Spin-Transfer Torque Magnetic Memory as a Stochastic Memristive Synapse

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Abstract—Spin-transfer torque magnetic memory (STT-MRAM) is currently under intense academic and industrial development, since it features nonvolatility, high write and read speed and high endurance. In this work, we show that when used in an original regime, it can additionally act as a stochastic memristive device, appropriate to implement a “synaptic” function. We introduce basic concepts relating to STT-MRAM cell behavior and its possible use to implement learning-capable synapses. System-level simulations on a problem of car counting highlight the potential of the technology for learning systems. Monte Carlo simulations show its robustness to device variations. These results open the way for unexplored applications of STT-MRAM in robust, low power, cognitive-type systems.

Keywords: STT-MRAM, neuromorphic, memristor, stochastic computation.

I. INTRODUCTION

Thanks to considerable progress in recent years, spin-transfer torque magnetic memory (STT-MRAM) – the second generation of magnetic memory – now appears as a breakthrough for embedded and standalone non-volatile memory, providing fast programming and high endurance [1]. However, a limitation of this technology is its stochastic switching nature [1]–[3]. The time required for programming from a memory state to another is a random quantity, which requires designing programming times with high security margins, to ensure reliable programming. Device physicists have intensely studied this effect of intrinsic probability [4], [5], and circuit designers have proposed ideas like self-enabled programming to mitigate the issue [2]. However, an alternative approach is to not consider this randomness as a drawback, but as a feature of the device. In particular, here we reinterpret STT-MRAM cell’s behavior as a “stochastic memristive device”. And we show by system-level simulations how it may be used in a neuromorphic system for real life applications.

In recent years, the exploitation of nanodevices with memory effects (or memristive devices) as synapses in neuromorphic systems has stimulated a growing interest [6]–[17]. They raise the hope for a breakthrough in electronics, bringing smarter, lower power and more adaptive systems. Most of these proposals use memory devices with multi-level capability – the original memristor paradigm [8]. However, an alternative idea is to use binary devices programmed in a stochastic fashion, or even to use binary devices with intrinsic stochastic properties [18]–[21]. In theory, the idea of using stochastic synapses instead of deterministic ones (in a broad meaning) has also been proposed with supervised neural networks [22]–[24]. We suggest that STT magnetic memory is ideal for this vision and illustrate it in the case of unsupervised learning.

In the present paper, we introduce the basic physics of STT memory and the foundations of its behavior as a stochastic memristive device. To support the idea we perform system-level simulations incorporating an accurate model of the stochastic effects for an application of car counting. Monte Carlo simulations show the relevance and the robustness of the approach to device variations.

II. STOCHASTIC MEMRISTIVE BEHAVIOR OF MAGNETIC TUNNEL JUNCTIONS

A. Low current regime

A magnetic tunnel junction (MTJ, the basic structure of magnetic memory, Figure 1(a)) is composed of a fixed magnetic layer, an oxide layer and a free magnetic layer, whose magnetization can be parallel or antiparallel to the one of the fixed layer. The antiparallel state AP is high resistive, the parallel state P is low resistive. Thanks to the spin transfer torque (STT) effect, a positive current can switch the MTJ from the AP to the P state, while a negative current can switch it from the P to the AP state. In this way, a MTJ is extremely reminiscent of a binary bipolar memristor [8].

The switching time depends heavily on the current and is itself a stochastic quantity as observed for example in the measurements of Figure 1(b). We see that a programming pulse of duration $\Delta t$ has a given probability of switching the memory. This stochastic effect is not caused by technological imperfections or filamentary effects like in other resistive

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memory technologies [18], [20], but is intrinsic to the physics of magnetic switching. This has been largely clarified by magnetism studies. In particular, at low current, memory switching is caused by thermal fluctuations. We can introduce a critical current of a MTJ (in the case of an “in-plane” device, and in SI units):

\[ I_{c0} = \frac{2e\alpha V}{h} \left( 1 + p^2 \right) \frac{\mu_0 M_s}{\mu} \frac{M_d}{2}, \]

where \( \alpha \), \( M_s \), and \( V \) are the Gilbert damping, the saturation magnetization and the volume of the free layer, \( P \) the spin polarization of the current, and \( M_d \) an effective magnetization (all the equations are written in SI units). The sign - in \( 1 \pm p^2 \) is for the \( \text{AP} \rightarrow \text{P} \) transition, the sign + for \( \text{P} \rightarrow \text{AP} \). It should thus be noted that \( I_{c0} \) has different values for the \( \text{P} \rightarrow \text{AP} \) and \( \text{AP} \rightarrow \text{P} \) transitions. However, basic calculations confirmed by measurements show that they correspond to the same voltages. The symmetry – in voltage – between the \( \text{P} \rightarrow \text{AP} \) and \( \text{AP} \rightarrow \text{P} \) transitions is an extremely nice property of MTJs used as memristive devices.

If a current \( I \) much smaller than \( I_{c0} \) flows through a MTJ, the mean switching time \( \langle \tau \rangle \) has been proven to behave as [1]

\[ \langle \tau \rangle = \tau_s \exp \left( \frac{E}{k_B T} \left( 1 - \frac{I}{I_{c0}} \right) \right), \]

where the energy barrier at zero current is \( E = \mu_0 M_s H_s V / 2 \), \( k_B T \) is the thermal energy, \( H_s \) the amplitude of anisotropy field. Switching time itself is determined by exponential random law of mean \( \langle \tau \rangle \) [1], [4]. This means that if a programming pulse of duration \( \Delta t \) is applied to the junction, its probability of switching is

\[ P = 1 - e^{-\Delta t / \langle \tau \rangle}. \]

Choosing the pulse duration \( \Delta t \) thus allows tuning the switching probability of the devices anywhere between a low \( (P \ll 1 \text{ for } \Delta t \ll \langle \tau \rangle) \) and a high probability \( (P \approx 1 \text{ for } \Delta t \gg \langle \tau \rangle) \). It should be noted that MTJ thus possess no hard threshold. Even an extremely low current has a probability to switch the junction, but the mean switching time is exponentially dependent with the current.

B. High current and intermediate current regimes

By contrast, when a current much higher than \( I_{c0} \) flows, the physics differs (precessional switching) and the switching time behaves as [1], [5]

\[ \tau = \frac{2}{\alpha \gamma \mu_0 M_s} \frac{I_{c0}}{I - I_{c0}} \ln \frac{\pi}{2|\eta|}, \]

where \( \theta \), the initial angle of the magnetization, is given by a normal random number with mean 0 and standard deviation \( \sigma = \sqrt{F / \mu_0 H_s M_s} \) \( \gamma \) is the electron gyromagnetic constant. This is no longer an exponential law as is seen for the measurements on Figure 1(b).

Although the two regimes \( I \ll I_{c0} \) and \( I \gg I_{c0} \) have been well studied, the intermediate regime is physically less clarified. For the present work we developed equations that fit MTJs’ behavior in all situations. The relatively complex equations are beyond the scope of the current paper and will be published in a sister publication [25]. Figure 1(b) shows that our equations can fit experimental measurements.

Figure 2 shows the mean switching time as a function of current (for the \( \text{AP} \rightarrow \text{P} \) transition) in all possible regimes, compared with physical simulations based on the magnetic Landau-Lifschitz-Gilbert-Slonczewski equation with thermal agitation. The low current, high current and intermediate current regimes are well visible. This graph also shows how the mean switching time can be tuned on several decades by choosing current or voltage, a unique feature of MTJs.
III. EXAMPLE OF APPLICATION FOR AN UNSUPERVISED LEARNING TASK OF CAR COUNTING

In this section, we validate by means of system-level simulation the use of stochastic MTJ synapses. For this, we adapted a scheme proposed for Conductive Bridge RAM (CBRAM) in [18], [19]. Figure 3 shows the basic architecture of the system. The system implements a spiking neural network capable of performing unsupervised learning through a simplified Spike Timing Dependent Plasticity (STDP) rule. CMOS input neurons present the input as asynchronous spikes, which may come directly from a neuromorphic sensor (e.g. DVS retina [27]). CMOS output neurons implement leaky integrate-and-fire spiking neurons and may be implemented by analog or digital circuits [28]. The MTJs are organized as a crossbar connecting input and output neurons. This scheme (1R) [29] can easily be adapted with selector devices (1T-1R) to suppress sneak paths during programming as in the case of CBRAMs [19]. Every input neuron is connected to every output neuron by a single MTJ.

The way the system works is straightforward. Input neurons present the input as short and low voltage spikes that generate current through the crossbar. The conductance of the MTJ thus acts as a synaptic weight converting voltage into current. This current is integrated by output neurons until one of them generates a spike. Then it inhibits the other output neurons (e.g. through a diffusor network), and it applies the voltage waveform (2) to its column of the crossbar, while the inputs that were active in a recent time window reapply an input pulse (1) (Figure 3). The combination of these voltage pulses implements a simplified STDP rule: when an output neuron spikes, a nanodevice connected to it

- has a given probability of switching to the P state if its input neuron was active in the same time window
- has a given probability of switching to the AP state if its input neuron was not active in the same time window.

This probabilistic rule is similar to the one that we proposed for CBRAM [18], [19]. However, the voltage waveforms are simpler because of the symmetry in voltage between P→AP and AP→P switching in MTJs. The learning rule allows unsupervised learning.

We based our simulations on a MTJ device representative of a 45 nm technology. The MTJ is an ellipse of a width of 40 nm, a length of 100 nm and a free layer thickness of 2 nm. The tunnel magnetoresistance is 150% (i.e. \( R_{AP}/R_P = 2.5 \)). The programming voltages are 0.21 V. We performed system simulations where nanodevices are modeled accurately according to the model of section II using a specialized neuromorphic spiking neural network simulator developed in our lab. CMOS circuits are simulated functionally. This kind of simulations is fast enough to simulate real life applications, including with Monte Carlo simulations. For our test application, simulation time was between 25 and 40 times the real time on a Xeon E5620 processor.

For our test application, we presented a 80 s video of cars passing on a freeway recorded with a neuromorphic retina [27] (the video is freely available [30]). Each input neuron corresponds to a pixel of the retina. We presented the video 10 times. The system has 20 output neurons. We observed that thanks to the STDP learning rule, the output neurons naturally specialize to lanes and the system effectively becomes a vehicle counter. The specialization of the output neurons is evident on Figure 4, which shows the final states of the MTJs (white is P, black is AP). If we take the systems as a vehicle counter the detection rate is 99.0% for the four inward lanes. Detection rate is 76.3% and 54.7% for the two outward lanes (where fewer vehicles are driving). A significant numbers (~50%) of vehicles are detected by different output neurons. This effect can easily be suppressed by adding a second layer to the network as proposed in [31]. The number of false detection is 11.0%, a number which can also be dramatically reduced by a second layer. The power consumption for reading and programming the nanodevices (excluding the power consumption of the CMOS neurons and of the rest of the system) is only 3.7 μW, making low power operation possible, and is smaller to the case of CBRAMs [19] thanks to the low voltage operation of MTJs in the probabilistic regime.

In reality, device variations will make that the different MTJs, when being applied the same programming pulses, will have different probabilities of switching. To evaluate the robustness of our approach to this apparently serious issue, we performed Monte Carlo simulations. Variations on the minimum and maximum resistances of the MTJs are considered (the variability is applied to the resistance of the P state and to the tunnel magnetoresistance). Since they affect the current that flow through the devices, they have a dramatic effect on their probabilities of switching. However, we
observed spectacular tolerance of the system. Up to 10% of relative standard deviation ($\sigma/\mu$) on $R_p$ and $R_{sp}$ no impact is seen on the system. For 10% of variations, the mean detection rate for the four inward lanes remains 98.8% (76.1% and 56.4% on the two outward lanes) and 11.7% of false detections (these results are obtained by averaging on several simulations). The decrease in functionality is observed with device variations of 25% of relative standard deviation. Although the system keeps its detection capability, it performs a high number (more than 50%) of false detections and is thus not selective anymore.

IV. CONCLUSION
In this work, we presented how magnetic tunnel junctions’ behavior may be interpreted as a stochastic memristive synapse. The stochastic effects were modeled accurately using analytic physical equations. The mean switching time can be tuned over many decades. Low voltages are used for programming and they are symmetric between positive and negative polarizations. We introduced a neural network-inspired system that can exploit this stochastic effect to perform unsupervised learning. The switching probabilities of the nanodevices do not need to be controlled perfectly since the system is robust to device mismatch, which is evidenced by Monte Carlo simulations.

This work gives insight on a new way to use memory nanodevices. Unpredictability caused by nanoscale physics is not necessarily an enemy but can become the fundament for efficient processing using novel computing paradigms. Future work will focus on physical realization of hybrid CMOS/stochastic synapse circuits.

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