

Systematic Analysis of Memristor Theory, manufacture and application status

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Abstract. Research into memristor technology has gained significant momentum because of its ability to revolutionize storage and neuromorphic computing. Memristors are two-terminal devices that retain an electrical resistance state based on prior voltage applications, embodying a nonlinear element suited for future electronic systems. Because they have low energy requirements, rapid switching capabilities, and ability to store multiple states, memristors are well-positioned to significantly influence the development of cutting-edge memory solutions and serve as artificial synapses within neuromorphic computing systems. This paper provides an exploration of recent advancements of the memristor technology, focusing on material composition, switching mechanisms, and their applications such as non-volatile memory, reconfigurable logic gates, and neuromorphic computing systems. By analyzing materials such as binary oxides, perovskites, and two-dimensional compounds, the review delves into how these materials enhance performance characteristics like speed, endurance, and energy efficiency. The discussion underscores the transformative potential of memristors in shaping next-generation computing architectures, making them a cornerstone of future innovations in both digital and analog computing.

Keywords: memristor, non-volatile memory, neuromorphic computing, perovskite, two-dimensional compounds.

1. Introduction

The field of memristor research has garnered significant attention due to its potential abilities. Memristors, or memory resistors, are two-terminal devices that retain the electrical resistance based on the voltage before, embodying a fundamental non-linear element for next-generation electronic circuits. Since their theoretical formulation by Leon Chua and practical realization by HP Labs, memristors have opened new pathways for creating ultra-dense memory and developing brain-like computing systems [1]. The promise of low power consumption, high switching speed, and the ability to store multiple states make them ideal candidates for advanced memory technologies and artificial synapses in neuromorphic networks. This dual functionality could potentially lead to substantial advancements in both conventional computing hardware and emerging paradigms like quantum computing and artificial intelligence.

This paper is to provide a overview of the latest advancements in memristor technologies, emphasizing their material compositions, switching mechanisms, and diverse applications. This paper explores various resistive switching materials, such as binary oxides, organic compounds, perovskites, and two-dimensional materials like graphene and transition metal dichalcogenides. These materials have distinct properties that influence the memristor's performance characteristics, such as switching speed, endurance, retention, and energy efficiency. The integration of these materials into memristor structures has enabled the fine-tuning of device characteristics for specific applications, ranging from non-volatile memory storage to logic gates in reconfigurable computing architectures. Additionally, this paper discusses the role of memristors in neuromorphic computing, where their ability to mimic synaptic functions opens up possibilities for hardware implementations of artificial neural networks. This review delves into the role of memristors in analog computing, as well as in hybrid architectures that integrate conventional digital processing with memristor-driven storage and computational capabilities. Through an in-depth exploration of these areas, it underscores the transformative potential of memristors in advancing future technologies.

2. The basic theory of memristors

2.1. Definition and working principle of memristor

Predicted by Leon Chua, the memristor stands as the fourth fundamental passive electronic component after capacitors, resistors, and inductors. Chua described it as a nonlinear, passive, two-terminal device which establishes a time-dependent relationship between voltage and current flow [1]. The memristor adjusts its resistance value mainly through the history of voltage and current, so as to realize the storage and processing of information. Its core operating principle lies in the variability of resistance, which depends on the relation between the accumulation of previous voltage and current flowing through it. If the current flows in one direction, the resistance value will increase, and if opposite, the resistance value begins to decrease. If the current stops flowing, the structure retains its resistance value. From the dependency analysis:

Voltage (V) is described as the rate of change in magnetic flux (φ) over time (t):

$$V = d\varphi / dt. \quad (1)$$

Current (I) is defined as the rate at which charge (q) changes with respect to time (t):

$$I = dq / dt. \quad (2)$$

Resistance (R) expresses the linear relationship between voltage (V) and current (I):

$$R = dV / dI. \quad (3)$$

Capacitance (C) represents the linear relationship between voltage (V) and charge (q):

$$C = dq / dV. \quad (4)$$

Inductance (L) is characterized by the linear relationship between magnetic flux (φ) and current (I):

$$L = d\varphi / dI. \quad (5)$$

Leon Chua pointed out that there should also be a linear correlation between magnetic flux (φ) and charge (q), expressed as:

$$d\varphi = Mdq. \quad (6)$$

Where M is the memristor.

Fig.1 illustrates the connection between fundamental circuit components and the key parameters that govern their behavior [2].

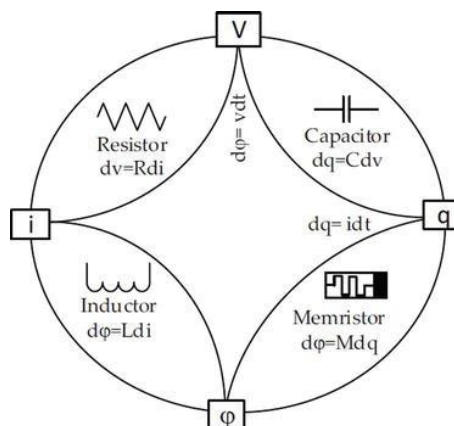


Fig. 1 The linkage between the four fundamental circuit elements and core parameters such as current (I), voltage (V), charge (q), and magnetic flux (φ) [2]

2.2. Mathematical model of memristor

In order to accurately describe and predict the electrical behavior of memristors, researchers have proposed a variety of mathematical models.

2.2.1 Linear drift model based on the classical approach

The linear drift model, introduced by Strukov after studying memristors with barium titanate (BaTiO_3) thin films, is one of the earliest mathematical frameworks for describing memristor behavior [3]. This model asserts that changes in conductivity are directly proportional to the current flowing through the memristor, making it applicable to memristors with straightforward structures. The relationship between the state variable $w(t)$ in the model and the current $I(t)$ can be expressed as:

$$\frac{dw(t)}{dt} = k \cdot I(t). \quad (7)$$

Where k is a constant determined by the material and structure of the memristor device. The relationship between voltage $V(t)$ and current $I(t)$ is represented by a dynamic resistance $R(w(t))$:

$$V(t) = R(w(t)) \cdot I(t). \quad (8)$$

This model effectively describes the linear behavior of simple memristors under low voltage and low current conditions.

2.2.2 Nonlinear drift model

Chua first put forward the concept of memristor and deduced the nonlinear relationship between its charge and magnetic flux, which formed the basis of the nonlinear drift model. The model assumes that the relationship between the state variable $w(t)$ of the memristor and the current $I(t)$ contains a nonlinear term:

$$\frac{dw(t)}{dt} = k \cdot I(t) \cdot g(w(t)). \quad (9)$$

Where, $g(w(t))$ is a nonlinear function, which is used to reflect the complex nonlinear characteristics of the memristor material. The model more accurately predicts the behavior of memristors under high current density or asymmetric voltage signals[1].

2.2.3 TEAM Model (Threshold Adaptive Memristor Model)

The TEAM model, an extension of the nonlinear drift mode, is designed to simulate memristors with threshold characteristics. Their study, which involved using materials like barium titanate and titanium oxide, found that the memristor's resistance state changes significantly when a certain threshold voltage V_{th} is applied [4]. Based on this discovery, Kvatinsky et al proposed the TEAM model, whose equation of state change is as follows:

$$\frac{dw(t)}{dt} = \begin{cases} k_1 \cdot I(t) \cdot g(w(t)) & \text{if } V(t) > V_{th} \\ 0 & \text{if } |V(t)| \leq V_{th} \\ k_2 \cdot I(t) \cdot g(w(t)) & \text{if } V(t) < -V_{th} \end{cases} \quad (10)$$

Where k_1 and k_2 are constants dependent on the direction of the current, and $g(w(t))$ is a nonlinear function. TEAM model successfully describes the complex dynamic behavior of memristors in multistable switching, synaptic plasticity and other applications, especially in the field of neuromorphic computing.

2.2.4 Simmons tunnel barrier model

The Simmons tunnel barrier model, introduced by Simmons, explains the quantum tunneling of electrons across the tunnel barrier in memristor devices. This model is especially relevant for evaluating tunneling effects in metal-insulator-metal (MIM) structures. The relationship between the current density J and the applied voltage V is given as follow:

$$J(V) = \frac{A}{d^2} \left[V \cdot \exp\left(-\frac{B\Phi^{\frac{1}{2}}d}{V}\right) - \frac{(V+V_0)}{d} \exp\left(-\frac{B(\Phi+V_0)^{\frac{1}{2}}d}{V+V_0}\right) \right]. \quad (11)$$

Where, A and B are constants related to the material and structure, d is the thickness of the tunnel barrier, ϕ is the barrier height, and V_0 is a constant related to the electrode material. Fig.2 illustrates the memristor configuration according to the Simmons tunnel barrier model, where w represents the width of the tunneling barrier, and R_s denotes the resistance of the channel [2].

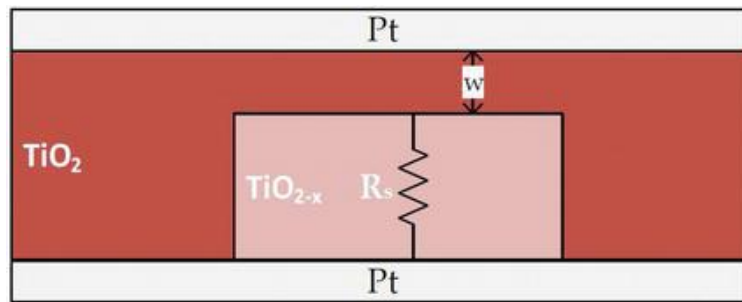


Fig. 2 Structure of the memristor according to the Simmons tunnel barrier model [2]

2.3. Main characteristics of memristor

2.3.1 Memory effect of impedance

The impedance of a memristor is influenced not only by the applied voltage or current but also by the history of these inputs, including the accumulation of charge or magnetic flux. This historical dependency manifests as a time-varying impedance. Memristors based on titanium oxide (TiO2) can reversibly transition between high resistance states and low resistance states, with this switching behavior associated with the movement of oxygen vacancies [3]. Specifically, the change in impedance can be described by the formula:

$$R(t) = R_{\min} + (R_{\max} - R_{\min}) \cdot (1 - e^{-\alpha q(t)}). \quad (12)$$

Where $R(t)$ is the impedance at time t , $R_{\min}$ and $R_{\max}$ are the lowest and highest resistance states respectively, $q(t)$ is the amount of charge flowing through the memristor, and α is the material dependent constant.

2.3.2 Nonlinear I-V characteristics

The I-V relationship of the memristor is usually significantly nonlinear, a property that reflects the dependence of the memristor on the historical voltage or current. The memristors based on perovskite materials exhibit strong nonlinearity at high current density, and the I-V relationship is often presented as a butterfly curve or a double curve, also known as a hysteresis loop, as shown in Fig.3 [2]. The shape and area of the hysteresis loop depend on the previous voltage amplitude, frequency, and the characteristics of the device material. The following formula describes the nonlinear I-V relationship of the memristor:

$$I(V) = \beta_1 \cdot V + \beta_2 \cdot V^2. \quad (13)$$

Where β_1 and β_2 are parameters related to the material and device geometry.

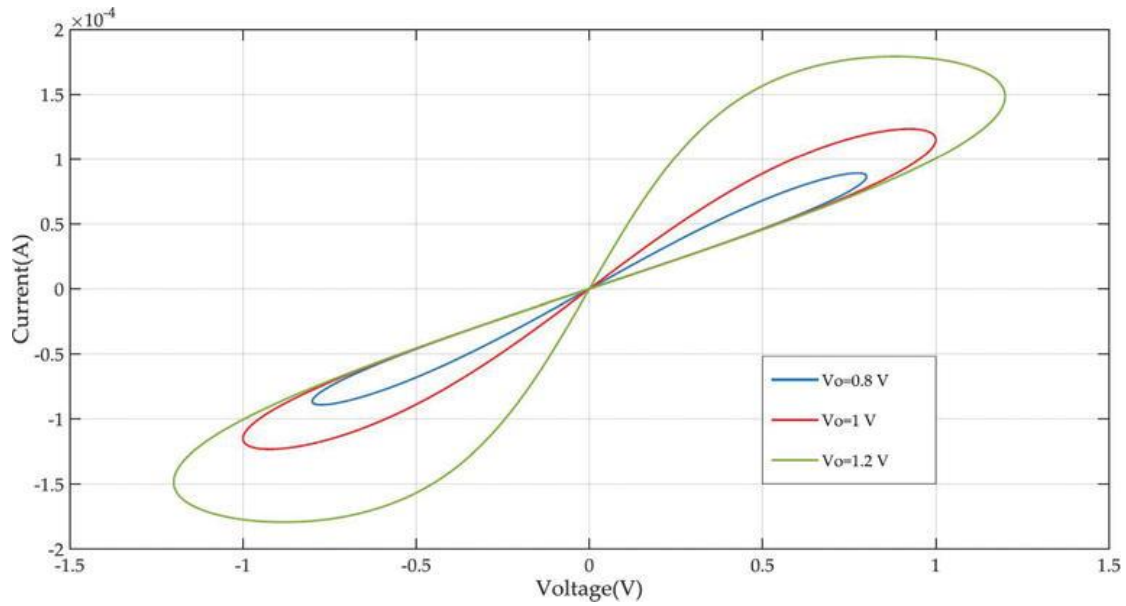


Fig. 3 The memristor I-V hysteresis loops at a frequency of $f = 1\text{Hz}$ and varying V_0 values [2]

2.3.3 Synaptic plasticity

Memristors can simulate the plasticity of the synapses of biological neurons, their resistance values change according to the strength and frequency of the input signal. This property is very important for the implementation of brain-like computing and neural network hardware. The TEAM model illustrates the synaptic plasticity behavior of the memristor well, and successfully simulates the long-term enhancement and long-term inhibition behaviors in experiments [4]. Fig.4 shows that stimulating a Ag/Si memristor with successive forward pulses can gradually increase its conductivity, similar to LTP. However, if the applied pulse is negative, it will reduce its conductivity, similar to LTD [6].

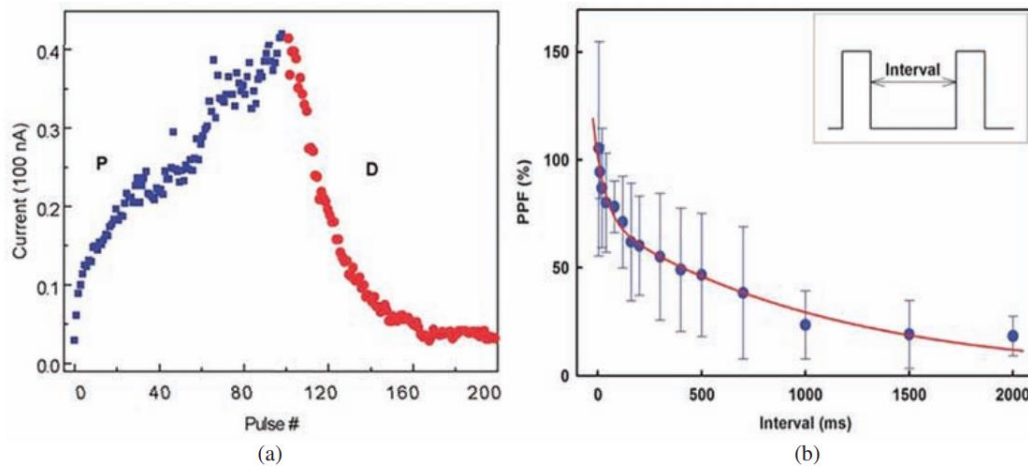


Fig. 4 (a) Response of the Ag/Si memristor to programming pulses for LTP and LTD, showing incremental changes in conductance with potentiating and depressing pulses. (b) PPF magnitude in a NiOx-based memristor as a function of pulse interval [6]

2.3.4 Non-volatile

The non-volatile characteristic of the memristor enables it to maintain its resistive state even after power failure, a property that has important applications in non-volatile memory. By adjusting the thickness and height of the tunneling barrier, a stable memory state can be achieved at the nanoscale [5].

$$J(V) = A \cdot (Ve^{-\Phi_B/V}). \quad (14)$$

Where $J(V)$ is the density of the current, ϕ_B is tunneling barrier height, and A is a constant related to the material and device geometry.

3. Design of key materials and devices for memristor

3.1. Key material types of memristors

The rapid development of memristor technology owes much to advances in materials science. Through the in-depth study of different materials, scientists were able to optimize the memristor in terms of performance, stability, compatibility, and so on.

3.1.1 Electrode material

In a memristor, the electrode serves more than just a conductive role; it directly affects the device's stability, conductivity, and response speed. Choosing an appropriate electrode material can enhance device performance and cater to various application requirements.

Conventional metals such as aluminum (Al) and copper (Cu) have become common choices for memristor electrodes because of their excellent electrical conductivity and low cost. But these metals may face the problem of electrochemical corrosion during long-term use, thus affecting the long-term stability [7]. Precious metals like gold (Au) and silver (Ag) are particularly suitable for demanding memory and computing devices due to their chemical inertness and extremely high electrical conductivity. Precious metal electrodes can lower the device's operating voltage and enhance data storage accuracy. Fig.5 illustrates the memory behavior of Ag/TiO₂:Ag/Pt [8]. Alloy materials, such as palladium-nickel (PdNi) alloys, can optimize electrical conductivity and mechanical properties by varying the metal component ratios. Adjusting the Pd-to-Ni ratio improves the memristor's thermal stability, maintaining stable electrical characteristics even at high temperatures. This makes alloy electrodes highly suitable for high-temperature and high-pressure applications.

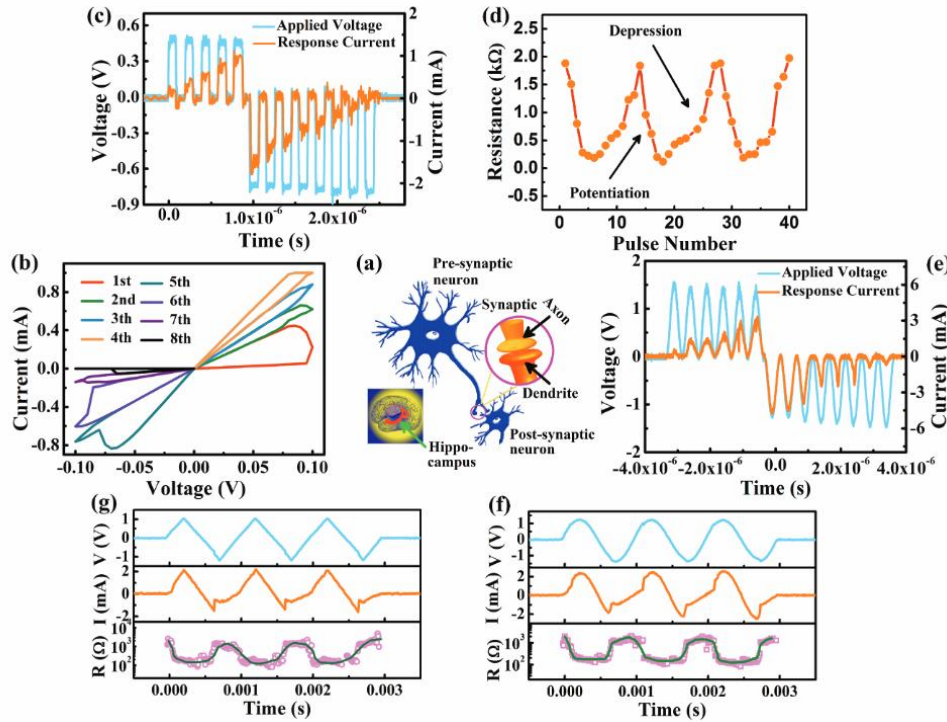


Fig. 5 Memristive behaviors of Ag/TiO₂:Ag/Pt[8]. (a) Synaptic plasticity regulation between axons and dendrites. (b) I-V curve showing up-down evolution of conduction, mimicking biological synapses. (c) Conduction modulation via pulse train. (d) Repetitive conductance modulation characteristics. (e) The applied voltage is $\pm v_0 \sin^2(\omega_0 t)$. (f) Communication model stimulus. (g) DC model stimulus.

Recent interest in flexible electronics has highlighted materials based on carbon such as graphene and carbon nanotubes (CNTs) due to their exceptional electrical conductivity and flexibility, good for wearable electronics. Fig.6(a) shows the structure of a Ta/Ta₂O₅/AlN/graphene memristor, where multi-layer graphene (MLG) acts as a postsynaptic neuron and the Ta top electrode serves as a presynaptic neuron [9]. Fig.6(b) displays the I-V sweeps of this memristor, revealing that both positive and negative currents vary with voltage changes, which is crucial for bidirectional resistance control in bio-synapse emulators [9].

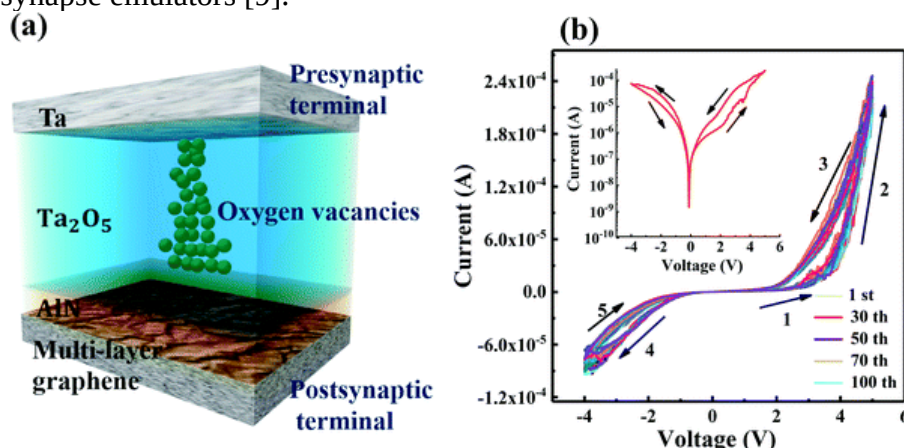


Fig. 6 (a) The structure of Ta/Ta₂O₅/AlN/graphene device[9]. (b) I-V curve of the device, with an inset showing the logarithmic representation of the I-V curves and the voltage scanning direction[9].

Nitrides such as titanium nitride (TiN) and tantalum nitride (Ta₂N) are widely used in devices with high reliability requirements due to their excellent high temperature stability and chemical inertness. Compared with conventional metal electrodes, nitride materials can still maintain good electrical properties and stability in harsh environments such as high temperature and high humidity.

Transparent conductive oxides like indium tin oxide (ITO) and doped tin fluoride oxide (FTO) show wide application potential in transparent electronic devices because of their combination of transparency and conductivity. In recent years, transparent electronic devices such as transparent displays and smart Windows have attracted much attention in the market, and ITO electrodes have become the key materials for such devices due to their high light transmittance and electrical conductivity.

3.1.2 Resistive storage material

The resistive storage layer of the memristor determines the core function of the device, and its material type and structure directly affect its resistive characteristics, response speed and data retention ability. “Resistive storage materials are categorized into inorganic and organic types.”

Inorganic materials are a key research focus due to their excellent stability and broad applicability. Binary oxides like titanium oxide (TiO₂) and silicon oxide (SiO₂) are particularly valued for their chemical stability, ease of preparation, and CMOS compatibility. Fig.7 illustrates the electrical properties of a memristor based on TiO₂ nanosheets [10]. Perovskite materials, with their diverse compositions and flexible crystal structures, offer tunable electrical and optical properties. Doping the A-site and B-site elements allows precise control over their resistance states. For instance, methylammonium lead iodide (MAPbI₃) perovskite exhibits both remarkable photoelectric properties and effective resistance switching. Two-dimensional materials like graphene oxide (GO) and molybdenum disulfide (MoS₂) are gaining more attention because of their thickness and electrical properties, enabling excellent conductance regulation and high-sensitivity photoelectric conversion.

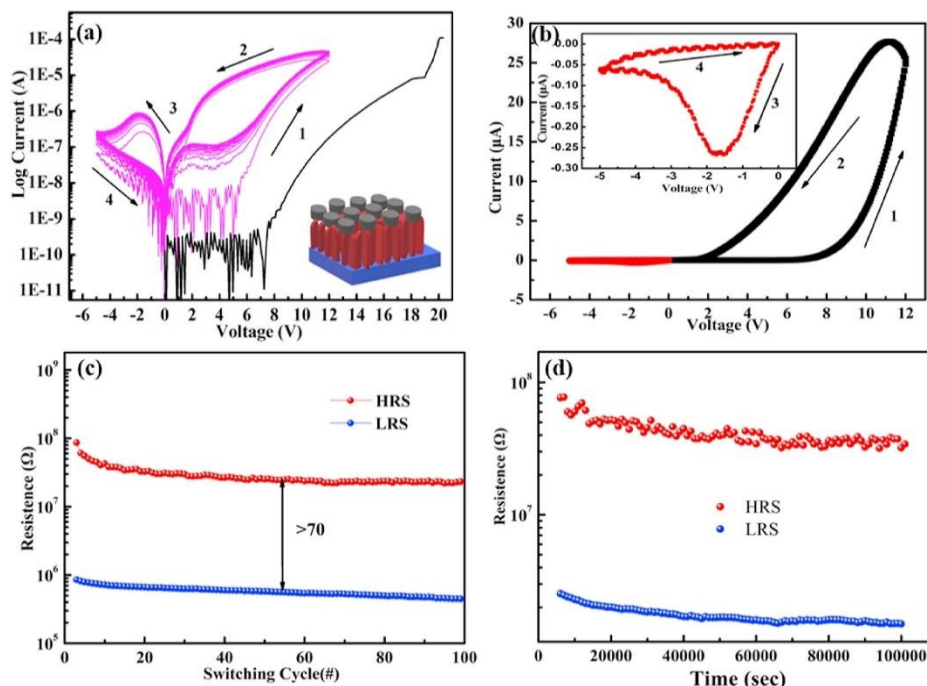


Fig. 7 TiO₂ nanosheets-based memristors electrical characteristics [10]. (a) I-V curve with an inset photo of the TiO₂ nanosheets memristor. (b) I-V characteristics shown in linear and semi-logarithmic plots. (c) The TiO₂ nanosheets memristors endurance test results. (d) Retention characteristics for HRS and LRS.

Organic materials, despite being less stable than inorganic counterparts, have gained prominence in flexible electronics due to their low cost, easy processing, and flexible, adjustable properties. Small organic molecules such as copper chloride phthalocyanine (ClCuPc) have good charge transport ability because of their unique molecular structure. ClCuPc can realize multistate storage at low voltage and exhibits excellent mechanical stability on flexible substrates. Organic polymers such as PEDOT:PSS are widely used in flexible memory devices due to their good electrical conductivity and high flexibility.

3.2. Design and manufacturing process of memristor device

The design and manufacturing process of memristor device directly affect its performance, stability and applicability. How to guarantee the high performance while taking into account the reliability of the device and the feasibility of large-scale manufacturing is the focus of current research.

3.2.1 Device structure design

The structure design of memristor is very important to achieve its excellent performance. Different structures not only affect the resistive characteristics, but also determine the switching speed, power consumption and integrated density of the device.

Single-layer memristors are widely used in basic research because of their simple structure and low manufacturing cost. However, the disadvantage of this structure is that the resistive performance is easily affected by external environmental factors, resulting in unstable switching voltage. Studies have shown that reducing the thickness of the film can reduce the volatility of the switching voltage, thereby improving the consistency of the device. As shown in Fig.8(a), an ultra-thin single-layer flash memristor is formed by spinning a 10 nm thick P6OV onto four identical pre-patterned cathode electrodes [11].

By introducing multiple resistive layers or interfaces, multilayer memristors can significantly improve the storage capability and data retention of devices. The design of multilayer structures usually involves the combination of different materials to achieve multistate storage using the electric field concentration effect of the heterogeneous interface, as shown in Fig.8(b) [12]. This design not

only improves the memory density of the memristor, but also improves the durability and fatigue resistance of the device.

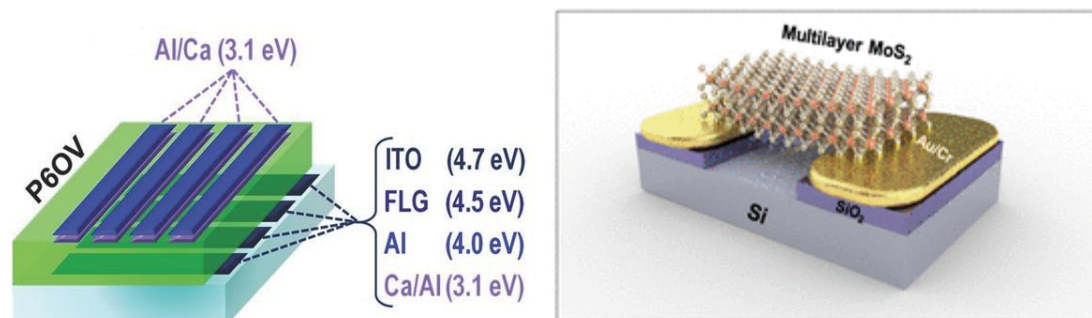


Fig. 8 (a) Single-layer P6OV memristor [11]. (b) A free-standing multilayer MoS₂ device [12].

The cross-beam structure design is an effective way to realize high density memory. The structure utilizes cross-aligned electrodes to maximize storage density and is ideal for neuromorphic computing and large-scale storage applications. A challenge in the design of cross-beam structures is how to effectively suppress crosstalk between adjacent elements to ensure the accuracy of data.

3.2.2 Manufacturing process

The manufacturing process of the memristor is also critical, and advanced deposition technology and precision nano machining methods are the basis for achieving high-performance devices.

Physical vapor deposition (PVD) is widely used in the preparation of resistant layers, especially at low temperatures, the PVD process can generate a dense and uniform film, suitable for deposition of a variety of materials. Further studies have shown that fine-tuning of deposition parameters such as pressure, power and substrate temperature can further optimize the microstructure of the film, thereby improving the stability and repeatability of the device. Atomic layer deposition (ALD) is the preferred process for the fabrication of nanoscale memristors due to its high precision and uniformity. ALD technology can deposit ultra-thin film layer on the surface of complex three-dimensional structure, which can not only significantly reduce the operating voltage of the device, but also improve the data retention ability and switching speed.

4. Application field of memristor

Memristors, as a novel circuit element, offer significant application potential across various fields due to their unique resistance transformation characteristics.

4.1. Applications of Storage Technology

In the field of memory technology, the core advantages of memristors are their non-volatile and adjustable resistance states. The memristor can change its resistance state by applying different voltages or currents, which allows it to switch between different resistance states, so as to achieve data storage and reading. Compared with traditional storage devices, memristors can provide both storage and logical operation functions in one single device, which greatly improves the data density and operation efficiency.

The performance optimization of the memristor can be achieved through material characteristics and structural design. For example, by doping specific elements or designing multilayer thin film structures, its conductive path can be stabilized and switching characteristics enhanced. These technical improvements allow for faster write and read speeds and lower power consumption, making memristors ideal for high-density storage applications. In addition, the three-dimensional stacked structure of the memristor provides a new way to increase memory density. By integrating multiple memristor units in the vertical direction, the storage capacity can be significantly increased without increasing the chip area, and this 3D integration technology has great potential in the field of mass

storage and high-performance computing in the future. Fig.9 presents a 3D flexible memristor array featuring a multi-layered crossbar architecture [13].

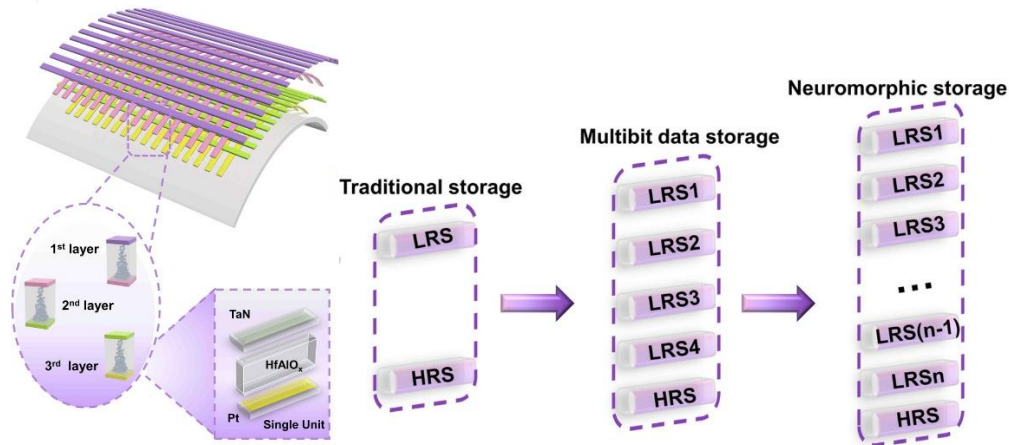


Fig. 9 A 3D crossbar memristor array comprising three layers of memory units, along with multibit storage capabilities within a 3D RRAM network [13]

4.2. Applications in neuromorphic computing

Neuromorphic computing replicates the function and structure of human brains, especially neural networks to enable more intelligent computing. The memristor's tunable resistance closely mimics synaptic plasticity, similar to neuron connections in the brain. By adjusting its resistance state, memristors can simulate dynamic synaptic changes, enabling the neural network's learning and memory functions. Fig.10 shows a neuronal memristor with its conductance behavior [14].

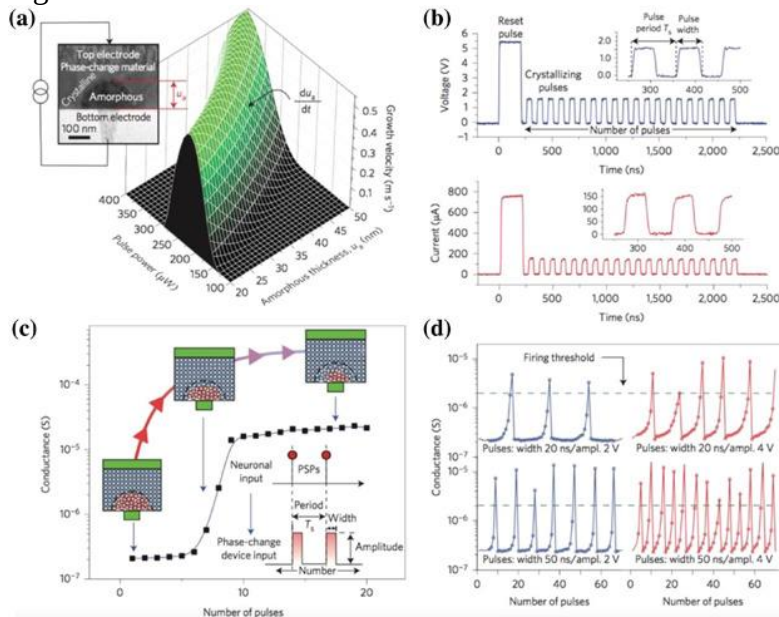


Fig. 10 Conductance behavior of a stochastic phase-change neuron [14]

Memristor based neuromorphic computing chips usually employ multi-layer memristor arrays, which can effectively simulate the synaptic connections of biological neural networks. In addition, the charge-pulse training method is used to optimize the learning algorithm, so that the memristor array can perform deep learning tasks more efficiently. Figure 11 presents a neuromorphic architecture utilizing STT neurons using synaptic memristor crossbar arrays to form a single neural network layer [14].

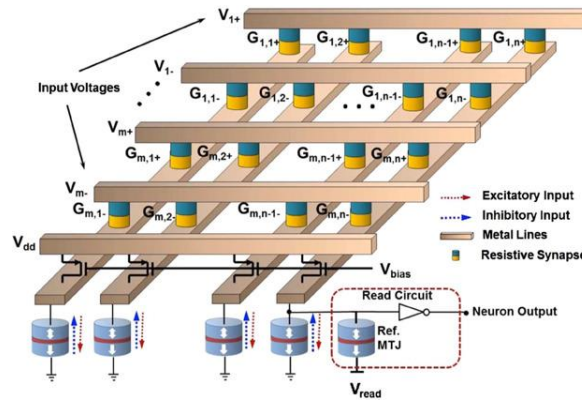


Fig. 11 Neuromorphic architecture utilizing STT neurons [14]

4.3. Applications of data encryption

In the field of data encryption, memristor provides a new technical solution for dynamic encryption and decryption because of its unique adjustable impedance. The memristor is able to implement multiple encryption modes by changing its resistance state, making each encryption operation unique and difficult to crack. In the study, the scientists developed a memristor based data encryption storage system, which leverages the memristor's nonlinear conductance to randomly assign resistance states during data encryption, forming a key that is difficult to predict. Through the performance test of various encryption modes, including speed, energy consumption and security, the system shows high anti-attack capability, which can effectively prevent data leakage and greatly improve the security of the system. Fig.12 shows the process of homomorphic encryption through HE-HW [15].

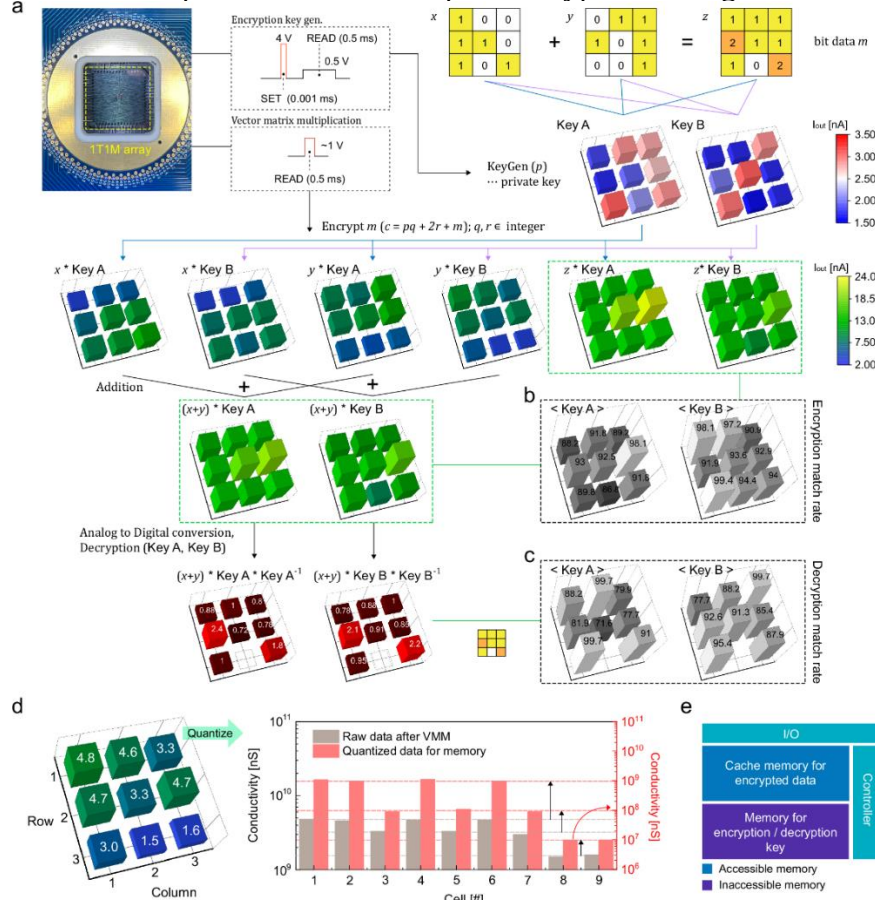


Fig. 12 (a) Diagram of demonstrating homomorphic encryption on binary input matrices. (b, c) Comparing the encryption and decryption match rates. (d) Process of quantized data storage after encryption. (e) Diagram of the HE-HW accelerator hardware architecture [15].

4.4. Applications in analog circuit design

In analog circuit design, the application of memristors is not limited to high-precision analog calculation, but also extends to the innovative design of adaptive circuits. The impedance tunability of the memristor enables it to dynamically respond to changes in the external environment in analog circuits, thereby optimizing circuit performance. For example, an adaptive filter based on memristor can adjust the filtering characteristics in real time by automatically adjusting the resistance state to achieve adaptive adjustment of signals of different frequencies.

5. Conclusion

In this paper, the latest progress in the field of memristor is reviewed, with emphasis on its material composition, switching mechanism and diverse applications in memory, brain-like computing and analog computing. Memristors, as novel nonlinear resistance devices, hold significant potential for future electronic circuits due to their ability to provide multi-state storage, rapid switching, and excellent durability, all with low power consumption. By studying different materials, such as binary oxides, perovskites, two-dimensional materials, etc., the researchers were able to optimize the performance of the memristor and provide customized solutions for specific application scenarios. Moreover, the use of memristors in neuromorphic computing, particularly their ability to simulate synaptic functions, opens new avenues for hardware implementation of artificial neural networks. This paper explores the material properties and application prospects of memristors, emphasizing their transformative potential for future technologies.

Despite their promising applications, memristors face several challenges in development. Key among these is ensuring material and process stability, particularly to guarantee the long-term reliability and repeatability of devices in practical applications. The memristors of different materials may be affected by material defects, interface instability and other factors in the process of preparation, which will affect the stability of device performance. The second is the problem of integration and large-scale manufacturing, how to effectively integrate memristor devices into existing silicon-based technology platforms, and achieve large-scale, low-cost manufacturing, is an urgent problem to be solved. In addition, how to efficiently cooperate the analog computing capability of memristor with existing digital computing systems is also an important direction of future research. To address these challenges, future research needs to explore material innovation, device design, integration technology, and system architecture in order to push memristor technology from the laboratory to practical applications, and truly realize its widespread application in the next generation of computing and storage systems.

By overcoming these challenges, memristors are expected to become a core component of a new generation of electronic devices, driving profound changes in information technology and computing architecture. In the future, research should continue to improve the performance and reliability of devices, develop new materials and structures, and explore more application scenarios to fully realize the potential of memristors in new types of storage and computing.

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