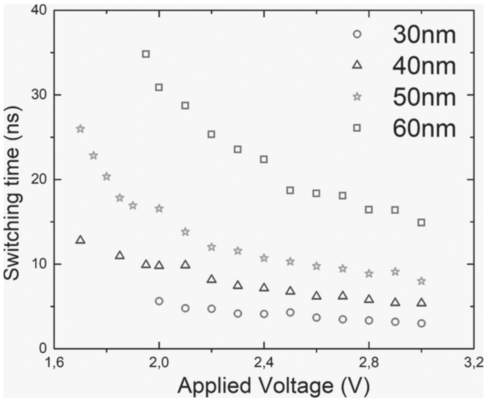

Fig.2. Switching time as a function of the applied voltage for different pillar thickness.

ET-14. Micromagnetic Simulations of First-Order Reversal Curves in Nanowire Arrays Using MuMax3.

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We used micromagnetic software MuMax3 [1] to model first-order reversal curves (FORC) in ordered arrays of magnetic nanowires. Our goal is to simulate the reversal processes in nanomagnet arrays and to map individual reversals to features in the FORC diagram. We simulated a set of reversal curves for a 3x3 array of nanowires, one μm in length and 80 nm in diameter. The nanowires are arranged in a square packing scheme, with a nearest neighbor distance of 200 nm. The average magnetization of each nanowire was recorded along with the total magnetization of the system at each field step. The reversal curves are transformed into the FORC distribution plotted in Fig. 1, showing that interacting nanowires create the so-called 'wishbone' FORC distribution. Two field distributions, one with constant coercive field and wide range of interaction fields (IFD) and one with constant interaction field varying coercive fields (CFD), are clearly visible [2]. Fig. 2 shows the relative FORC, indicating nine major changes in the magnetization of the system; these nine features are magnetization reversals of individual nanowires. By recording reversal process for all nine nanowires along the FORC curves, we are able to relate various switching processes to features in the FORC distribution. The location of the IFD along the coercive axis represents the nanowire's intrinsic coercivity, and the extent of the IFD along the interaction axis represents the upper and lower limits of the interaction field experienced by the system. We find that the CFD shows the real switching events, but the coercivity at which these reversals occur depends on the current state of the interaction field.

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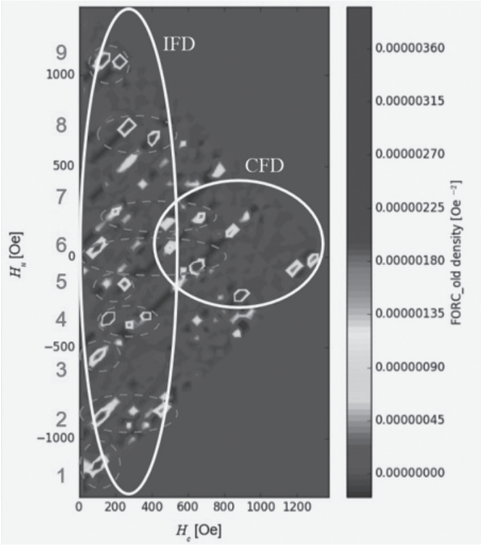

Fig.1 FORC distribution showing Interaction Field Distribution (IFD) and Coercive Field Distribution (CFD)

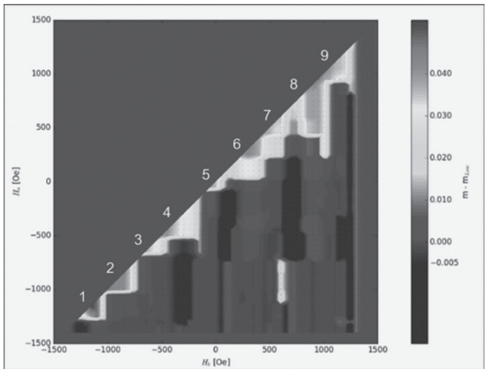

Fig.2 Relative FORC distribution

ET-15. Optimized Lateral Inhibition in Magnetic Domain Wall Tracks for Neuromorphic Computing.

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Lateral inhibition is the neuron behavior that an active neuron cell prevents the firing of its less-active neighbors. It is a neural strategy commonly present in human brain[1]. So far, this important feature of neurons is either missing from devices or implemented through additional circuitry. Recently, an integrate-and-fire neuron based on magnetic domain wall (DW) racetracks has been demonstrated in modeling to be inherently inhibitory[2]. In Fig.1a, two adjacent magnetic nanowires have current-driven DW motion along +*y* via spin transfer torque. Neuron 1 (N1) with higher current density and DW velocity has a larger chance to "fire". Its stray field aligns Neuron 2 (N2) magnetization near DW2 in -*z*. DW2 motion is thus impeded, mimicking lateral inhibition. However, magnetic field has very limited control over average DW velocity in the precession regime of motion shown in this initial work. In this work, we show that significant lateral inhibition can be achieved with current- and field- induced DW motion below Walker breakdown[3] (WB). To this end, stray field must be controlled below Walker field for the inhibited neuron to operate in sub-WB regime. One way to realize such control is to vary the neuron spacing. We simulate in Mumax3 two side-by-side wires 32nm wide x 1.5nm thick x 3μm long using standard material parameters for Co. In Fig.1, the wires are spaced apart 30nm. We see in Fig.1b simulation snapshot that when N1 has current density $J_1 = 2$ x 10^{12}A/m^2 and N2 $J_2 = 1$ x 10^{12}A/m^2, DW2 is inhibited compared to Fig.1c where when $J_1 = 0$ A/m^2 DW2 travels farther in the same amount of time. In Fig.2, we simulate DW2 velocity for wire spacings from 10 to 80 nm for both cases. The dip in inhibited velocity curve suggests an interaction strength for maximum lateral inhibition. We will further show optimized parameters for lateral inhibition implementation in magnetic DW neuron design via material and geometry engineering.

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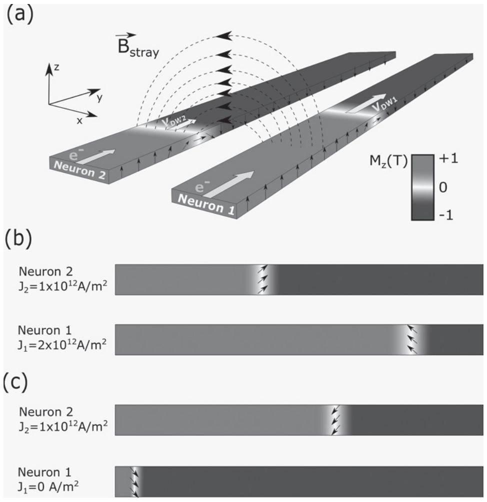

Fig. 1. Simulation setup. (a) Lateral inhibition condition: N1 stray field impedes DW2 motion. (b) Inhibited DW2 motion when DW1 is ahead. (c) Uninhibited DW2 motion when DW1 is behind.

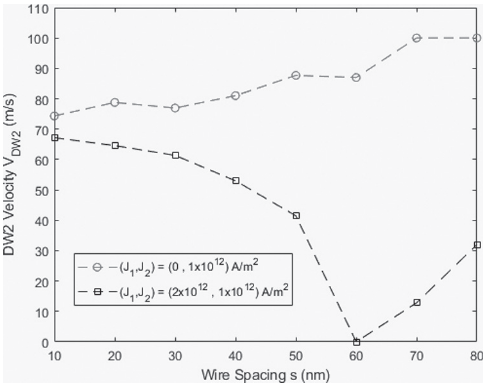

Fig. 2. Simulated DW2 velocity versus wire spacing, for non-inhibited (circles) and inhibited (squares) motion.

ET-16. A Hopfield Neural Network-Based Bouc-Wen Model for Magnetic Shape Memory Alloy Actuator.

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With the development of modern science, the smart actuators are widely used in micro-nano positioning technology. As one of the smart actuators, magnetic shape memory alloy (MSMA) actuator, which is capable of positioning with the nanometer resolution, large energy density and small volume, has attracted much interest [1]. However, there are some difficulties in application of MSMA actuator, namely, 1) asymmetric loop between ascending and descending branches and 2) the output of MSMA actuator depends on the input frequency, which causes the deterioration of positioning accuracy in the system response. Therefore, precise modeling of MSMA actuator is the key to its applications. In this paper, a Bouc-Wen (BW) model is innovatively identified online by Hopfield neural network (HNN) to describe the hysteresis of MSMA actuator. BW model is a kind of differential equation hysteresis model. Compared with other models, such as Prandtl-Ishlinskii model, it has fewer parameters to be identified. Nevertheless, BW model is rate-independent. Identifying the applicable parameters is a significant part of modeling BW model. Neural network has the features of the nonlinear mapping property to be applied to adjust the model parameters online [2]. As a kind of fully interconnected recursive neural network, HNN has feedback connections from output to input and each neuron in HNN is connected to others. Hence, it has more computing power and better global searching capability. In this paper, HNN is innovatively used to identify the parameters of BW model online. Because it has ability of associative memory, it possesses the dynamic nonlinearity and can adjust the parameters of BW model adaptively. The identification results are shown in Fig. 1 and Fig. 2. The maximum modeling error rate at 1Hz and mixed frequency signal is 0.37% and 1.75%, respectively. The BW model identified in this paper can accurately describe the hysteresis of MSMA actuator at different input excitation. Therefore, the ability of precise modeling by HNN-based BW model is certified.

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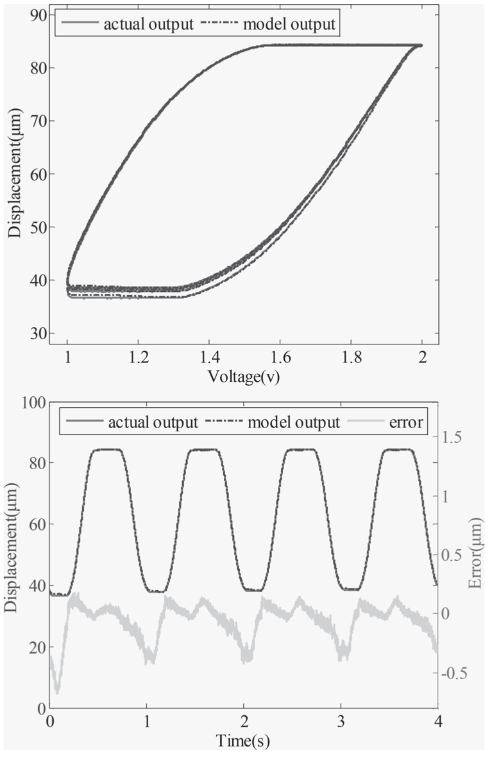

Fig. 1. Identification results of Bouc-Wen model in this paper at 1Hz.