A magnetic Hopfield neural network capable of self-learning

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Physical neural networks (PNN) using physical materials and devices to mimic synapses and neurons offer an energy-efficient way to implement artificial neural networks. Yet, training PNN is difficult and heavily relies on external computing resources. An emerging concept, "physical self-learning," uses intrinsic physical parameters as trainable weights. Here, a real spintronic system mimicking Hopfield neural networks (HNN) is demonstrated, where unsupervised learning is intrinsically performed via the evolution of the physical process. Using a magnetic texture–defined conductance matrix as trainable weights, it is shown that under external voltage inputs, the conductance matrix naturally evolves and adapts Oja's learning algorithm in a gradient descent manner. The self-learning HNN is scalable and can achieve associative memories on patterns with high similarities. Fast spin dynamics and reconfigurability of magnetic textures offer a platform toward efficient autonomous training directly in materials.

***Index Terms*—associative memory, Hopfield neural network, magnetic textures, self-learning, spintronics**

I. INTRODUCTION

Machine learning relies increasingly on energy-intensive artificial neural networks (ANNs). Physical neural networks (PNNs) emulate neural function using real materials—spintronics, memristors, optics, and more—to achieve energy efficiency beyond silicon processors. However, most experimental PNNs, especially for training, depend extensively on external computers, limiting their practical advantage.

A central challenge is realizing **physical self-learning**: mapping trainable weights directly to intrinsic, tunable material parameters, so training occurs through natural evolution following physical laws—mimicking biological learning. If such evolution adapts modern learning rules (e.g., gradient descent), autonomous material-based training becomes possible.

The Hopfield neural network (HNN) is a classic model for associative memory. It is widely implemented in various physical forms, but typically uses only simple Hebbian/outer-product rules, limiting capacity to highly orthogonal patterns and requiring off-chip weight calculation.

This work reports a spintronic realization of a **magnetic HNN with intrinsic gradient descent**. Synaptic weights are mapped to a conductance matrix defined by the configuration of magnetic textures in a Permalloy (Py) film. Voltage training pulses applied to gold electrodes induce Oersted fields, reshaping these textures and evolving the network according to Oja's rule—a more powerful, convergent learning strategy—entirely through physical dynamics.

II. DEVICE AND PHYSICAL LEARNING MECHANISM

Device Architecture and Measurement. The core device consists of three layers: a bottom Py (Fe80Ni20) film, insulating Al_2O_3, and top Au (gold) patterned into four electrodes (neurons). Voltage pulses applied to Au encode binary input patterns; these pulses generate in-plane currents and corresponding Oersted fields, modulating local magnetization in the underlying Py.

Conductance between each node pair (G_{ij}) forms a

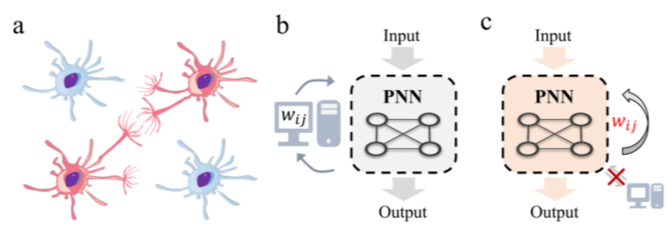

Figure 1 Concept of physical self-learning . a) Biological neural network learns by itself where activated neurons intend to strengthen their connection. b) Physical Neural Networks (PNNs) whose internal learning parameters w_{ij} are determined via external computation and updated in the physical system. c) PNNs with self-learning capability, whose learning parameters are determined and updated in an autonomous way according to inherent physical dynamics without interference of external computation.

symmetric matrix mapped to HNN weights. The evolution of Gij under pulse input is tracked via the anisotropic magnetoresistance (AMR) effect: the local resistance of Py depends on the angle between electrical current and magnetization, measurable with small probe currents.

Intrinsic Gradient Descent Learning. Upon repeated voltage pulse training, the conductance matrix elements G_{ij} evolve in a manner described by:

$$G_{ij}(t) - G_{ij}(t-1) = \eta\left[V_i^{\mathrm{Au}}V_j^{\mathrm{Au}} - 2\alpha_{ij}\left(G_{ij}(t-1) - G_{ij}^{\mathrm{avg}}\right)\right], \quad (1)$$

where η is the evolution speed, α_{ij} an effective learning rate determined by voltage differences, and G_{ij}^{avg} a constraint average.

This evolution is mathematically equivalent to Oja's rule, a well-known modification to Hebbian learning that ensures weight normalization and stability. The key physical insight: the network's energy minimization under external driving directly implements gradient descent on a cost function, with purely local updates and no need for software supervision.

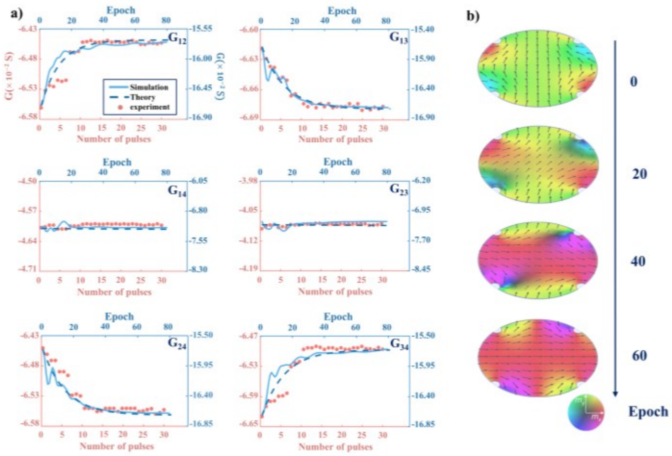

Figure 2 Intrinsic gradient descent learning. a) Evolution of conductance matrix G_{ij} when the voltage pattern is switched from initial "+ − + −" to "+ + − −" under "+ + − −" voltage pulses in the Au layer. The experiment, simulation and theory curves are plotted respectively where the matrix evolution is equivalent to the Oja's learning rule for unsupervised learning. b) Snapshots of corresponding evolution of spin textures from simulation.

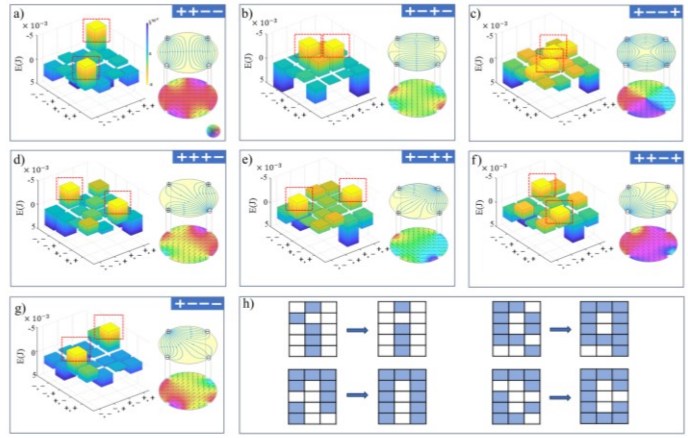

Figure 3 Examination of the magnetic HNN. a) The effective energy diagram (left) and corresponding current and spin texture distribution (right) for the trained pattern "+ + − −". The effective energy E is minimal for the trail state "+ + − −" or equivalent "− − + +" as marked by red dashed box. b)-g) Results for other six trained patterns. h) Associated memory. When a distorted letter is fed to the network, the correct letter can be recalled during inference. Four letters (i, n, q, c) are demonstrated respectively.

III. ASSOCIATIVE MEMORY PERFORMANCE & SCALABILITY

Experimental Demonstration and Inference. The 4-node system enables seven independent binary patterns. For each, training proceeds via pulse input; the conductance matrix converges, mapping the network attractor to the desired pattern as confirmed by energy minimization and recurrent inference, even with noisy/distorted inputs. The trained device robustly recalls correct patterns via iterative updates, matching Hopfield energy criteria.

Scalability and Advanced Application. Micromagnetic simulation of a scaled-up device (e.g., 35 nodes) shows robust associative memory for complex, low-orthogonality patterns (e.g., recognition of similar letters), achieving up to 97% recall accuracy—substantially outperforming the standard outer-product rule (approx. 33%). The self-learning approach is inherently parallel: multi-node training occurs simultaneously as magnetic textures evolve, offering fast operation limited only by the nanosecond-scale spin dynamics.

Additionally, the programmable magnetic network supports Boolean logic functions (e.g., AND, OR, NAND, NOR) with stability and reconfigurability—key steps towards neuromorphic computing.

IV. DISCUSSION AND CONCLUSION

This demonstration establishes that tunable magnetic textures in spintronic devices can implement powerful, autonomous training rules for neural networks, with:

1. nanosecond-scale, parallel, and energy-efficient training;
2. robust, nonvolatile storage and reconfigurability;
3. effective recall of similar patterns exceeding previous physical HNNs.

Future improvements include signal amplification using giant magnetoresistance (GMR) and extension to more complex networks (e.g., deep networks, Boltzmann machines), potentially realizing fully neuromorphic, material-driven learning hardware.

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