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The concept of Metal-Insulator-Metal nanostructures as Adaptive Neural Networks

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Abstract
Present computer processing capabilities are becoming a restriction to meet modern technological needs. Therefore, approaches beyond the von Neumann computational architecture are imperative and the brain operation and structure are truly attractive models. Memristors are characterized by a nonlinear relationship between current history and voltage and were shown to present properties resembling those of biological synapses. Here, the use of metal-insulator-metal-based memristive devices in neural networks capable of simulating the learning and adaptation features present in mammal brains is discussed.

Subject Headings. Nanotechnology, Computer Systems, information technology and data processing
Author Keywords. Neural Networks, Resistive Switching, Metal-Insulator-Metal

1. Introduction

The extraordinary rise in processing power, speed and storage capacity of computers is coming to a stall. There is thus an enormous opportunity to completely rethink the foundations of the present information age and open new paths into alternative forms of computation. In particular, computational architectures departing from the present von Neumann paradigm are being intensively sought after. For example, memory and adaptation are essential building blocks in learning and decision-making in biological systems (Chang, Jo, and Lu 2011). von Neumann systems rely on a deterministic approach in which learning and adaptation to new environments cannot be captured, whereas biological systems rely on an indeterministic approach with massive parallelism of simple processing units (neurons). This results in huge power efficiency, adaptation and resilience to unit failure (Yu, Wu, and Jeyasingh 2011; Liu et al. 2011).

Artificial systems in which processing and memory functions are located in the same level have been a long scientific dream, since they promise large improvements in performance along with the opportunity to design and build brain-like systems. This has moved a step closer following recent investigations of so-called memristive devices, which are two-terminal devices characterized by nonlinear relationships between histories of current and voltage (Corinto, Ascoli, and Gilli 2011). Their dynamics and small size have suggested their use as synapses and have inspired the neuromorphic community to explore the potential for building low-power intelligent machines (Kozma, Pino, and Pazienza 2012).

Here, one will review present state-of-the-art on adaptive neural networks using metal-insulator-metal nanosctructures.

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2. Learning and Adaptation in Biological Systems

Two fundamental units of the human brain, the neuron and the synapse, play essential roles in learning and in the formation of memory. Neurons are electrically excitable cells and are able to respond to stimuli, to conduct impulses and to link to other neurons of the neural

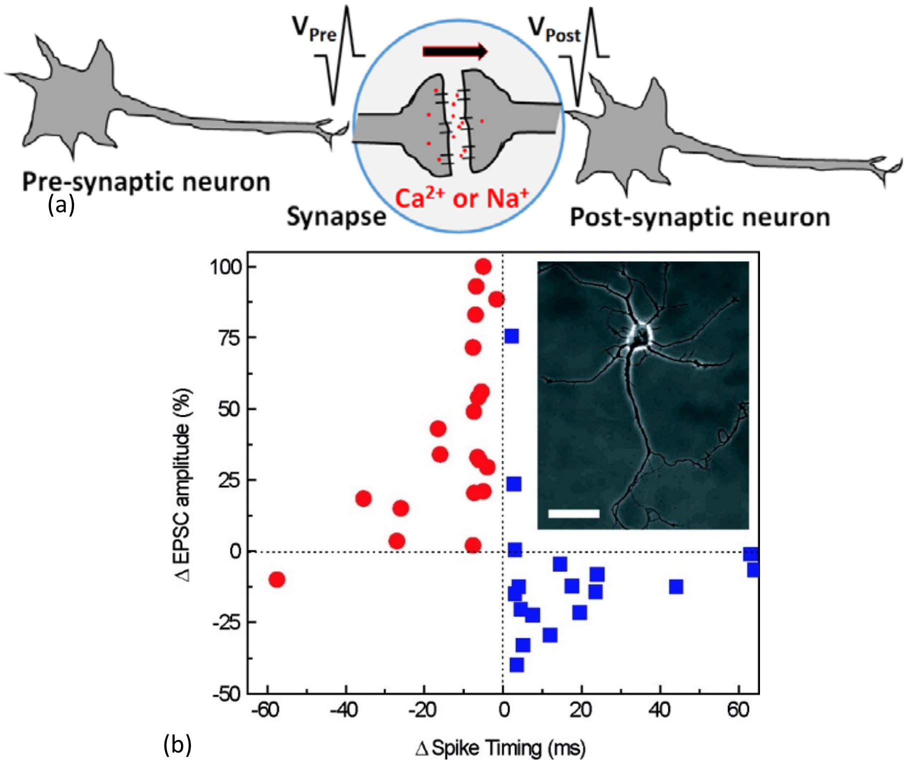


Figure 1: (a) Simplified diagram of a biological synapse interconnecting two neurons. (b) Experimental STDP data of a biological synapse [Reprinted with permission from (Jo et al. 2010). Copyright 2010 American Chemical Society]

pathway. Synapses are specialized structures in-between neurons that allow the rapid transmission of electrical and chemical signals so that neurons can communicate with each other (Shi et al. 2011). When an action potential generated by a neuron reaches a pre-synaptic terminal, a cascade of events leads to the release of neurotransmitters that give rise to a flow of ionic currents into or out of the post-synaptic neuron. Figure 1(a) illustrates two neurons connected by a synapse. The pre-synaptic neuron sends a pre-synaptic spike $V_{mem-pre}$ through one of its axons to the synaptic junction, while the post-synaptic neuron receives a post-synaptic spike $V_{mem-pos}$. Neural spikes are voltages from the outside of the cellular membrane V_{pre+}/V_{pos+} with respect to the inside V_{pre-}/V_{pos-}. Large spikes (hundreds of mV) make selective membrane channels to open (or close) allowing for ionic substances to flow (or not) through the membrane. Neurotransmitters released from pre- contribute to a change in the post-synaptic membrane's conductivity (Zamarreño-Ramos et al. 2011).

Learning and memory in human brains is the capability to gain new information, store it and be able to recall it. It is now generally accepted that information is stored in the synaptic strength, with learning being accomplished by modifying (either increasing or decreasing) the strength of the synapses (Wang et al. 2012). Such synaptic plasticity makes possible to store information and to react to inputs based on past knowledge (Choi et al. 2011). However, there are many rules to describe learning, one of them being spike timing dependent plasticity.

2.1. Spike Timing Dependent Plasticity

Spike timing dependent plasticity (STDP) is an experimentally verified biological phenomenon in which the precise timing of spikes affects the sign and magnitude of changes in synaptic strength. STDP can be divided into long-term potentiation (LTP) and long-term depression (LTD). In the former, synapses increase their efficiency if the pre-neuron activation consistently precedes the post-neuron activation, while in the latter synapses decrease their efficiency if the pos-neuron activation consistently precedes the pre-neuron activation (Seo et al. 2011).

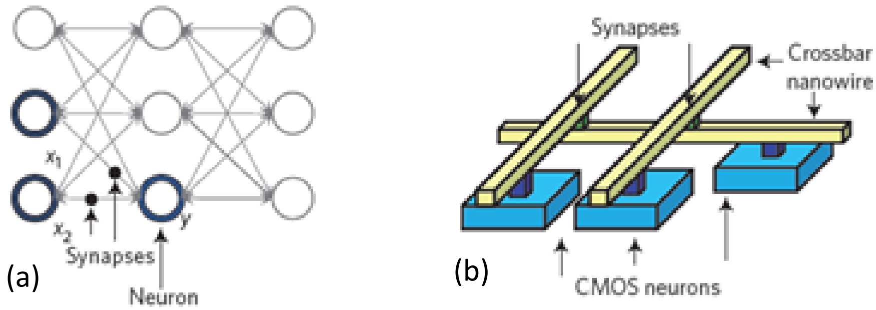


Figure 2: (a) Graph and (b) crossbar network architectures [Reprinted by permission from Macmillan Publishers Ltd: Nature Nanotechnology (Yang, Strukov, and Stewart 2013), copyright 2012]

As depicted in Fig. 1(b), the interspike interval (ISI) between action potentials in the pre- and post-synaptic cells modulates STDP. The smaller the timing between pre- and post-synaptic spikes, the larger plasticity change is induced in both LTP and LTD. On the other hand, longer intervals (above 50 ms) produce little or no change in synaptic strength (Karmarkar and Buonomano 2002; Choi et al. 2011). The relative synaptic conductance change $G = (G_{after} - G_{before})/G_{before}$, where G_{before} (G_{after}) is the conductance before (after) the pre- and postspike pair, has a range of [0, +∞[for potentiation and [-1, 0] for depression (Yu, Wu, and Jeyasingh 2011; Choi et al. 2011). The importance of STDP relies on the fact that it establishes a critical time window in which pre- and post-synaptic activity must occur to produce long-term changes in synaptic strength, and it provides a simple learning rule that decreases synaptic strength.

3. Artificial Neural Networks

Several attempts have been made to mimic the biological learning rules in artificial synapses and to construct artificial neural networks (ANNs) capable of performing complex functions. A network is based on the transmission of events from one source node (neuron) to multiple nodes by edges [synapses; see Fig. 2]. In most ANN models, synapses are dynamical two-terminal entities that connect a pre- (source) to a post-synaptic neuron (sink). The source emits a signal that is modified by a synaptic transfer function and delivered to the sink. To facilitate the communication between neurons, the action potential is propagated as a digital pulse (Schemmel and Grubl 2006). The output of a neural network node is a function of the sum of all input signals (Ha and Ramanathan 2011). The sink has a state variable that partially depends upon the history of incoming signals received from synapses that drive it. This variable along with the source signal determine the evolution of the synaptic state variable. For a very large number of synapses, a practical implementation of an artificial network allows the weights to be updated in parallel, by multiplying the logic value of the input ('1' and '0') by the memristance value, due to the high interconnectivity (Cruz-Albrecht, Yung, and Srinivasa 2012; Pershin and Di Ventra 2011; Dmitri B Strukov et al. 2008).

A radical approach in the construction of artificial neural networks is to use very large scale integration (VLSI) to implement directly in silicon the required computational model of a neural system. IBM researchers built a complex chip using 5.4 billion transistors to simulate 1 million neurons and 256 million synapses (Merolla et al. 2014).

In neuromorphic implementations, the key challenge is to design circuits with large time constants while keeping the neuronal structure simple, occupying small silicon area and using only one electronic device as an artificial synapse. However, the silicon area occupied by the synaptic circuit can vary significantly, as it depends on the choice of layout design solutions and more conservative solutions use large transistors. Implementing the large connectivity of

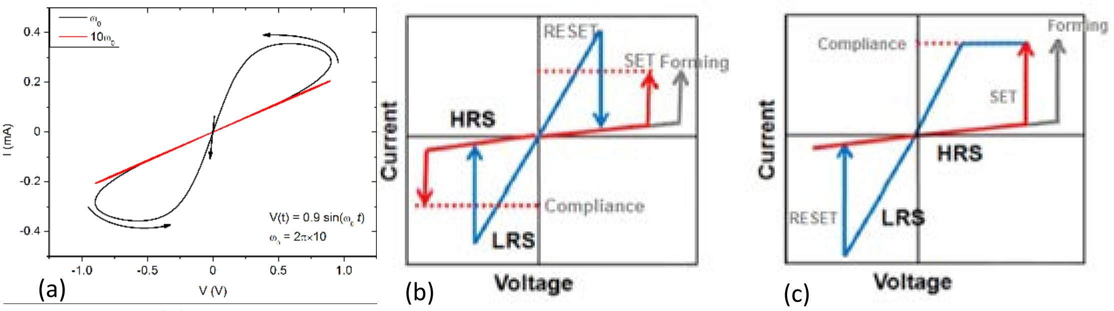


Figure 3: (a) I-V curves and hysteresis collapse with a tenfold increase in sweep frequency. I-V curves with forming for (b) unipolar and (c) bipolar switching [adapted from (Wong et al. 2012)]

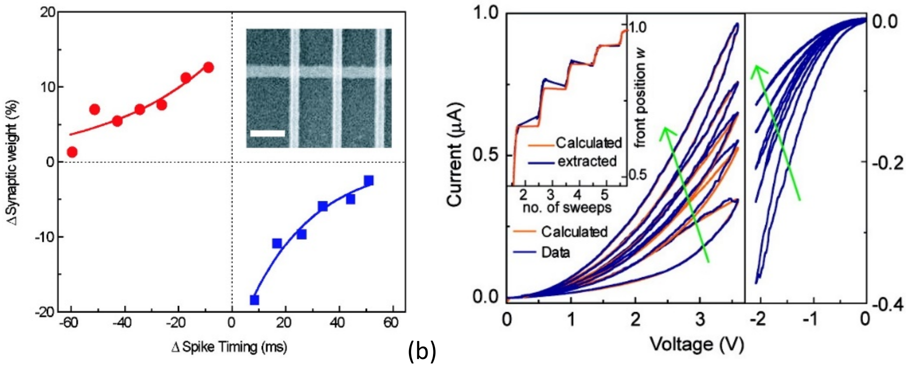
the brain with transistors on a single chip is a huge challenge, since a large number of transistors are needed. Therefore, the electronic conventional implementation is not practical and a simple and scalable device able to emulate synaptic functions is required (Shi et al. 2011; Seo et al. 2011). The resistance of such device must be continuously variable, depending on the history of the input signals, mimicking the gradual potentiation (or depression) of biological synapses (Choi et al. 2011; Seo et al. 2011). As we will see, the memristor displays such properties, making it the most promising candidate to be used in scalable neural networks.

4. Memristors and Memristive Systems

In 1971, Chua theoretically introduced the concept of the memristor (abbreviation of memory-resistor) as the fourth basic circuit element alongside the resistor, the capacitor, and the inductor (Gatet, Tap-Béteille, and Bony 2009). Chua postulated that there are four fundamental circuit variables (voltage V, current I, charge q and magnetic flux φ) which can be combined two at a time in six possible ways. In short, there exists the resistor, in the linear case, and the memristor to relate flux and charge. In 1976, Kang and Chua (Bo, Wang, and Jiao 2006) further extended their previous analysis to memristive systems and showed that diverse groups such as thermistors, Josephson junctions and ionic transport in neurons are special cases of memristive systems (Bo, Wang, and Jiao 2006; Joglekar and Wolf 2009).

The response of a memristive system to a periodic current (or voltage) input is a pinched hysteretic loop [Fig. 3], which is one of the most important properties of these systems, as hysteresis is a typical signature of memory devices. With respect to the periodic stimulus, for very high frequencies, a memristive system operates as a typically linear resistor since the state variable is not able to follow the stimulus in each oscillation, while for low frequencies it operates as a non-linear resistor, in which the state variable is given enough time to adjust. A variety of I(V) characteristics based on the frequency (Joglekar and Wolf 2009) and depending on the voltage time history are possible (Rosenblantt 1957).

The experimental realization of a memristor device was only recently achieved, with the pioneering work of Strukov *et al*. (Chang, Jo, and Lu 2011). They showed that a sinusoidal voltage produces a pinched-hysteretic I(V) characteristic in Pt/TiO_2/Pt nanostructures due to the motion of charged dopants. Since its experimental realization, the memristor has become one of the most promising candidates for the post-complementary metal oxide semiconductor (CMOS) era.



(a) (b)

Figure 4: (a)Memristor synaptic weight as a function of the relative timing of the neuron spikes. Inset: SEM image of the crossbar array (scale: 300 nm). (b)Measured (blue) and calculated (orange) I-V characteristics [Reprinted with permission from (Jo et al. 2010). Copyright 2010 American Chemical Society]

4.1. Metal-Insulator-Metal Memristors

The simplest nanostructure displaying memristive properties is the metal-insulator-metal (MIM) junction. A MIM device is simply an insulator material sandwiched between electrochemically active and/or inert metallic electrodes in a capacitor structure (Wong et al. 2012; Waser and Aono 2007; Ha and Ramanathan 2011; Tsuruoka et al. 2012). The recent large interest in these structures aims at a new class of memories called resistive random access memories (ReRAMs), since their switching is fast, non-volatile and can result in large ON/OFF ratio. Furthermore, MIM structures are the only where both unipolar and bipolar switching (defined below) can be observed, depending on the dielectric/electrode interfacial properties (Wong et al. 2012; Dias et al.). Interestingly, Choi *et al*. also demonstrated that a single MIM structure successfully stores the biological-like synaptic weight variations without any external storage node or circuit (Choi et al. 2011).

The most appealing property in memristive systems (for memory applications) is their resistive switching (RS) between a low resistive state (LRS; RON) and a high resistive state (HRS; ROFF), upon the application of an external voltage or current. The HRS to LRS switching is called set (or write), while the reverse is called reset [or erase; Figs. 3(b) and (c)] (Chen 2011). For some devices based on filamentary switching (see below), an electroforming step is needed before the first set. When the switching direction does not depend on the polarity of the applied bias, but just on its amplitude, the switching is called unipolar. Thus, set and reset can occur for the same polarity [Fig. 3(b)]. When it depends on the polarity, the switching is called bipolar and reset can only occur at the reverse polarity of the set process [Fig. 3(c)] (Wong et al. 2012). Current-voltage sweeps are frequently used for the identification of switching behavior, whereas pulses are useful for the quantitative investigation of switching kinetics. The state can be retrieved by measuring the electrical current when a small read voltage is applied (Kügeler et al. 2011).

5. Neuromorphic Properties of Memristors

To relate memristance to biological STDP, one requires a voltage/flux controlled bipolar memristor with voltage threshold, below which no variation of the resistance is observed, and an exponential behavior beyond threshold to be able to increment and decrement the conductance (Zamarreño-Ramos et al. 2011). Jo *et al*. (Jo et al. 2010) were the first to demonstrate STDP in nanoscale Si-based memristors in a crossbar structure [Fig. 4(a)]. The I(V) slope of each subsequent sweep picks up where the last one left off, showing that the conductance continuously increases (decreases) during the positive (negative) voltage sweeps [Fig. 4(b)]. It was also found that the strength of STDP learning in memristors can be

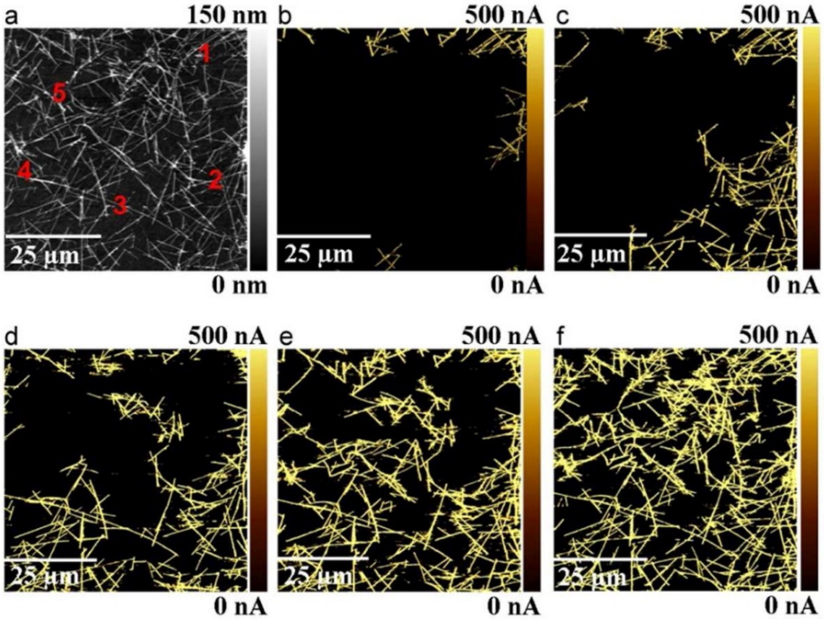


Figure 5: (a) Topography of a random network of Ag nanowires. A metal coated atomic force microscope tip was used to locally activate sites in the network by applying a voltage pulse. The current maps shown in (b)-(f) are the result of applying the voltage pulses at selected regions [marked 1-5 on the topographic map; Reprinted with permission from (Nirmalraj et al. 2012). Copyright 2012 American Chemical Society]

modulated by changing the amplitudes (or shapes) of the electric spikes, i.e., the conductivity can be tuned depending on the precise timing between the post- and pre-synaptic spikes and the learning window by changing the shape of the pulses (Zamarreño-Ramos et al. 2011). Choi *et al*. fabricated $Pt/Cu_2O/W$ MIM structures and experimentally demonstrated the successful storing of biological synaptic weight variations. They also showed the reliability of plasticity by varying the amplitude and pulse-width of the input voltage signal matched to the biological plasticity (Choi et al. 2011). Furthermore, Pavlov's experiment was implemented using memristive synapses in a two-input, one-output system (Ha and Ramanathan 2011). The output is initially only triggered by one input but after a learning step in which both inputs rely, the output can be triggered by either input.

5.1. Artificial Network Systems

Many different learning laws have been proposed for edges (Snider 2007). Adjustable edge weights are the defining characteristic of neural networks and are the origin of their broad adaptive functionality (Ha and Ramanathan 2011). An edge's conductance changes as a function of the voltage drop across the edge induced by forward spikes from the source node and back spikes from the sink node (Dias et al. 2015). Using memristive nanodevices to implement edges, conventional analog and digital electronics to implement nodes, and pairs of bipolar pulses, called spikes, to implement communication, it is possible to develop fully electronic neuron emulators (Snider 2007). It should be noted that, for ANN systems, the density of the memristive devices is the most important property. Also, ANNs are much more resilient to variations in synapses and neurons (D.B. Strukov and Kohlstedt 2012). For example, instead of a single pulse, the average effect on hundreds of parallel synapse inputs into one neuron determines whether the neuron will fire or not. Therefore, there is no need to completely eliminate the randomness of the RS (Yu, Wu, and Jeyasingh 2011).

One of the possible applications of memristor-based ANNs is to carry out position detection. This was simulated in Ref. (Ebong and Mazumder 2012), using ANNs that combine winner-take-all and STDP learning rules. Random nanowire networks [NWNs; Fig. 5(a)-(f)], where placement is not important and differences in properties are averaged out, also presented I(V) memristive-like behavior. So, the electrical properties of the NWN can be modeled as a leaky resistor-capacitor network with randomly distributed junctions, taking into account the distribution of breakdown voltages across individual junctions (Nirmalraj et al. 2012).

6. Conclusions

The performance of present day computers is a limiting factor in the progress of computational neuroscience research. It is envisaged that the understanding of the biological brain will lead to the building of brain-like computer systems, and that the overall architecture and principles of operation of these future computing devices could be closely modeled on biology. Considering memory an essential building block in learning and decision-making, the demonstration of such functionalities in a nanoscale memristor synapse is crucial to emulate neuromorphic systems and artificial neural networks (Chang, Jo, and Lu 2011). Memristor technology has the potential to revolutionize computing and scientific research in the coming decades.

References

Bo, Liefeng, Ling Wang, and Licheng Jiao. 2006. “Multi-Layer Perceptrons with Embedded Feature Selection with Application in Cancer Classification.” *Chinese Journal of Electronics*. https://homes.cs.washington.edu/~lfb/paper/cjoe06.pdf.

Chang, Ting, Sung-Hyun Jo, and Wei Lu. 2011. “Short-Term Memory to Long-Term Memory Transition in a Nanoscale Memristor.” *ACS Nano* 5 (9) (September 27): 7669-76. DOI: 10.1021/nn202983n.

Chen, An. 2011. “Ionic Memory Technology.” In *Solid State Electrochemistry II: Electrodes, Interfaces and Ceramic Membranes*, 1st ed., 1–18. DOI: 10.1002/9783527635566.ch1.

Choi, Sang Jun, Guk-Bae Kim, Kyoobin Lee, Ki-Hong Kim, Woo-Young Yang, Soohaeng Cho, Hyung-Jin Bae, Dong-Seok Seo, Sang-Il Kim, and Kyung-Jin Lee. 2011. “Synaptic Behaviors of a Single Metal-Oxide-Metal Resistive Device.” *Applied Physics A* 102 (4) (January 22): 1019–1025. DOI: 10.1007/s00339-011-6282-7.

Corinto, Fernando, Alon Ascoli, and Marco Gilli. 2011. “Class of All I-v Dynamics for Memristive Elements in Pattern Recognition Systems.” In *International Joint Conference on Neural Networks*, 2289–2296. DOI: 10.1109/IJCNN.2011.6033514.

Cruz-Albrecht, Jose M., Michael W. Yung, and Narayan Srinivasa. 2012. “Energy-Efficient Neuron, Synapse and STDP Integrated Circuits.” *IEEE Transactions on Biomedical Circuits and Systems* 6 (3) (June): 246–256. DOI: 10.1109/TBCAS.2011.2174152.

Dias, C, L M Guerra, J Ventura, and P Aguiar. 2015. "Memristor-Based Willshaw Network : Capacity and Robustness to." *Applied Physics Letters*. Vol. 106. DOI: 10.1063/1.4922148.

Dias, C., M. P. Proença, J. P. Araújo, and J. Ventura. "Tuning the Stoichiometry of Ag2S Thin Films for Resistive Switching Applications." *Journal of Nanoscience and Nanotechnology*.

Ebong, Idongesit E., and Pinaki Mazumder. 2012. "CMOS and Memristor-Based Neural Network Design for Position Detection." *Proceedings of the IEEE* 100 (6) (June): 2050–2060. DOI: 10.1109/JPROC.2011.2173089.

Gatet, Laurent, Hélène Tap-Béteille, and Francis Bony. 2009. "Comparison between Analog and Digital Neural Network Implementations for Range-Finding Applications." *IEEE Transactions on Neural Networks* 20 (3) (March): 460–70. DOI: 10.1109/TNN.2008.2009120.

Ha, Sieu D., and Shriram Ramanathan. 2011. "Adaptive Oxide Electronics: A Review." *Journal of Applied Physics* 110 (7) (January): 071101. DOI: 10.1063/1.3640806.

Jo, Sung Hyun, Ting Chang, Idongesit Ebong, Bhavitavya B Bhadviya, Pinaki Mazumder, and Wei Lu. 2010. "Nanoscale Memristor Device as Synapse in Neuromorphic Systems." *Nano Letters* 10 (4): 1297–301. DOI: 10.1021/nl904092h.

Joglekar, Yogesh N, and Stephen J Wolf. 2009. "The Elusive Memristor: Properties of Basic Electrical Circuits." *European Journal of Physics* 30 (4) (July 1): 661–675. DOI: 10.1088/0143-0807/30/4/001.

Karmarkar, Uma R, and Dean V Buonomano. 2002. "A Model of Spike-Timing Dependent Plasticity: One or Two Coincidence Detectors?" *Journal of Neurophysiology* 88 (1) (July): 507–13. http://www.ncbi.nlm.nih.gov/pubmed/12091572.

Kozma, Robert, Robinson E. Pino, and Giovanni E. Pazienza. 2012. *Advances in Neuromorphic Memristor Science and Applications*. Springer Publishing Company, Incorporated.

Kügeler, Carsten, Roland Rosezin, Eike Linn, Rainer Bruchhaus, and Rainer Waser. 2011. "Materials, Technologies, and Circuit Concepts for Nanocrossbar-Based Bipolar RRAM." *Applied Physics A* 102 (4) (January 29): 791–809. DOI: 10.1007/s00339-011-6287-2.

Liu, Y., T. P. Chen, Z. Liu, Y. F. Yu, Q. Yu, P. Li, and S. Fung. 2011. "Self-Learning Ability Realized with a Resistive Switching Device Based on a Ni-Rich Nickel Oxide Thin Film." *Applied Physics A* 105 (4) (September 23): 855–860. DOI: 10.1007/s00339-011-6605-8.

Merolla, P. a., J. V. Arthur, R. Alvarez-Icaza, a. S. Cassidy, J. Sawada, F. Akopyan, B. L. Jackson, et al. 2014. "A Million Spiking-Neuron Integrated Circuit with a Scalable Communication Network and Interface." *Science* 345 (6197) (August 7): 668–673. DOI: 10.1126/science.1254642.

Nirmalraj, Peter N, Allen T Bellew, Alan P Bell, Jessamyn a Fairfield, Eoin K McCarthy, Curtis O'Kelly, Luiz F C Pereira, et al. 2012. "Manipulating Connectivity and Electrical Conductivity in Metallic Nanowire Networks." *Nano Letters* 12 (11) (November 14): 5966–71. DOI: 10.1021/nl303416h.

Pershin, Yuriy V., and Massimiliano Di Ventra. 2011. "Memory Effects in Complex Materials and Nanoscale Systems." *Advances in Physics* 60 (2) (April): 145–227. DOI: 10.1080/00018732.2010.544961.

Rosenblantt, F. 1957. "The Perceptron, A Perceiving and Recognizing Automation." *Cornell Aeronautical Laboratory* ….

http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:The+perceptron--a+perceiving+and+recognizing+automaton#4.

Schemmel, Johannes, and A Grubl. 2006. "Implementing Synaptic Plasticity in a VLSI Spiking Neural Network Model." In *Neural Networks, International Joint Conference on*, 1–6. DOI: 10.1109/IJCNN.2006.246651.

Seo, Kyungah, Insung Kim, Seungjae Jung, Minseok Jo, Sangsu Park, Jubong Park, Jungho Shin, et al. 2011. "Analog Memory and Spike-Timing-Dependent Plasticity Characteristics of a Nanoscale Titanium Oxide Bilayer Resistive Switching Device." *Nanotechnology* 22 (25) (June 24): 254023. DOI: 10.1088/0957-4484/22/25/254023.

Shi, L. P., K. J. Yi, K. Ramanathan, R. Zhao, N. Ning, D. Ding, and T. C. Chong. 2011. "Artificial Cognitive Memory - Changing from Density Driven to Functionality Driven." *Applied Physics A* 102 (4) (February 5): 865–875. DOI: 10.1007/s00339-011-6297-0.

Snider, G S. 2007. "Self-Organized Computation with Unreliable, Memristive Nanodevices." *Nanotechnology* 18 (36) (September 12): 365202. DOI: 10.1088/0957-4484/18/36/365202.

Strukov, D.B., and H. Kohlstedt. 2012. "Resistive Switching Phenomena in Thin Films: Materials, Devices, and Applications." *MRS Bulletin* 37 (02) (February 17): 108–114. DOI: 10.1557/mrs.2012.2.

Strukov, Dmitri B, Gregory S Snider, Duncan R Stewart, and R Stanley Williams. 2008. "The Missing Memristor Found." *Nature* 453 (7191) (May 1): 80–3. DOI: 10.1038/nature06932.

Tsuruoka, Tohru, Tsuyoshi Hasegawa, Kazuya Terabe, and Masakazu Aono. 2012. "Conductance Quantization and Synaptic Behavior in a Ta2O5-Based Atomic Switch." *Nanotechnology* 23 (43) (November 2): 435705. DOI: 10.1088/0957-4484/23/43/435705.

Wang, Zhong Qiang, Hai Yang Xu, Xing Hua Li, Hao Yu, Yi Chun Liu, and Xiao Juan Zhu. 2012. "Synaptic Learning and Memory Functions Achieved Using Oxygen Ion Migration/Diffusion in an Amorphous InGaZnO Memristor." *Advanced Functional Materials* 22 (13) (July 10): 2759–2765. DOI: 10.1002/adfm.201103148.

Waser, Rainer, and Masakazu Aono. 2007. "Nanoionics-Based Resistive Switching Memories." *Nature Materials* 6 (11) (November): 833–40. DOI: 10.1038/nmat2023.

Wong, H.-S. Philip, Heng-Yuan Lee, Shimeng Yu, Yu-Sheng Chen, Yi Wu, Pang-Shiu Chen, Byoungil Lee, Frederick T. Chen, and Ming-Jinn Tsai. 2012. "Metal-Oxide RRAM." *Proceedings of the IEEE* 100 (6) (June): 1951–1970. DOI: 10.1109/JPROC.2012.2190369.

Yang, J Joshua, Dmitri B Strukov, and Duncan R Stewart. 2013. "Memristive Devices for Computing." *Nature Nanotechnology* 8 (1) (January): 13–24. DOI: 10.1038/nnano.2012.240.

Yu, Shimeng, Yi Wu, and Rakesh Jeyasingh. 2011. "An Electronic Synapse Device Based on Metal Oxide Resistive Switching Memory for Neuromorphic Computation." *IEEE Transactions on Electron Devices* 58 (8) (January): 2729–2737. DOI: 10.1109/TED.2011.2147791.

Zamarreño-Ramos, Carlos, Luis a Camuñas-Mesa, Jose a Pérez-Carrasco, Timothée Masquelier, Teresa Serrano-Gotarredona, and Bernabé Linares-Barranco. 2011. "On Spike-Timing-Dependent-Plasticity, Memristive Devices, and Building a Self-Learning Visual Cortex." *Frontiers in Neuroscience* 5 (January). DOI: 10.3389/fnins.2011.00026.

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