CMOS Compatible Hf$_{0.5}$Zr$_{0.5}$O$_2$ Ferroelectric Tunnel Junctions for Neuromorphic Devices

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While machine learning algorithms are becoming more and more elaborate, their underlying artificial neural networks most often still rely on the binary von Neumann computer architecture. However, artificial neural networks access their full potential when combined with gradually switchable artificial synapses. Herein, complementary metal oxide semiconductor-compatible Hf$_{0.5}$Zr$_{0.5}$O$_2$ ferroelectric tunnel junctions fabricated by radio-frequency magnetron sputtering are used as artificial synapses. On a single synapse level, their neuromorphic behavior is quantitatively investigated with spike-timing-dependent plasticity. It is found that the learning rate of the synapses mainly depends on the voltage amplitude of the applied stimulus. The experimental findings are well reproduced with simulations based on the nucleation-limited-switching model.

1. Introduction

The human brain presents an unrivaled capacity to perform cognitive tasks involving big data such as pattern recognition. This impressive ability rests on the strengthening or the weakening of the synapses that interconnect neurons, also called synaptic plasticity. In an attempt to mimic the brain’s ability for learning and efficiently computing big data sets, bio-inspired computing systems, or neuromorphic systems, have been attracting increasing attention.\(^1\) However, in the state-of-the-art applications of neuromorphic computing, the analog computational processes similar to those taking place in the brain have to be transferred to the digital von Neumann architecture of computers.\(^2\) As a result, the performance of these artificial systems remains far from that of the human brain due to high power dissipation and long computational times. The most promising contender for bio-inspired neuromorphic systems is the resistive random-access memory (RRAM) whose resistance depends on earlier applied potentials.\(^3\) A crossbar structure of RRAM cells can directly emulate an artificial neural network (ANN), where the conductance values of the individual cells represent the weights. When the input variables for the ANN are applied as voltage, the summation of the weights for one layer is directly given by Ohm’s law and Kirchhoff’s current law with the current as output.\(^4\) Initially proposed for memory device applications, RRAM is highly scalable, consisting of a simple two-terminal metal–insulator–metal structure that offers analog and binary properties.\(^5\) Its working mechanism relies on resistive switching, a reversible phenomenon where the device changes from a high-resistance state (HRS, OFF resistance state) to a low-resistance state (LRS, ON resistance state) under an applied electric field\(^6\). In addition, these devices display multiple resistance levels, enabling them to mimic synaptic activity.\(^7\) This multilevel switching is achieved through intermediate states between HRS and LRS that can be reached by inducing gradual resistance changes in the material. Amongst RRAM, ferroelectric tunnel junctions (FTJs) have been attracting a lot of interest due to their high scalability, nonvolatility, and nondestructive readout. FTJs also operate a low-switching energies with a high-switching speed and a high endurance.\(^8\) In FTJs, two metallic electrodes are separated by a few nanometers thick ferroelectric layer acting as a potential barrier, across which the charges travel via direct tunneling.\(^9\) The multilevel switching is achieved through a multidomain switching process.\(^10\) Furthermore, to ensure analog large-scale integration, artificial neuromorphic systems need to be compatible with complementary metal oxide semiconductor (CMOS) technology. A CMOS-compatible FTJ exploiting hafnium zirconium oxide (Hf$_{0.5}$Zr$_{0.5}$O$_2$) as the ferroelectric layer was reported earlier.\(^11\) Hf$_{0.5}$Zr$_{0.5}$O$_2$ has the advantage of crystallizing at low temperature, compatible with the CMOS process, while displaying ferroelectricity at very low thicknesses due to the presence of an orthorhombic phase.\(^12\) While Chen and coworkers has proposed Hf$_{0.5}$Zr$_{0.5}$O$_2$ FTJs for bio-inspired artificial synapses, quantitative experimental verification is yet to be demonstrated.\(^13\) Spike-timing-dependent...
plasticity (STDP) tests are the technique of choice to evaluate the material’s ability to mimic synaptic plasticity. \cite{25,26} STDP emulates the behavior of the brain’s neuronal activity, where two neurons stimulate the synapse interconnecting them by each applying a voltage pulse. \cite{24,27,28} This pulse is also referred to as action potential and the time difference between the two action potentials defines the strengthening or the weakening of the synapse, and therefore the resistive switching in FTJs. The STDP measurements directly reveal the learning rate of the synapse. The learning rate is an important parameter for the training of an ANN and to a great extent influences its training algorithm. While STDP has already been employed to evaluate RRAM’s learning behavior,\cite{24,27,28} a quantitative study of describing the influence of the action potential on the learning rate of the synapse has yet to be reported.

In this study, we report on a quantitative STDP study of CMOS-compatible Hf\(_{0.5}\)Zr\(_{0.5}\)O\(_2\) FTJs. We show that by adjusting the action potential amplitude of the STDP, we can vary the learning rate. The agreement with a nucleation-limited-switching (NLS) model suggests that the underlying mechanism is indeed domain switching.

2. Results

2.1. Spike-Timing-Dependent Plasticity

Artificial synapses for neuromorphic computing try to mimic the synaptic plasticity of biological synapses. A synapse is a directional connection between two neurons, which can therefore be referred to as a pre-synaptic and a post-synaptic neuron. The neurons “fire” and send action potentials, which go through the synapse. Various shapes of action potentials can be found in mammalian brains depending on their function.\cite{29} Here, a piecewise function of two exponential branches is employed and is shown in Figure 1, where the red and blue functions represent the post-synaptic and pre-synaptic action potentials, respectively. A mathematical description of the function can be found in the Supporting Information. In the framework of a spiking neural network (SNN), the synaptic plasticity, i.e. change of the synapse’s resistance, depends on the time difference \(\Delta t\) between pre- and post-synaptic action potentials. A schematic of the STDP mechanism is shown in Figure 1. While individual action potentials (red and blue curves) are too small to trigger a change in resistance of the synapse, their superposition for small \(|\Delta t|\) (black curves) may exceed the threshold voltage (black dashed curve) required to change its resistance. The central plot in Figure 1 shows the STDP function, and more specifically the change in the synapse resistance plotted against \(\Delta t\). For a small positive \(\Delta t\), the pre-synaptic action potential is followed by a post-synaptic potential, which implies a causality in the communication of the two neurons. The resulting large positive superposition of the two action potentials (small positive \(\Delta t\), right part of Figure 1) decreases the resistance of the synapse, right part of Figure 1 decreases the resistance of the synapse to enhance such interactions between the two neurons in the future. Vice versa, a small negative \(\Delta t\) increases the resistance.

If \(|\Delta t|\) is too large, representing firing of the neurons without causal relation, the superposition voltage is insufficient to switch the synapse (negative \(\Delta t\), left part of Figure 1). Each point of the scatter plot is the gradual change in resistance caused by the superposition of the two action potentials for one specific \(\Delta t\)

\[
\frac{\Delta R}{R_0} (\Delta t) = \frac{R_{\text{after}} (\Delta t) - R_{\text{before}} (\Delta t)}{\min (R_{\text{before}} (\Delta t), R_{\text{after}} (\Delta t))}
\]

where \(R_{\text{after}}\) and \(R_{\text{before}}\) are the resistance values of the synapse measured after and before applying the superposition of the action potentials, respectively. The denominator uses the minimum value of \(R_{\text{after}}\) and \(R_{\text{before}}\) as scaling factor.

To quantify and be able to compare the individual STDP measurements with each other, the STDP functions \(\frac{\Delta R}{R_0} (\Delta t)\) are fitted with the following equations

\[
\frac{\Delta R}{R_0} (\Delta t) = A_0 e^{\frac{-\Delta t}{\tau}} \quad \text{for} \quad \Delta t > 0
\]
with the two linear scaling factors $A_+$, $A_-$ and the two exponential parameters $\tau_+$, $\tau_-$. Figure 2 shows a typical STDP measurement acquired on a TiN/Hf$_{0.5}$Zr$_{0.5}$O$_2$/Pt FTJ cell with a maximum change in resistance of approximately $\pm 3.5$. To obtain the exponential and linear parameters, the STDP curve is fitted with Equation (2) (red curve). Values of $-16$ and $12$ were obtained for $A_+$ and $A_-$, and $-0.034$ and $0.033$ ms for $\tau_+$ and $\tau_-$, respectively. The exponential parameters $\tau_+$, $\tau_-$ indicate how strongly the STDP function depends on $\Delta t$, while the linear factors $A_+$ and $A_-$ represent the maximum change in resistance for a single switching event and are therefore directly linked to the learning rate of the synapse. The heuristic Equation (2) employed to fit the STDP measurement only serves the purpose of providing quantitative parameters for an internal comparison between individual STDP measurements.

Figure 3 shows the influence of the maximum amplitude of the individual action potentials on the fitted parameters of the STDP function. Figure 3a depicts the change in scaling parameters with the action potential maximum amplitude, which ranges from $\approx 0.05$ to over $100$ for an action potential amplitude varying between $0.7$ and $1.2$ V. For each voltage value, the STDP measurements are reproduced three times and three values for $A_+$ and $A_-$ are extracted. Similar values are obtained for all three scans, as shown in Figure 3a. Furthermore, the semi-log plot depicts a linear behavior up to $1.1$ V, corresponding to an exponential dependence of the scaling parameters on the amplitude of the action potentials. After this action potential amplitude, the scaling parameter saturates. The higher the amplitude of the individual action potential, the higher the value of the resulting superposition for small $\Delta t$. This causes a larger change in resistance that can be attributed to a larger amount of switched domains of the FTJ. Therefore, a more intense stimulus on the synapse leads to a higher learning rate. Figure 3b presents the effect of the action potential amplitude on the exponential parameters. It can be seen that $\tau_+$ and $\tau_-$ remain constant for action potential amplitudes in the $0.7$–$1.2$ V range.

The effect of varying the width of the action potential on the STDP function is shown in Figure 4. Here, the maximum amplitude of the action potential is fixed at $0.7$ V whereas its width is varied between $0.8$ and $2.0$ ms. In this case, the $A_+$ and $A_-$ only show negligible variations (Figure 4a), but $\tau_+$ and $\tau_-$ depend on the action potential width (Figure 4b). This indicates that a change in resistance, and therefore the learning rate, is independent of the width of the incoming stimulus. In addition, the exponential parameters describe how fast the STDP function declines with the width of the action potentials.

2.2. Partial Switching and Model of Domain Polarization

To validate the experimental STDP results and the heuristic fit, a physical model of the gradual polarization switching is compared with the measurement data. First, the grain orientation induced by the STDP is determined. The polycrystalline grain structure of Hf$_{0.5}$Zr$_{0.5}$O$_2$ includes certain statistical factors. As a result, the switching time and required activation field can be expressed as probability distributions. This allows fractional switching of domains, depending on pulse time and amplitude. The grain structure is restricted to a columnar composition by the small thickness of the film. The grains layout can be assumed to be approximately parallel, due to grain diameters typically at least as large as the film thickness. Thus, the structure is modeled as a parallel resistor network where the total current is given by

$$\frac{\Delta R}{R_0} (\Delta t) = A_- e^{\frac{\Delta t}{\tau_-}} \text{ for } \Delta t < 0$$

$$\frac{\Delta R}{R_0} (\Delta t) = A_+ e^{\frac{\Delta t}{\tau_+}} \text{ for } \Delta t > 0$$

Figure 2. Typical STDP curve acquired on a TiN/Hf$_{0.5}$Zr$_{0.5}$O$_2$/Pt device with a maximum action potential amplitude of $0.9$ V and width of $2$ ms. The red curve is the fit of the data using Equation (2).

Figure 3. Effect of the maximum action potential amplitude on a) the scaling parameters $A_+$ and $A_-$ and b) exponential parameters $\tau_+$ and $\tau_-$ for a constant action potential width of $1$ ms.
the sum of currents over the individual grains. This mode of conduction is given by the WKB model, which describes one dimensional, direct tunneling over a trapezoidal potential barrier.\[31\] The polarization-dependent interface potentials are taken from Ambriz vargas and coworkers, yielding current densities for the LRS and HRS state\[18\]. The linear combination with grain fraction $g$ in LRS then reads

$$j(g) = gj_{\text{LRS}}(U,d) + (1-g)j_{\text{HRS}}(U,d)$$

where $j(g)$ is the current density from a fraction $g$ of the grains oriented toward the low-resistive state. The current densities $j_{\text{LRS}}$ and $j_{\text{HRS}}$ are extracted from the experimental measurements, using a common prefactor. Thus, the resistivity is given by

$$R(g) = \frac{U}{Aj(g)}$$

where $A = \pi(150 \mu m)^2$ is the surface area of the FTJ, and $U = 200$ mV is the applied voltage. Inverting this equation yields $g(R)$.

$$g(R) = \frac{U/(RA - j_{\text{HRS}})}{j_{\text{HRS}} + j_{\text{LRS}}}$$

This equation provides the grain orientations $g$ corresponding to the measured resistivities, as shown in Figure 5 (green region). This shows that the amount of switched grains increases with $\Delta t$, and with the action potential maximum amplitude, consistently with the trend observed in Figure 3 and consistent with ref. [11].

### 2.3. Modeling the Action Potential-Dependent Switching Behavior

During the measurements, the ferroelectric tunnel junction is switched by a series of STDPs for positive and negative time delays $\Delta t$ between 20 and 320 $\mu$s. This measurement is repeated for spike amplitudes between 0.8 and 1.1 V, effectively resulting in an almost rectangle pulse of width $\Delta t$, and an exponentially decaying voltage amplitude with increasing $\Delta t$. Before and after each pulse, the resistivity is measured at 0.2 V. The grain orientation thereby induced and determined with Equation (4) is shown in Figure 5 (green area).

![Figure 4](image-url) a) Scaling parameters $A_+$ and $A_-$ and b) exponential parameters $\tau_+$ and $\tau_-$ of the STDP plotted against the width of the action potential for a constant maximum action potential amplitude of 0.7 V.

![Figure 5](image-url) Amount of grain switching $g$ and corresponding resistance for spike amplitudes of a) 0.8 V b) 0.9 V c) 1.0 V, and d) 1.1 V and offsets $\Delta t$. The green area corresponds to the grain orientation switching induced by two overlapping spikes with $\Delta t$ in the positive and negative orientations. The black line shows the model prediction when starting from the measured value.
To describe these results, the NLS model is used.[32] This model is an extension of the classical Kolmogorov–Avrami–Ishibashi (KAI) model, describing the ferroelectric switching dynamics in polycrystalline thin films. As previously reported by Li et al.,[33] the NLS model is applicable to ferroelectric HfO\(_2\)ZrO\(_2\)O\(_5\) and provides an analytical expression for the field- and time-dependent polarization reversal. With the initial polarization fully polarized in one direction (Δ\(P = 0\) at \(t = 0\)), the switching is described by[33]

\[
\Delta P(t) = P_0 \text{erfc}\left\{ \frac{E_\sigma}{\left[E_f(t) \left[ \ln\left(\frac{t}{\tau_0}\right)\right]^{1/n} - 1\right]} / \sqrt{2}\sigma \right\}
\]

where \(E_f(t)\) is the externally applied electric field, \(P_0\), \(E_\sigma\), \(\tau_0\), \(n\), and \(\sigma\) are material parameters described in Table 1, and \(\text{erfc}(x)\) is the complementary error function. The asymmetry visible in the polarization response is taken into account using separate parameters sets for both switching directions for Equation (6).

While Equation (6) describes the polarization reversal starting from \(\Delta P(t) = 0\) at time \(t = 0\), our devices possess an initial non-zero polarization. Therefore, we first solve the equation to obtain the initial time \(t_{\text{init}}\) corresponding to our device’s initial polarization. Then, as the shape, the STPD pulses can be treated as a rectangle for small \(\Delta t\) and the evolution of the polarization is obtained by solving Equation (6) with a time step of \(\Delta t\).

As the device switching behavior is asymmetric, the characteristic time constant \(\tau_0\), the activation field \(E_a\), the standard deviation \(\sigma\) of \(E_f/E_a\), and the empirical exponent \(n\) are determined individually for both orientations as listed in Table 1. The mean grain orientation is determined by the polarization as \(g = \Delta P/2P_t\). The comparison between the model and the experimental results is shown in Figure 5. In this figure, the FTJ starts at a \(\Delta t\) of 20 \(\mu\)s in LRS. The devices is then switched from the LRS to the HRS by \(+ \Delta t\) and \(- \Delta t\) for each time step. The lower part of each curve therefore corresponds to the HRS, while the upper part corresponds to the LRS.

As can be seen in Figure 5, the device exhibits a clear asymmetry. Starting at small \(\Delta t\), switching to the maximum HRS takes about 60 \(\mu\)s. After switching to the HRS, the device switches to the initial LRS, resulting in the almost flat upper part of the curves. For \(\Delta t\) above 150 \(\mu\)s and action potential maximum amplitudes of 1.0 and 1.1 V, the amount of grains switched in the LRS switching increases. This suggests that it takes larger \(\Delta t\) to switch the remaining domains in the LRS. The fast switching observed for low \(\Delta t\) is associated with the formation of nuclei with reversed polarization, while the slower mechanism (\(\Delta t\) above 150 \(\mu\)s) is a successive expansion of existing domain walls that occurs when the electric field is too small to induce nucleation.[34] The asymmetry could be caused by the asymmetric electronic structure of the interfaces or different interfacial strains.

Using the model described above, the STDP curves are reproduced, as illustrated in Figure 6a. To do so, the resistance values

| Switching direction | \(P_0\) (\%) | \(\tau_0\) us | \(E_a\) (MV/cm) | \(\sigma\) | \(n\) |
|---------------------|-------------|-------------|----------------|-------|------|
| HRS to LRS          | 2 \(P_0\)   | 6.9         | 3.85           | 0.60  | 1.72 |
| LRS to HRS          | 2 \(P_0\)   | 22          | 4.53           | 0.089 | 3.77 |

Figure 6. a) Typical STDP obtained using the NLS model for a maximum action potential amplitude of 0.9 V and width of 2 ms. b) Dependence of the scaling parameters and c) the exponential parameters on the maximum action potential.
obtained from the calculated grain orientation are plotted as a function of $\Delta t$. Figure 6a shows a similar behavior as that of the experimental STDP, where the resistance of the FTJ varies with the time delay $\Delta t$. These modeled curves were fitted using Equation (2) to investigate the effect of the action potential amplitude on the scaling and exponential parameters (Figure 6b,c). Consistently with the experimental results (Figure 3), the scaling parameter increases exponentially with the maximum action potential amplitude, while the exponential parameters remain constant. Between 0.7 and 1.0 V, the scaling parameters increase from $\approx$0.01 and 100, consistently with the experimental results. At higher voltage, the scaling parameters keep increasing, while the experiments depict a saturation.

3. Conclusion

In summary, the neuromorphic behavior of a TiN/Hf$_{0.5}$Zr$_{0.5}$O$_2$/Pt ferroelectric tunnel junction acting as an artificial synapse is investigated quantitatively. Spike-timing-dependent plasticity measurements are performed with varying amplitude and width of the action potentials. A quantitative analysis of the resulting STDP functions shows that the learning rate of the synapse mainly depends on the amplitude of the action potential. This experimental result is supported with a physical model of the gradual switching behavior, which relies on gradual switching of grain polarization of the Hf$_{0.5}$Zr$_{0.5}$O$_2$. A simulation based on the NLS confirms the experimental findings. These results will be beneficial for the understanding and training of ANNs built of artificial synapses.

4. Experimental Section

**FTJs Synthesis:** The samples were deposited by radio frequency (RF)-magnetron sputtering (tabletop SPT310 system from Plasmionic Inc.) on (100) p-type Si substrates. Using a TiN target, the TiN bottom electrode was sputtered at 600 °C for 15 min in a N$_2$ atmosphere with a power of 125 W and a pressure of 10 mTorr. The Hf$_{0.5}$Zr$_{0.5}$O$_2$ was deposited at 450 °C for 35 min in a 1:1 sccm Ar:O$_2$ sputtering medium, to achieve a thickness of $\approx$4 nm. For the Hf$_{0.5}$Zr$_{0.5}$O$_2$ deposition, a 50:50, 1 inch diameter, HfZrO$_2$ target was employed. The pressure was kept constant at 5 mTorr, and the power, at 20 W. 45 nm thick circular Pt electrodes with 300 $\mu$m diameter were deposited using a shadow mask. The deposition were performed for 3 min at room temperature by RF-magnetron sputtering with a 1 inch diameter Pt target, an RF-power of 30 W, and a sputtering pressure of 6.0 mTorr.

**Device Characterization:** STDP measurements were performed with an ArC ONE™ hardware platform, where one cell was connected through BNC terminals. The top and the bottom electrode were contacted with two tungsten probes using micromanipulators inside a Faraday cage. All read operations were carried out at a read voltage of 0.2 V thus not to switch the FTJs. For the STDP measurements, rather than applying two individual action potentials, we directly apply the sum of both for any given $\Delta t$.

**Supporting Information**

Supporting Information is available from the Wiley Online Library or from the author.

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**Conflict of Interest**

The authors declare no conflict of interest.

**Keywords**

ferroelectric tunnel junctions, Hf$_{0.5}$Zr$_{0.5}$O$_2$, nucleation-limited-switching models, spike-timing-dependent plasticity, synaptic learning rate

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[1] E. Chicca, F. Stefanini, C. Bartolozzi, G. Indiveri, Proc. IEEE 2014, 102, 1367.
[2] P. A. Merolla, J. V. Arthur, R. Alvarez-Icaza, A. S. Cassidy, J. Sawada, F. Akgayan, B. L. Jackson, N. Imam, C. Guo, Y. Nakamura, B. Brezzo, I. Vo, S. K. Esser, R. Appuswamy, B. Tabo, A. Amir, M. D. Flickner, W. P. Risk, R. Manohar, S. M. Dharmendra, Science 2014, 345, 668.
[3] D. Sek, Jeong, I. Kim, M. Ziegler, H. Kohlstedt, RSC Adv. 2013, 3, 3169.
[4] D. Kuzum, S. Yu, H.-S. P. Wong, Nanotechnology 2013, 24, 382001.
[5] H. Xu, Y. Xia, B. Xu, J. Yin, G. Yuan, Z. Liu, Sci. Rep. 2016, 6, 1.
[6] M. A. Zidan, J. P. Strachan, W. D. Lu, Nat. Electron. 2018, 1, 22.
[7] L. O. Chua, IEEE Trans. Circuit Theory 1971, 18, 507.
[8] R. Waser, M. Aono, Nat. Mater. 2007, 6, 833.
[9] A. Beck, J. G. Bednorz, C. Gerber, C. Rossel, D. Widmer, A. Beck, J. G. Bednorz, C. Gerber, C. Rossel, D. Widmer, Appl. Phys. Express 2000, 77, 139.
[10] S. Q. Liu, N. J. Wu, A. Ignatiev, Appl. Phys.lett. 2000, 76, 2749.
[11] A. Gruverman, B. J. Rodriguez, C. Dehoff, D. J. Waldrep, A. L. Kingon, R. J. Nemanich, J. S. Cross, Appl. Phys. Lett. 2005, 87, 14.
[12] E. Y. Tsymbal, H. Kohlstedt, Science 2006, 313, 181.
[13] V. Garcia, M. Biber, Nat. Commun. 2014, 5, 1.
[14] M. Y. Zhuravlev, R. F. Sabirianov, S. S. Jaswal, E. Y. Tsymbal, Phys. Rev. Lett. 2005, 94, 246802.
[15] H. Kohlstedt, N. A. Pertsev, J. R. Contreras, R. Waser, Phys. Rev. B 2005, 72, 124341.
[16] A. Chanthbhouala, V. Garcia, R. O. Cherif, K. Bouzehouane, S. Fusil, X. Moya, S. Xavier, H. Yamada, C. Deranlot, N. D. Mathur, M. Biber, A. Barthélémy, J. Grollier, Nat. Mater. 2012, 11, 860.
[17] H. Yamada, V. Garcia, S. Fusil, S. Boyon, M. Marinova, A. Gloter, X. Xavier, J. Grollier, E. Jacquet, C. Carrétéro, C. Deranlot, M. Biber, A. Barthélémy, ACS Nano 2013, 7, 5385.
[18] F. Ambriz-Vargas, G. Kolhatkar, M. Broyer, A. Hadi-Joussaf, R. Nouar, A. Sarkissian, R. Thomas, C. Gomez-Yáñez, M. A. Gauthier, A. Ruediger, ACS Appl. Mater. Interfaces 2017, 9, 13262.
[19] F. Ambriz-Vargas, G. Kolhatkar, R. Thomas, R. Nouar, A. Sarkissian, C. Gomez-Yáñez, M. A. Gauthier, A. Ruediger, Appl. Phys. Lett. 2017, 110, 093106.
[20] M. Hyuk Park, H. Joon Kim, Y. Jin Kim, W. Lee, H. Kyeom Kim, C. Seong Hwang, *Appl. Phys. Lett.* 2013, 102, 8.

[21] H. J. Kim, M. H. Park, Y. J. Kim, Y. H. Lee, W. Jeon, T. Gwon, T. Moon, K. Do Kim, C. S. Hwang, *Appl. Phys. Lett.* 2014, 105, 192903.

[22] M. Hyuk Park, H. Joon Kim, Y. Jin Kim, W. Lee, T. Moon, C. Seong Hwang, *Appl. Phys. Lett.* 2013, 102, 242905.

[23] M. H. Park, H. J. Kim, Y. J. Kim, W. Lee, T. Moon, K. Do Kim, C. S. Hwang, *Appl. Phys. Lett.* 2014, 105, 072902.

[24] L. Chen, T. Y. Wang, Y. W. Dai, M. Y. Cha, H. Zhu, Q. Q. Sun, S. J. Ding, P. Zhou, L. Chua, D. W. Zhang, *Nanoscale* 2018, 10, 15826.

[25] G. Q. Bi, M. M. Poo, *J. Neurosci.* 1998, 18, 10464.

[26] S. H. Jo, T. Chang, I. Ebong, B. B. Bhadviya, P. Mazumder, W. Lu, *Nano Lett.* 2010, 10, 1297.

[27] S. Boyn, J. Grollier, G. Lecerf, B. Xu, N. Locatelli, S. Fusil, S. Girod, C. Carrétéro, K. Garcia, S. Xavier, J. Tomas, L. Bellaiche, M. Bibes, A. Barthélémy, S. Saighi, V. Garcia, *Nat. Commun.* 2017, 8, 14736.

[28] R. Guo, Y. Zhou, L. Wu, Z. Wang, Z. Lim, X. Yan, W. Lin, H. Wang, H. Y. Yoong, S. Chen, *Ariando, ACS Appl. Mater. Interfaces* 2018, 10, 12862.

[29] B. P. Bean, *Nat. Rev. Neurosci.* 2007, 8, 451.

[30] C. Künneth, R. Materlik, A. Kersch, *J. Appl. Phys.* 2017, 121.

[31] A. Gruverman, D. Wu, H. Lu, Y. Wang, H. W. Jang, C. M. Folkman, M. Y. Zhuravlev, D. Felker, M. Rzchowski, C. Eom, E. Y. Tsymbal, *Nano Lett.* 2009, 9, 3539.

[32] S. Zhukov, Y. A. Genenko, H. Von Seggern, *J. Appl. Phys.* 2010, 108, 014106.

[33] Y. Li, J. Li, R. Liang, R. Zhao, B. Xiong, H. Liu, H. Tian, Y. Yang, T.-L. Ren, *Appl. Phys. Lett.* 2019, 114, 142902.

[34] V. Boddu, F. Endres, P. Steinmann, *Sci. Rep.* 2017, 7, 1.