Realizing Hopfield Network by Magnetic Textures

We propose that the mutual interaction between a magnetic texture and an electric current leads to a self-adaptive behavior of the whole system, which can be used to construct an artificial neural network such as the Hopfield network, realizing an associate memory. Different from other approaches, here the learning rules are naturally imbedded in the physical system.

Neuromorphic computing, or brain-inspired computing receives inspiration from the human brain, which is both powerful and extremely energy efficient. The Artificial Neural Network (ANN) is a prime model to mimic the working mechanism of the brain. An ANN consists of a pool of simple processing units (neurons) that communicate with each other by means of a large number of weighted connections. Such a model has already been successfully implemented into algorithms and is widely used in facial/vocal recognition, pattern classification etc. However, most industry-level algorithms are running on conventional digital computers. Due to the drawbacks of classical computers (such as Joule heating and the von-Neumann bottleneck), the realizations of these algorithms are energy inefficient. One solution of this issue is to customize chips for ANN algorithms, or to build a hardware ANN.

Spintronics offers opportunities for this evolution [1]. For example, Spin Torque Nano Oscillators based on Magnetic Tunnel Junctions (MTJs) have been used as "spintronic neurons" to implement simple classification tasks [2,3]. Here we demonstrate that the magnetic system with adaptive magnetic textures offers a platform for neuromorphic computing. In a uniform film, the internal magnetic textures give rise to a rich degree of freedom. Due to the Anisotropic MagnetoResistance (AMR) [4,5], the electric conductance depends on the local magnetization, which induces a nonuniform electric current distribution in the presence of a voltage bias. On the other hand, the magnetic texture can be modified by electric currents via the current-induced spin transfer torque (STT).

Fig.1 (a)-(d) shows the time revolution of a magnetic stripe texture (black and white color for magnetization pointing out-of and into the paper) with applied voltage from the top to the bottom edge. Due to the current-induced spin transfer torque, the stripes tend to align perpendicularly to the current direction. The evolving texture leads to a change in the electric conductance due to the AMR. Therefore, with current applied on vertical direction, the vertical conductance increases while the horizontal one decreases, indicating that the mutual interaction between a magnetic texture and the electric current leads to a self-adaptive behavior of the whole system.

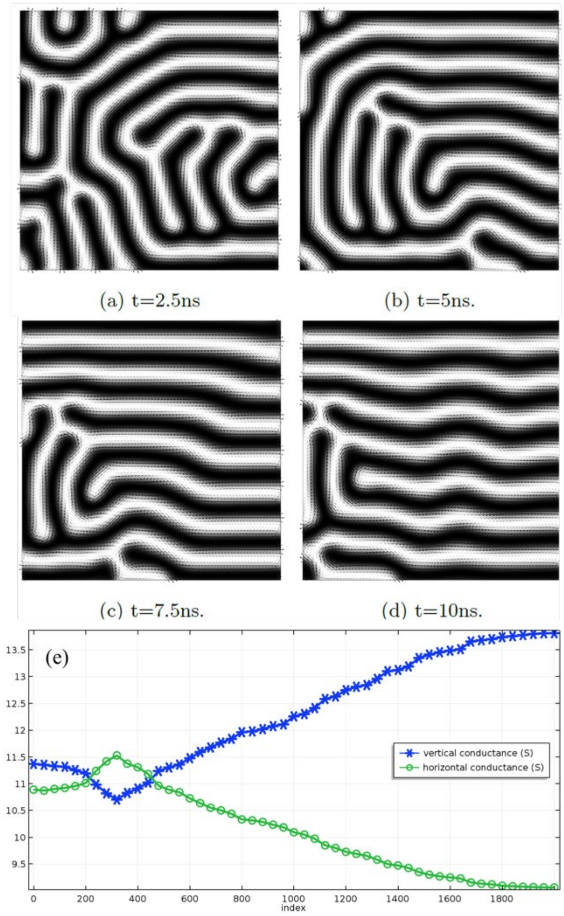

Fig. 1 (a)-(d) Time evolution of magnetic texture with voltage bias applied on top and bottom boundaries. (e) Time evolution of electric conductance detected in vertical direction (blue) and horizontal direction (green).

By interpreting the voltage on each node as input, and electric current flowing into/out of the node as output, the weight can be described by the electric conductance, which is a matrix when there are multiple nodes. Therefore, the magnetic system can be used to construct an artificial neural network via a trainable conductance matrix.

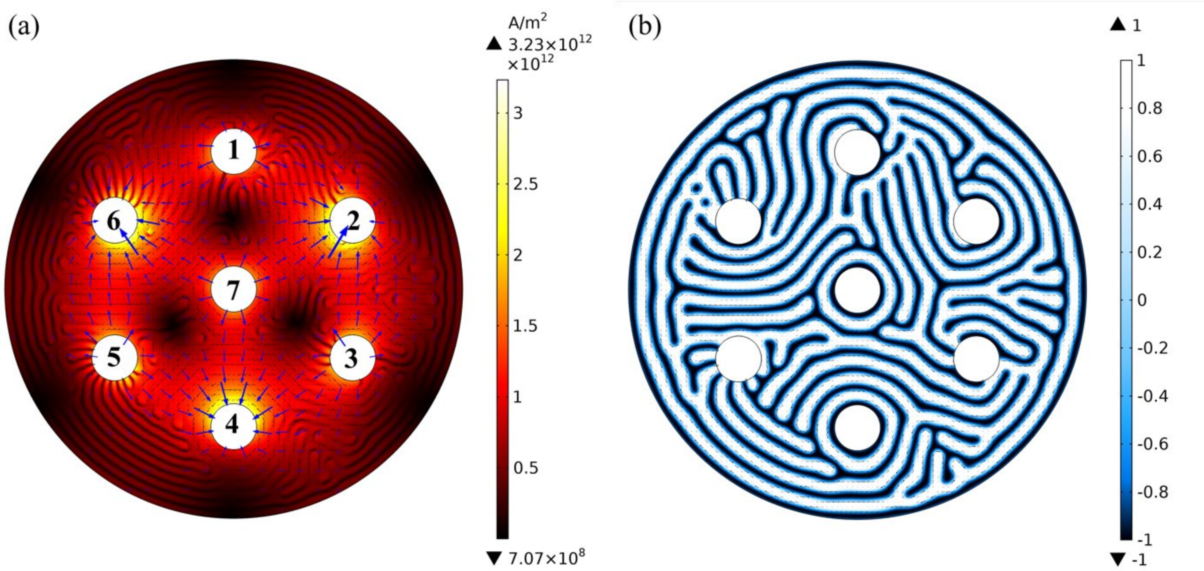

Fig. 2 Proof of principle for a Hopfield network with 7 nodes mimicking the configuration of IMR logo. (a) Current distribution during the learning process, where the nodes are applied with voltages $V=V_0\{1,-1,1,-1,1,-1,1\}$. (b) The configuration of magnetic texture when the learning process is finished.

Fig. 2 demonstrates the proof-of-principle structure for a network composed of 7 nodes. In this configuration, all nodes are treated as input and output at the same time. This is therefore a Hopfield network that can be used as an associative memory. By applying a voltage to each node, the current will be distributed according to Kirchhoff's law and drive the magnetic texture accordingly. When the texture reaches a stable configuration, the learning process is finished. The information about the weight matrix can be extracted by measuring the conductances, realizing the function of an associative memory, i.e. the pattern we input to the network can be recognized again even if we input a wrong pattern.

In conclusion, we propose a self-adaptive magnetic system that can be used to perform neuromorphic computing. In contrast to competing setups, the learning process in this setup (or the learning rules) is naturally imbedded in the physical system.

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Keywords: spintronic, magnetoresistance, spin current
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