Neuromorphic computing based on an antiferromagnet-heavy metal hybrid structure under the action of laser pulses

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Abstract. The paper proposes a model of a neuromorphic processor, consisting of excitatory and processing neurons that are oscillators and detectors. The concept of neuromorphic computing, implemented by generating a spin current due to optical excitation of magnetic oscillations in an antiferromagnet is considered. The inverse spin Hall effect causes the generation of an electric current in the heavy metal layer. A constant driving current flows through the common bus. Magnetic oscillations in the receiving neuron occur due to the spin Hall effect. A biaxial nickel oxide crystal was used as a material for the base cells of AFM insulators and platinum was utilized as a heavy metal. The use of optical excitation can significantly increase the processing speed of neuromorphic computing with low power consumption. The presented model implements the simplest operations of neuromorphic computations, such as logical “OR”, “AND”.

1. Introduction

Nowadays, algorithms based on the principles of deep and machine learning are often used to process information [1, 2], since they are able to solve problems as a human, taking into account the “experience” obtained from previously seen information. However, to the present day, these algorithms are associated with the problem of slow training, which is partially solved by the GPU [3] and TPU [4]. Neuromorphic systems are devices that by themselves are able to mimic biological neural networks they have a potential to speed up the training process of neural networks.

For neuromorphic computing, as well as for neural networks, an elementary processing unit is an artificial neuron that is an adder of input signals with the addition of nonlinearity (activation function), implemented as a mathematical model or a physical phenomenon. Antiferromagnetic oscillator (AFM oscillator) operating on the basis of the spin Hall effect (SHE), in which nonlinearity is already built in, can be considered as a neuron [5, 6].

In addition to AFM oscillators, skyrmions, domain walls, as well as other types of oscillators are LC oscillators, oscillators based on transistors, etc. can be used as neurons [7, 8]. However, the use of
antiferromagnetic materials opens the way to the terahertz frequency range, which is due to the enhancement of the relatively weak crystallographic anisotropy by the exchange interaction [9]. The use of antiferromagnets will speed up computations while reducing resource consumption. The anisotropy field can be controlled, for example, by varying the DC bias current [10] or by applying a DC voltage to the piezoelectric layer [11].

In this work, antiferromagnetic oscillators are used to reproduce neuromorphic dynamics and implement logical operations. Excitation of spin waves occurs under the action of laser pulses on the antiferromagnet, which leads to the emerging of electrical pulses.

This paper is structured as follows. Section 2 presents the structure of the proposed neuromorphic system, drawing parallels between the concepts of neural networks and physical implementation. A demonstration in Section 3 different logic operations and gives a brief description of the mathematical model is performed. Finally in Section 4 the obtained results are discussed.

2. Neuromorphic system structure
Consider a neuromorphic system of four types of layers, two of which are EM-SC and SC-SC layers contain excitatory neurons (AFM oscillators), and the other two are SC-DC and DC-SC layers contain processing neurons (detectors). The layers of the neuromorphic system are named according to the types of input and output signals. A biaxial nickel oxide NiO antiferromagnetic insulators as active elements for oscillators is considered. The detectors are heavy metal buses, in our case, platinum. An illustration of such a system is shown in figure 1.

![Figure 1. Neuromorphic system in the language of neural network diagrams.](image)

The input data of the neuromorphic system under consideration are electromagnetic (EM) laser pulses of picosecond duration of frequency $f_{in}$ of different amplitudes, i.e. the electric-field vector $E$ and magnetic-field vector $H$ of electromagnetic wave propagating along Z-axis change according to laws $E_i = \left(\cos \theta_i, \sin \theta_i, 0\right) E_i (t)$ and $H_i = \left(\cos \theta_i, \sin \theta_i, 0\right) H_i (t)$, where $\theta_i$ is the angle that specifies the orientation of the plane of polarization of the wave, and the functions $E_i (t)$ and $H_i (t)$ determine the terahertz pulse profile for $i$-th AFM oscillator, $i = 1, 2, ..., n$, where $n$ is the amount of neurons in EM-SC layer.
The nonlinearity of excitatory neurons is determined by the dynamics of the AFM oscillators. In particular, in the neurons of the EM-SC layer the electromagnetic signal causes oscillations of the Neel wall near the equilibrium position. Thus, the outputs of the EM-SC and SC-SC layers are spin currents. The nonlinearity of the SC-DC and DC-SC layers is determined by the inverse spin Hall effect and the spin Hall effect, due to which the spin current is converted into direct current and vice versa. To ensure direct propagation of signal over the network, i.e. to prevent the input and output signals from interfering with each other, the antiferromagnet must be an insulator.

In addition to alternating currents, a direct electric current flows along the common input platinum bus being governing and setting the level of direct current to the critical level of the onset of self-excitation. The output can be a superposition of electric currents.

3. Simulation results

Mathematical model of AFM-based neuron can be investigated as a pendulum-like model [5]

\[
\frac{1}{\omega_{ex}} \ddot{\phi} + \alpha \dot{\phi} + \frac{\omega_{\alpha}}{2} \sin 2\phi = \sigma j, \quad (1)
\]

where \( \omega_{ex} \) is the exchange frequency, \( \alpha \) is a Gilbert damping constant, \( \omega_{\alpha} \) is the anisotropy frequency, \( \sigma \) is the spin-torque efficiency and \( j \) is the electric current density.

Now a coupling term will be added for a model (1) of oscillator \( n \) connected with other \( m \) oscillators.

\[
\frac{1}{\omega_{ex}} \ddot{\phi}_n + \alpha \dot{\phi}_n + \frac{\omega_{\alpha}}{2} \sin 2\phi_n = \sigma j + \sum_m k_{nm}\phi_m. \quad (2)
\]

Here \( [k_{nm}] \) is a matrix of coupling coefficients.

Since spin current is induced by laser pulses, the mathematical model must contain their frequencies \( \omega_{ex} \) and amplitudes \( A \). Then the equation takes the following form for a single AFM oscillator and for the coupled ones, consequently

\[
\frac{1}{\omega_{ex}} \ddot{\phi} + \alpha \dot{\phi} + \frac{\omega_{\alpha}}{2} \sin 2\phi = \sigma (j + A \sin(\omega_{ex} t)), \quad (3)
\]

\[
\frac{1}{\omega_{ex}} \ddot{\phi} + \alpha \dot{\phi} + \frac{\omega_{\alpha}}{2} \sin 2\phi = \sigma (j + A \sin(\omega_{ex} t)) + \sum_m k_{nm}\phi_n. \quad (4)
\]

Equation (3) can be written in the Cauchy-form as

\[
\begin{align*}
\dot{\phi} &= \eta, \\
\dot{\eta} &= -\alpha \omega_{ex} \eta - \frac{\omega_{\alpha}}{2} \sin 2\phi + \sigma \omega_{ex} (j + A \sin(\omega_{ex} t)).
\end{align*}
\]

The nonlinear system (5) with the corresponding initial conditions was solved numerically in MATLAB. Built-in function ode15s was utilized as a differential equation solver, although at the chosen step it was also possible to use the Runge-Kutta methods implemented in core function ode45. The values of the simulation parameters are given in the table 1, where \( j_{TH} \) is the density of the DC threshold current, \( j_{OR}^{DC} \) and \( j_{AND}^{DC} \) are \( j \) for corresponding logic operations. Results of simulations are shown in figure 2 and figure 3.

| \( \alpha \) | \( \sigma \) | \( \omega_{ex} \times 10^3 \) | \( \omega_{\alpha} \times 10^3 \) | \( j_{TH} \) | \( j_{DCj} \) | \( j_{OR}^{DCj} \) | \( j_{AND}^{DCj} \) | \( A \) | \( k \times 10^{-3} \) |
|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 2\pi \cdot 4.32 | 2\pi \cdot 1.75 | 2\pi \cdot 27.5 | 2\pi \cdot 25 | \omega_{\alpha} \times (2\sigma)^{-1} | 0.985 | 0.950 | 0.945 | 0.05 \( j_{TH} \) | 1.5 |

Table 1. Simulation parameters.
4. Conclusion

In a summary, a model of neuromorphic computing in which the excitatory and processing neurons are the AFM insulator base cells and the buses of heavy metal was presented. Nickel dioxide and platinum materials were utilized to simulate a neuron. The nonlinearity of neurons was provided by the inverse and spin Hall effects, as well as by the dynamics of antiferromagnets.

The emergence of a current in the AFM occurs due to its excitation by laser pulses. Direct current flows along the common input bus, in addition to alternating currents, which governs and sets the direct current level to the critical level of the onset of self-excitation. Correspondence of current pulses to logical “0” or “1” depends on the amplitude of the electromagnetic field and the value of the DC threshold current.

Using the pendulum model of the AFM oscillator, the simplest logical operations of neuromorphic computations on the proposed model such as logical “OR”, “AND” were implemented. The introduced model of neuromorphic computation is able to be a building-block for a reservoir computer system, which opens the way to solving classification problems.

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