Metal Oxide Neural Devices and Their Applications

Boxin Song *

School of Materal Science and Engineering, CenturalSouth University, Changsha, China

* Corresponding Author Email: 8204211708@csu.edu.cn

Abstract. Metallic oxide neurons are a potential candidate for future applications in neuroscience and neuroscience, where they can be used as a model for simulating synaptic functions in biology. This paper mainly introduces two kinds of oxide-based memristors: memristor and neural transistor, as well as briefly discuss their integration. Because of the two devices' simple structure, similar to synaptic structure, high efficiency, low power consumption, high-density integration, compatibility with CMOS process conditions, and continuous control of conductance, it is considered to be the first choice for brain-like computing hardware. And the memristor can realize the integration of computing and storage functions in a single device. However, some problems and challenges still exist in memristor application. In the process of the device, there is a problem of insufficient miniaturization, because of the influence of leakage current, which limits the integration of the array and increases the operation energy consumption. In conclusion, despite their significant barriers before becoming commercially viable, their promising future is certain.

Keywords: Metal Oxides, Neural Devices, Memoristors, Neuromorphic computing.

1. Introduction

In the past few years, they have surfaced as tangible evidence of the convergence between material science and neural engineering, offering new opportunities for the evolution of bio-inspired computing [1]. This engaging synthesis includes the operational principles and recent advancements of these devices, showcasing their capacity to replicate the functions of natural neural computation. At the forefront of this domain is the concept of a memristor, a memory resistor, which embodies the essence of this field [2], echoing the plasticity of biological synapses? Research into oxide-based synaptic transistors reinforces the importance of neuromorphic devices, demonstrating electronic behaviors that echo natural synapses [3].

These developments are establishing the foundation for significant advances in integrated systems. The role they play in neuromorphic computing and sensorimotor networks is crucial, emphasizing the growth and future prospects of cognitive computing [4-7]. As demonstrated by recent research, the role of these neuromorphic devices in artificial intelligence is even more accentuated. Investigations into photonic spiking neural networks and multi-wavelength photonic neuromorphic computing point to an optimistic future for swift and energy-efficient neuromorphic systems [8, 9]. These advancements signify the continuous progress of metal oxide neuromorphic devices, attesting to their potential to reshape AI.

This article aims to explore the complexities of such devices and their potential as a tool for further development of cognitive computing. The introduction gives a context basis for explaining the key role of neural devices in the constantly changing landscape of artificial intelligence. Owing to the increasing need for energy efficient and high performance computing, metal-oxide-based solutions are becoming increasingly popular because of their capacity to mimic synaptic behaviour. In this article, we discuss the development of membrane and oxide based MOSFET, and their design and operation complexity.

2. Typical Metal Oxide Devices

2.1. Memoristor

Based on in-depth research as well as a profound insight in electronic science, L. Chua in 1971 proposed from the perspective of the symmetry and logical integrity of the four basic circuit quantities of current, voltage, charge and magnetic flux, in addition to the three types of devices: capacitor, inductor and resistor. , there is also a fourth passive electronic device defined by the relationship between charge and magnetic flux, as shown in Figure 1, namely memristor [10]

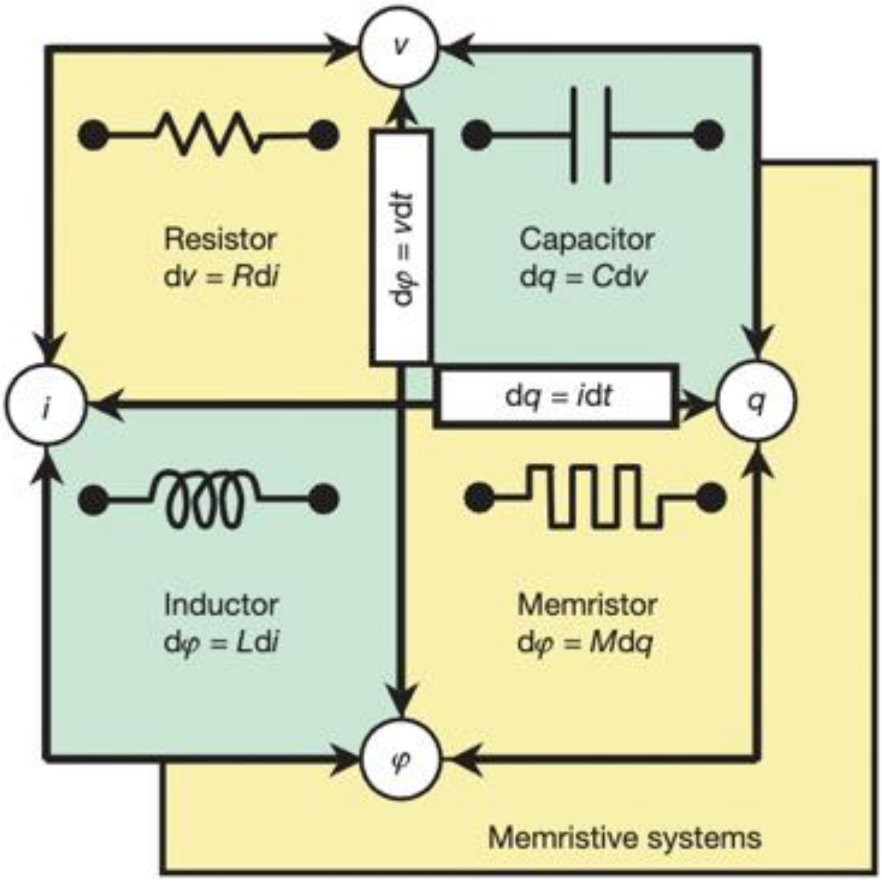

Fig 1. The four fundamental two-terminal circuit elements are resistor, capacitor, inductor, and memristor [10].

The memristor, an electronic component characterized by its memory function, shares the compact dimensionality with its passive counterpart, the resistor. It exhibits a unique property where it responds to various stimuli such as electric fields, pressure, and light; these interactions influence the internal charge dynamics, resulting in modulations of the memristor's resistance.

Professor Leon Chua later broadened the definition of memristors to include a wider range of devices whose resistance could be modulated by external stimuli, without necessarily adhering to a strict charge-flux (q-φ) relationship. Under this generalized framework, various memory technologies like Resistive Random-Access Memory (RRAM), Phase-Change Memory (PCRAM), Ferroelectric Memory (FeRAM), and Magnetic Random-Access Memory (MRAM) are embraced as members of the memristor family [11].

Despite the theoretical validation and circuit-level emulation of memristors, their physical realization in semiconductor devices remained unattained for an extended period. It wasn't until 2008 that HP Labs achieved a landmark with the fabrication of a memristor device using a TiO2 resistive layer. This milestone, which filled a longstanding void in preparation techniques, was published in the esteemed journal Nature [12], propelling the field of memristor technology into a new era of materialization and application.

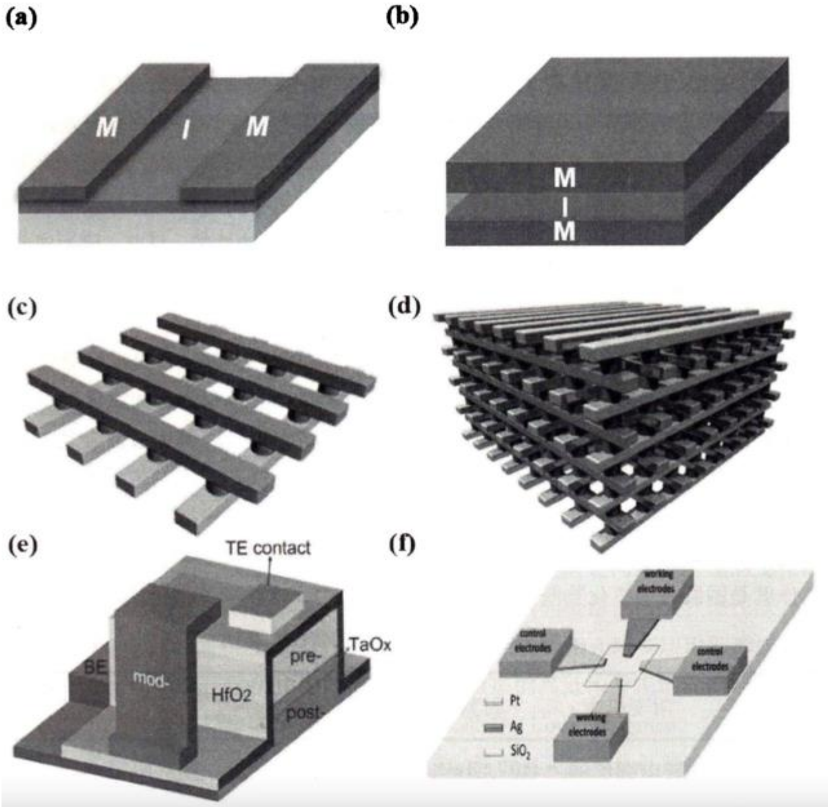

Fig 2. Common structural diagram of memristor. (a) Planar structure at both ends, (b) Vertical structure at both ends, (c) Cross structure, (d) three-dimensional stacking structure (e) three-terminal vertical structure [13] (f) four-terminal planar structure [14, 15].

As shown in Figure 2a metal/insulator/metal (MIM) structure resembling the shape of a sandwich is commonly used on memoristors’ design. It is well worth noting that the "M" here represents metal materials and refers to all of the good electronic conductive materials. The "I" is a good ion conductor and is used as the resistive layer of the memristor. Structurally, memristors can be divided into planar structures and vertical structures. The planar structure shown in Figure 2a means that the top and bottom electrodes are on the same plane, and the resistive layer is filled between the electrodes. Since this structure can intuitively detect the movement of ions under various characterization methods, it is usually used to characterize the resistive switching mechanism of the device [16][17]. The vertical structure adopts the stacking method of top electrode/resistive layer/bottom electrode from top to bottom, usually in the form of shared bottom electrode and cross form. Sharing the bottom electrode can reduce the steps of the photolithography process and is mainly used to study the suitability of the material structure; the cross form is that the top and bottom electrodes intersect vertically, and the intersection point is the device unit of the memristor. The cross structure facilitates miniaturization and large-scale integration of memristors, especially extending from two-dimensional integration to three-dimensional integration. Longitudinal continuous stacking will further increase the integration density of the array, as shown in Figure 2 [13]. This potential for high-density integration makes memristors an important research object in neural network building systems. Memristor can also be easily prepared as a multi-terminal device due to its simple structure, that is, in addition to the top and bottom electrodes, it also contains one or more modulation electrodes. Figure 2e and Figure 2f show multi-terminal memristive devices based on vertical structure and planar structure 3 respectively. Both of them control the dynamics of conductive filament generation by applying an external electric field to optimize device performance.

Different choice of materials will lead to different contact states and interface conditions between the electrodes, thus affecting the performance of the memristor. Therefore the selection of resistive materials in memristors should be reguarded as the core of memristor design. For now, the more mature resistive materials include transition metal oxides, such as ZrO2, TiO2, HfO2, Ta2O5, WO3, etc.; ferroelectric materials, such as HfxZryO, SrZrO3, SrTiO3, etc.; two-dimensional materials, such as MOS2 etc. Among all the materials that were selected, transition metal oxide materials have simple composition, controllable chemical ratio, simple process, low cost, and the preparation process is compatible with the traditional CMOS process; in addition, oxide memristors can also be used to simulate and implement Biological synapses and neuron function. Therefore, oxide-based memristors are considered the first choice for hardware to implement brain-inspired computing.

2.2. Oxide-based Synaptic Transistors

The intriguing domain of oxide based synaptic transistors has enthralled sophisticated electronics. The transistors use metallic oxides to simulate the behaviour of a biological synapse, giving a striking analogy to the complex workings of a human brain. The extraordinary properties of metallic oxides, for example, their malleability to conduct electrical conduction and storage, make them particularly suitable for developing highly effective and adaptable synaptic transistors.

The functional mechanism of oxide-based synaptic transistors is that they can regulate conductance, similar to the plasticity seen in real synapses. This dynamic property allows them to change the intensity of the signal and build a link between the artificial neurons, thus facilitating the development of a dynamic neural network. Notably, the use of materials such as titanium dioxide and hafnium-oxide has shown great potential in achieving this goal, which could potentially lead to exciting future developments in neuromorphic computing and AI.

It is even more attractive that an oxide-based MOSFET can be incorporated into a computer architecture, producing energy efficient, high-performance systems. Because of the lack of information lost upon deactivation of the power supply, these devices require a minimum amount of energy and seamlessly integrate into existing electronics systems. When we go further in the field of metal-oxide nerve devices, it is necessary to get a full picture of the complex details of the oxidation based synaptic transistors. In this way, we will be able to release all of our potential and infinite possibilities in this fascinating field of neuromorphic engineering.

3. Advances in Integrated Applications

For memristors, its cross structure can realize large-scale integration of arrays. Usually, we divide the integration of memristor into active array and passive array. In active arrays, the area of the memory cell is mainly determined by the size of the transistor, so the size of the transistor limits the scalability of the integrated structure of the active array. Passive devices have more advantages in terms of process and integration density. First of all, the passive array is not affected by the front-end process of the CMOS process, while improving the chip output, but also save costs, in the passive array, the memory unit is composed of the intersections of the word line and the bit line, so the minimum size can be reduced. And the structure is also conducive to the realization of 3D stacked integration, which can further improve the integration density, and the effective size of the storage unit can be reduced

Moreover, advances in the integration of metal-oxide neural devices have gone beyond the medical field. A remarkable development is the ability to seamlessly integrate metal-oxide-based devices into existing neural networks, promoting increased connectivity and cognitive abilities. This collaboration has created a new way to deal with data efficiently, and has resulted in the emergence of a new type of nervous system that has never been seen before. Recent advances in this field have led to significant advances in the field of biomedical engineering and artificial intelligence. In biomedical applications, they developed complicated neural interfaces that helped to achieve more accurate electronic communication with the nervous system.

Additionally, in the scope of AI, the integration of metal oxide based devices significantly improved the performance of neural networks, enabling them to carry out more complicated tasks as well as more massive computation. As we enter the Industrial 4.0 Era, the importance of metal oxide neural devices in integrated circuits has become greater than ever.

4. Conclusion

The development of Metal-oxide neural devices (MONDs) have marked the progress of neurocomputing. MONDs stand at the forefront of this computing revolution by connecting biological functionality with energy-efficient design. This synergy paves the way for groundbreaking developments in the realm of intelligent systems. In this review, we have mapped out a path by introducing two most typical neural devices in which metal oxide plays an indispensible role. Among the complex web of MONDs, materials science is at its core, in which metallic oxides are used to construct devices that mirror the plasticity and resiliency of our minds. While there has been an enormous expansion in knowledge about those materials, in order for MONDs to be truly effective, continuous research will have to address the problem of their stable and durable nature. Furthermore, reducing the size of instruments challengs the limitations of today's manufacturing technology, which requires creativity in order to attain the density and efficiency required for complicated computation. Advanced conponents such as Memory-based Optoelectronic Neural Devices pledges to transform machine learning with their potential to accelerate computational speed while conserving energy.

Despite the promiseing future these devices hold, they still need to overcome significant barriers before they become commercially viable.Though Challenges related to scaling production processes remain as a major concern, advances in the area have been driven by the common effort of scientists from different disciplines ranging from chemistry, physics, materials, electronics, and computing neuroscience. In order to fully tap MONDs' potential, cross-disciplinary research must continue to promote in-depth knowledge and push innovation out of lab environments into real-world practice.

References

[1] Frenkel C, Indiveri G, Legat J D, et al. A fully-synthesized 20-gate digital spike-based synapse with embedded online learning[C]//2017 IEEE international symposium on circuits and systems (ISCAS). IEEE, 2017: 1-4.

[2] Lanza M, Sebastian A, Lu W D, et al. Memristive technologies for data storage, computation, encryption, and radio-frequency communication[J]. Science, 2022, 376(6597): eabj9979.

[3] Ha S D, Ramanathan S. Adaptive oxide electronics: A review [J]. Journal of applied physics, 2011, 110(7).

[4] Frenkel C, Lefebvre M, Legat J D, et al. A 0.086-mm^2 12.7-pJ/SOP 64k-synapse 256-neuron online-learning digital spiking neuromorphic processor in 28-nm CMOS [J]. IEEE transactions on biomedical circuits and systems, 2018, 13(1): 145-158.

[5] Thakur C S, Molin J L, Cauwenberghs G, et al. Large-scale neuromorphic spiking array processors: A quest to mimic the brain [J]. Frontiers in neuroscience, 2018, 12: 891.

[6] Tamakloe S. Perovskite nickelate device reconfigurable for different functions [J]. 2022.

[7] Lin Y P, Bennett C H, Vodenicarevic D, et al. Electro-grafted Organic Memristors as Synapses: Spike Timing-Dependent Plasticity and Supervised Function Learning[C]//E-MRS 2016 Spring Meeting. 2016.

[8] Owen-Newns D, Robertson J, Hejda M, et al. Photonic spiking neural networks with highly efficient training protocols for ultrafast neuromorphic computing systems [J]. Intelligent Computing, 2023, 2: 0031.

[9] Wang B, De Lima T F, Shastri B J, et al. Multi-wavelength photonic neuromorphic computing for intra and inter-channel distortion compensations in wdm optical communication systems[J]. IEEE Journal of Selected Topics in Quantum Electronics, 2022, 29(2: Optical Computing): 1-12.

[10] Chua L. Memristor-the missing circuit element [J]. IEEE Transactions on circuit theory, 1971, 18(5): 507-519.

[11] Chua L. Resistance switching memories are memristors [J]. Handbook of memristor networks, 2019: 197-230.

[12] Strukov D B, Snider G S, Stewart D R, et al. The missing memristor found [J]. Nature, 2008, 453(7191): 80-83.

[13] Yang Y, Yin M, Yu Z, et al. Multifunctional Nanoionic Devices Enabling Simultaneous Heterosynaptic Plasticity and Efficient In-Memory Boolean Logic [J]. Advanced Electronic Materials, 2017, 3(7): 1700032.

[14] Jeong D S, Schroeder H, Waser R. Abnormal bipolar-like resistance change behavior induced by symmetric electroforming in Pt/TiO2/Pt resistive switching cells [J]. Nanotechnology, 2009, 20(37): 375201.

[15] C Cheng. Performance Modulation and Functional Application of Neuromorphic Devices Based On metal Oxides[D].Unversity of science and technology Beijing,2021.DOI:10.26945/d.cnki.gbjku.2021.000411

[16] Guo X, Schindler C, Menzel S, et al. Understanding the switching-off mechanism in Ag+ migration based resistively switching model systems[J]. Applied Physics Letters, 2007, 91(13).

[17] Yang Y, Gao P, Gaba S, et al. Observation of conducting filament growth in nanoscale resistive memories[J]. Nature communications, 2012, 3: 732.