translates to an average of 0.02 fJ/unit.

A comparison of the neuron and synapse devices studied in this work is shown in Table I. These results show that DW-based device has advantages in lower energy consumption and the same device geometry may be used as a neuron and synapse with just a modification in the $K_u$ profile. The lower energy consumption is because the current needed to drive the DW motion is 10% of that needed in the skyrmionic devices. Both the skyrmionic and DW-based synapses produce highly symmetrical and linear weight update characteristics, which is one of the key requirements for an artificial synapse. However, the number of conductance states is higher in the DW-based synaptic device as compared to its skyrmionic counterpart, in which the number of conducting states depends on the number of available skyrmions. It can be anticipated that the DW-based synapse emulates SNNs with 4-bit weights, which can lead to improved inference accuracy as compared to 3-bit weights in the skyrmionic synapse. Also, due to the active repulsion force between the skyrmions, a longer device is required to accommodate the large number of skyrmions needed for the number of conducting states.

| Technology | Device | Lateral Dimension | Net Energy |
|------------|--------|-------------------|------------|
| Skyrmion   | Neuron | 260 $\times$ 30 nm$^2$ | 8.775 fJ  |
| Synapse    | 50 nm  | 1.25 fJ           |
| DW         | Neuron | 512 $\times$ 32 nm$^2$ | 0.36 fJ   |
| Synapse    | 512 $\times$ 32 nm$^2$ | 1.25 fJ           |
In summary, spintronics neuron and synapse device concepts using skyrmion and DW were investigated. For the neuron devices, the membrane potential is represented by the position of the skyrmion or the DW, whereas the synaptic weight is determined by the number of conductance states in a detector area of the synapse device. Between DW and skyrmion devices, DW-based devices seem more advantageous as it consumes 86% and 97% less energy for the neuron and synapse devices respectively. These impressive advantages in energy consumption stem from the 9× larger current needed for skyrmion motion as compared to DW motion.

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