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Application of memristors for efficient neuromorphic computing in tactile sensing

Xintong Liu[1], Rongrong Bao[2,†], and Caofeng Pan[2,†]

[1]School of Materials Science and Engineering, Beihang University, Beijing 100191, China
[2]Institute of Atomic Manufacturing, Beihang University, Beijing 100191, China

Abstract: With the rapid development of the Internet of Things (IoT) and wearable electronics, tactile sensors play an indispensable role in intelligent sensing systems. However, traditional tactile sensing systems follow the von Neumann architecture, where sensors and processing units are physically separated. This leads to frequent data transfer of large raw data volumes, causing high latency and energy consumption. Such bottlenecks cannot meet the requirements of real-time closed-loop control and edge intelligence. Inspired by the highly integrated "perception-storage-computation" mechanism of biological sensory systems, memristor-based neuromorphic computing offers a groundbreaking solution beyond conventional approaches. Memristors combine non-volatile storage with tunable resistance. They enable *in-situ* emulation of synaptic plasticity, in-memory computing, and brain-inspired processing, thereby holding the potential to significantly improve the energy efficiency and response speed of tactile systems. This review systematically discusses the physical mechanisms of mainstream memristors, highlights recent progress in memristor-based neuromorphic computing for tactile sensing, and outlines key challenges and future directions for neuromorphic tactile perception systems.

Key words: memristor; flexible tactile sensing; artificial synapse; artificial neuron

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1. Introduction

Neuromorphic computing is a computational paradigm that more closely mimics how the human brain works. It is capable of overcoming the inherent limitations of the traditional Von Neumann architecture and more accurately simulating the functioning of biological neurons and synapses[1]. As early as the 1950s, researchers used vacuum tubes to build a network of 40 neurons. This was the first attempt to create an artificial neural machine called SNARC (Stochastic Neural Simulation Reinforcement Computer)[2]. Since then, researchers have conducted extensive studies on how to simulate the complex dynamics of neurons and synapses based on CMOS integrated circuits. However, as the performance gap between memory and processors continues to grow, silicon-based CMOS computing hardware is rapidly approaching its theoretical limits in terms of speed and energy efficiency. Against this backdrop, emerging materials and devices are extensively explored for the efficient realization of neuromorphic computing. Among these, memristors have gradually come into the research spotlight. They offer a simple structure, extremely low power consumption, strong scalability, and dynamic characteristics similar to biological synapses and neurons. As a result, they have become one of the key devices for enabling efficient neuromorphic computing[3].

Correspondence to: R R Bao, baorongrong@ucas.ac.cn; C F Pan, pancaofeng@buaa.edu.cn
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Tactile perception serves as the core channel for organisms to interact with the physical world[4]. It can transmit rich information such as pressure, texture, vibration, and temperature[5]. Therefore, it constitutes a critical foundation for robotic fine manipulation, natural control of intelligent prosthetics, and environmental perception achieved by wearable electronic devices[6]. In the human tactile sensory system, cutaneous mechanoreceptors are classified into fast-adapting and slow-adapting types based on their adaptation velocity[7–9]. Merkel cells are one type of slow-adapting receptors. They exhibit slow adaptation responses to tactile stimuli, allowing them to maintain continuous responses from the onset to the cessation of stimulation. By generating signals throughout the entire stimulus duration, they facilitate the detection of static stimuli, such as sustained pressure. In contrast, Meissner corpuscles and Pacini corpuscles exhibit rapid adaptation responses. Their non-neuronal components display specific spatial arrangements within the corpuscles, which reveal the mechanisms by which vibrations and dynamic movements are encoded. These receptors primarily generate signals at the onset and cessation of stimuli. Both types of mechanoreceptors possess synaptically connected structures that enable them to detect specific tactile patterns while modulating signals to achieve filtering, adaptation, and sensory memory. The processed information is then transmitted to the brain[10], in Fig. 1(a).

Inspired by human skin cells, researchers are dedicated to developing more intelligent tactile sensing systems[11–13]. However, traditional manual haptic systems are constrained by the von Neumann architecture. This architecture separates sensing, storage, and computation. As a result, it not

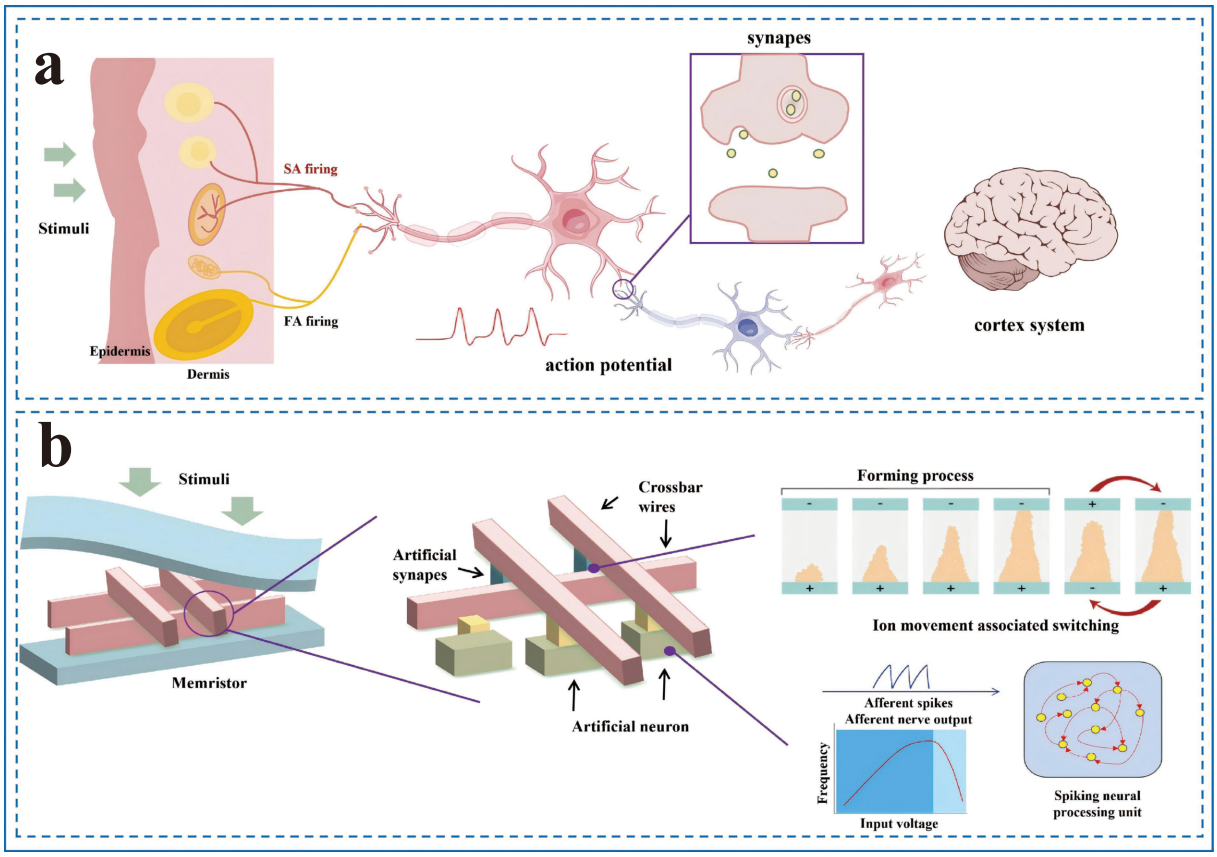

Fig. 1. (Color online) Memristors can mimic human tactile sensing systems and are applicable to artificial neurons and artificial synapses. (a) Human tactile sensing system[10]. (b) Different types of neural networks architectures. These neural networks can be mapped to the intersection matrix of artificial synapses and neurons. Copyright 2019, Wiley. Copyright 2020, Nature Publishing Group.

only leads to high power consumption and significant system latency but also becomes a bottleneck that limits real-time closed-loop haptic interaction applications[14]. As shown in Fig. 1(b), the advent of memristors offers a novel approach to overcome this bottleneck. Memristors possess dual capabilities in information storage and processing. They enable local signal processing at the sensing end. This capability significantly reduces latency and energy consumption associated with data transfer. This inherent characteristic aligns with the tactile sensing system's requirements for low latency and high energy efficiency. Against this backdrop, this paper aims to systematically review the working mechanisms of several common memristors. It also focuses on the application progress of memristors in tactile sensing for efficient neuromorphic computing.

2. Classification of memristors based on different physical mechanisms

2.1. Ion migration mechanism

The memristor is the fourth fundamental passive electronic component, following the resistor, capacitor, and inductor. Unlike conventional passive devices, its resistance depends on the history of the applied voltage or current[15, 16]. This property is typically realized through ion migration mechanisms within the active layer of the device. Under an external electric field, ions—such as oxygen vacancies or metal cations—undergo directional migration and changes in valence state[17]. These processes alter the local or overall conductivity of the device. Importantly, the resulting resistance state can be maintained even after the electric field is removed, enabling tunable and non-volatile behavior. Based on the type of migrating ions and the formation mode of conductive pathways, these mechanisms are broadly classified into two main categories.

2.1.1. Valence change mechanism (VCM)

Valence-change resistive memory (VCM) based on transition metal oxides (TMOs) is one of the most promising material systems. Electrochemical reduction-oxidation processes and oxygen vacancy migration play critical roles in this type of memory, governing the formation and fracture of conductive filaments (CFs). Electric field-driven oxygen ion migration alters the local concentration of oxygen vacancies in the oxide. This changes the valence states of metal cations, and as a result, the electrical resistance of the device is modulated. These bistable MIM units exhibit reversible switching between a high-resistance state (HRS) and a low-resistance state (LRS)[18]. The operation of VCM memristors involves the coupled evolution of conductive-filament geometry, charge-transport behavior, and local temperature[19]. The detailed nucleation and growth processes of conductive filaments have been directly recorded in certain materials using *in-situ* transmission electron microscopy (TEM)[20]. These observations have led to the development of numerous effective methods to optimize the performance of VCM-based resistive random-access memory (RRAM), including doping, electrode engineering, and interface engineering. The primary conduction mechanisms of VCM-based RRAM can be divided into two major categories. The first type depends on the electrical properties of the electrode-dielectric interface, including the inter-

face barrier height and the conduction carriers in the dielectric film. The second type depends on the intrinsic characteristics of the dielectric material itself, such as trap energy levels, trap spacing, trap density, carrier drift mobility, dielectric relaxation time, and conduction state density[21]. In VCM memristors, the typical conduction mechanism in the low-resistance state is ohmic conduction, where current is predominantly carried by established conductive filaments, typically aggregation channels of oxygen vacancies. In the high-resistance state, multiple conduction mechanisms may be involved, which can be either electrode-limited or bulk-limited. Examples include trap-assisted tunneling and Poole–Frenkel emission[22]. These mechanisms correspond to carrier transport through a defect-rich dielectric matrix after the filament has been fractured or contracted. As a bipolar switching device, the VCM memristor has become the mainstream choice in current research and development due to its fast switching speed, excellent endurance, and good compatibility with CMOS processes. However, its development faces a significant challenge. High-precision control of oxygen ion migration is required to ensure stable device performance.

2.1.2. Electrochemical metallization mechanism(ECM)

The ECM mechanism typically occurs in electrolyte materials and represents a classic "metal–electrolyte–metal" structure. Its core principle involves the electrochemical deposition and dissolution of active metal cations (such as Ag^+, Cu^{2+}) driven by an electric field, resulting in the formation or removal of metallic conductive filaments[18]. In this structure, two metal electrodes are separated by a solid electrolyte, and the device initially exhibits a high-resistance state. The resistance switching behavior is determined by the formation and fracture of metallic conductive filaments, enabling the transition between low-resistance and high-resistance states. However, there are inherent challenges. The bulk injection of metal ions into the electrolyte and the arbitrary migration of ions within the electrolyte lead to randomization and unpredictability in filament formation, inevitably affecting device uniformity and reliability[23]. Therefore, it is crucial to explore novel approaches for precise control of interfacial pathways and localized ion transport in ECM memristors. The Lee team proposed the concept of interfacial triggering sites (ITSs)[24]. Active ITSs (a-ITSs) are located at the interface between the bottom electrode (made of active metal Ag) and the polymer electrolyte, guiding the injection of metal ions. Inert ITSs (i-ITSs) are situated at the interface between the top electrode (made of inert metal Au) and the polymer electrolyte, serving as nucleation sites for conductive filament growth and effectively directing and regulating the growth path of the conductive filaments. In the pursuit of more precise and efficient positioning methods, two-dimensional materials have demonstrated significant potential and unique advantages as an emerging material platform for regulating the growth of conductive filaments in ECM memristors. Unlike traditional ECM mechanisms, two-dimensional material-based ECM memristors exhibit unique structural advantages and enhanced electron transport capabilities that facilitate conductive filament formation and enable controlled initiation of filament fracture. This behavior is attributed to the low interlayer ion mobility of two-dimensional materials, which leads to early reduction of metal ions during migration and causes conductive filaments to grow from the anode toward the cathode[25]. Yin utilized abundant sulfur vacancies on the surface of two-dimensional MoS_2 as migration channels for silver ions, enabling the formation of conductive filaments composed of silver nanoparticle chains. As a result, the memristor exhibited continuous electrical conductivity gradient behavior, achieving a transition in the conductive response from digital switching to analog gradient[26]. Based on these advantages, two-dimensional materials have gradually become an ideal choice for constructing memristors with high performance, low power consumption, and high integration density.

VCM and ECM are two representative filamentary switching mechanisms involving ion migration and redox reactions. Their primary distinction lies in the mobile ionic species: VCM is mainly governed by oxygen ions or oxygen vacancies, whereas ECM involves metal cations derived from an electrochemically active electrode[27, 28]. In typical ECM devices, Ag or Cu is oxidized under an applied electric field, generating metal cations. These cations subsequently migrate through the dielectric layer and are reduced near the counter electrode, forming metallic conductive filaments[27]. Comparatively, VCM is more sensitive to the defect structure of the oxide, oxygen vacancy concentration, and interfacial redox processes, and usually exhibits better material compatibility and more continuous conductance modulation. ECM, owing to the more direct formation and dissolution of metallic filaments, often shows comparatively lower operating voltage, higher ON/OFF ratio, and faster switching response in many material systems; however, the stochastic growth and rupture of metallic filaments may also lead to larger device-to-device and cycle-to-cycle variations[28]. In summary, the VCM mechanism holds advantages in terms of stability, endurance, and CMOS process compatibility, making it suitable for memory and computing applications that demand stringent reliability. In contrast, the ECM mechanism excels in its extremely high ON/OFF ratio and tunable volatile behavior, offering irreplaceable application prospects in specific functional devices such as high-density cross-point memory, selectors, and neuronal simulation. It should be noted that VCM and ECM are not always completely independent in practical oxide-based memristors. Particularly in devices containing active metal electrodes, metal cation migration and oxygen vacancy migration may jointly participate in the construction and evolution of conductive pathways, resulting in a hybrid switching behavior dominated by ECM with VCM as an auxiliary contribution, or a mixed-filament mechanism arising from the synergistic interaction between VCM and ECM[29]. Therefore, the analysis of resistive switching behavior in memristors should comprehensively consider multiple interacting factors, including the migrating species, conductive filament composition, electrode activity, dielectric defects, and interfacial redox reactions.

2.2. Phase transition mechanism

The core principle of phase-change memory (PCM) technology relies on reversible structural phase transitions in materials between amorphous and crystalline states[30]. Applied electrical pulses generate Joule heat, enabling reversible switching between high and low resistance states. Sulfide compounds are the most commonly used materials for this pur-

pose[31]. In the crystalline state, atoms exhibit long-range order and form a regular lattice structure, resulting in weak electron scattering and low resistivity. In the amorphous state, atomic arrangement is long-range disordered but short-range ordered (with localized structures such as Peierls distortion), leading to strong electron scattering and high resistivity[32]. More importantly, PCM not only enables binary switching but also supports continuous analog resistance modulation[33]. By precisely controlling the amplitude or duration of SET pulses during partial crystallization, the volume ratio of recrystallized amorphous regions can be accurately regulated. Although PCM exhibits significant advantages in neuronal computing, it also faces substantial challenges. The first challenge is resistance drift[34]. In the amorphous state, the material remains in a metastable glassy state, and even in the absence of electrical effects, its atomic structure undergoes extremely slow relaxation toward a more stable state through physical aging. The second challenge is operational noise and fluctuations[35]. At the nanoscale, phase transition processes involve a finite number of atoms and the randomness in atomic precise positions and nucleation sites leads to fluctuations in resistance values during each SET and RESET operation. Additionally, atomic-level local rearrangements in amorphous structures generate inherent resistance noise[36]. Atomic-scale structural rearrangement in memristive materials induces resistance fluctuations and the underlying free energy landscape is not only energy-dominated but also significantly regulated by entropy contributions[36]. Lim proposed a novel approach to address these challenges by enhancing the learning performance of neural networks through utilization of resistance drift, innovatively introducing spontaneous sparse learning (SSL)[37]. In this approach, resistance drift is regarded as a "spontaneous consistency distillation process". If a weight remains in the high-resistance state (amorphous state), the resistance increases over time, equivalent to the enhancement of the "positive contribution" of that weight. If the gradient updates the system to a low-resistance state (crystalline state) during training, the weights remain unchanged. This functions as a "memory reinforcement mechanism" that spontaneously strengthens weights consistently contributing to correct classification, thereby improving classification accuracy. The operating mechanism of PCM fundamentally involves a chain reaction of electrical energy, thermal energy, structural phase transitions, and conductive changes. Through precise thermal engineering, the ordered arrangement of microscopic atoms is controlled, enabling predictable and reversible electrical resistance switching at the macroscopic level[38].

2.3. Electron-association mechanism memristor

An electron-association mechanism memristor is a novel type of memristive device that achieves resistance plasticity through insulator–metal transition (IMT) induced by electron-electron interactions in strongly electron-association materials such as transition metal oxides and Mott insulators[39]. Its working principle differs from that of traditional memristors, with the core mechanism involving the use of external electric fields or currents to drive collective electron state reconstruction in the electron-association system. In these materials, the strong Coulomb repulsion force (U) between electrons exceeds their kinetic energy bandwidth (W). As a result, materials that should theoretically conduct electricity exhibit insulator-like behaviorv[40]. This metal–insulator transition can be triggered on the nanosecond timescale[41] and results in non-volatile and highly durable resistance switching. Peronaci proposed a theoretical model of Mott memristors based on the nonlinear carrier avalanche multiplication effect observed in Mott insulators under strong electric fields[42]. In Mott insulator-based memristors, the resistance state encoding is characterized by the density of twin and hole excitations, and the insulating state and conductive state are separated by negative differential resistance regions, resulting in pronounced hysteresis behavior in the current–voltage characteristic curves[43]. Although several theoretical models have been proposed, the precise nature and mechanisms of nonlinear dynamic behaviors such as carrier avalanche multiplication in Mott memristors still require further elucidation[44]. Mott memristors can simulate the spike behavior and synaptic plasticity of biological neurons. Owing to their fast insulator–metal transition and high sensitivity to material doping[45], Mott memristors are particularly suitable for emulating neuronal spiking and synaptic plasticity in neuromorphic systems[46].

2.4. Ferroelectric memristor

Ferroelectric memristors utilize the ferroelectric polarization state of ferroelectric materials to control device resistance[47]. The resistance state is determined by the polarization direction of ferroelectric domains and can be retained in a non-volatile manner. The ferroelectric tunnel junction (FTJ) is a typical "metal–insulator–metal" sandwich structure[47]. In this structure, the ultra-thin ferroelectric layer simultaneously serves as a tunneling barrier. Its core working mechanism primarily relies on the response of ferroelectric polarization direction to the applied electric field. When the applied electric field exceeds the coercive field, ferroelectric domains undergo flipping. This flipping results in alterations to the Schottky barrier height or the effective width of the tunneling barrier at the interface. As a result, the device's conductivity is exponentially modulated[48]. This mechanism fundamentally avoids several issues. Traditional conductive-filament-based memristors suffer from high inter-device variability and poor durability. These issues are caused by random filament formation or fracture. By avoiding these problems, ferroelectric memristors provide a physical foundation for achieving high-precision and high-stability synaptic weight simulation[49]. The coupling mechanism between polarization and defects in ferroelectric memristors is the core physical basis. It determines their switching behavior and computational functionality diversity. On one hand, the coupling between intrinsic defects and ferroelectric polarization can be utilized to modulate interfacial barrier and bulk transport properties. Studies have demonstrated that the coupling effect between defects such as oxygen vacancies and ferroelectric polarization significantly influences switching behavior[50]. Rational regulation of this relationship can effectively enhance switching ratio and stability[51]. Building upon this foundation, researchers further introduced dipole coupling of dual ferroelectric materials. This approach leverages the synergistic interaction between two intrinsic polarizations. It does not rely on defects. This method simultaneously enhances static multipole storage capacity. It also enables dynamic terahertz-band

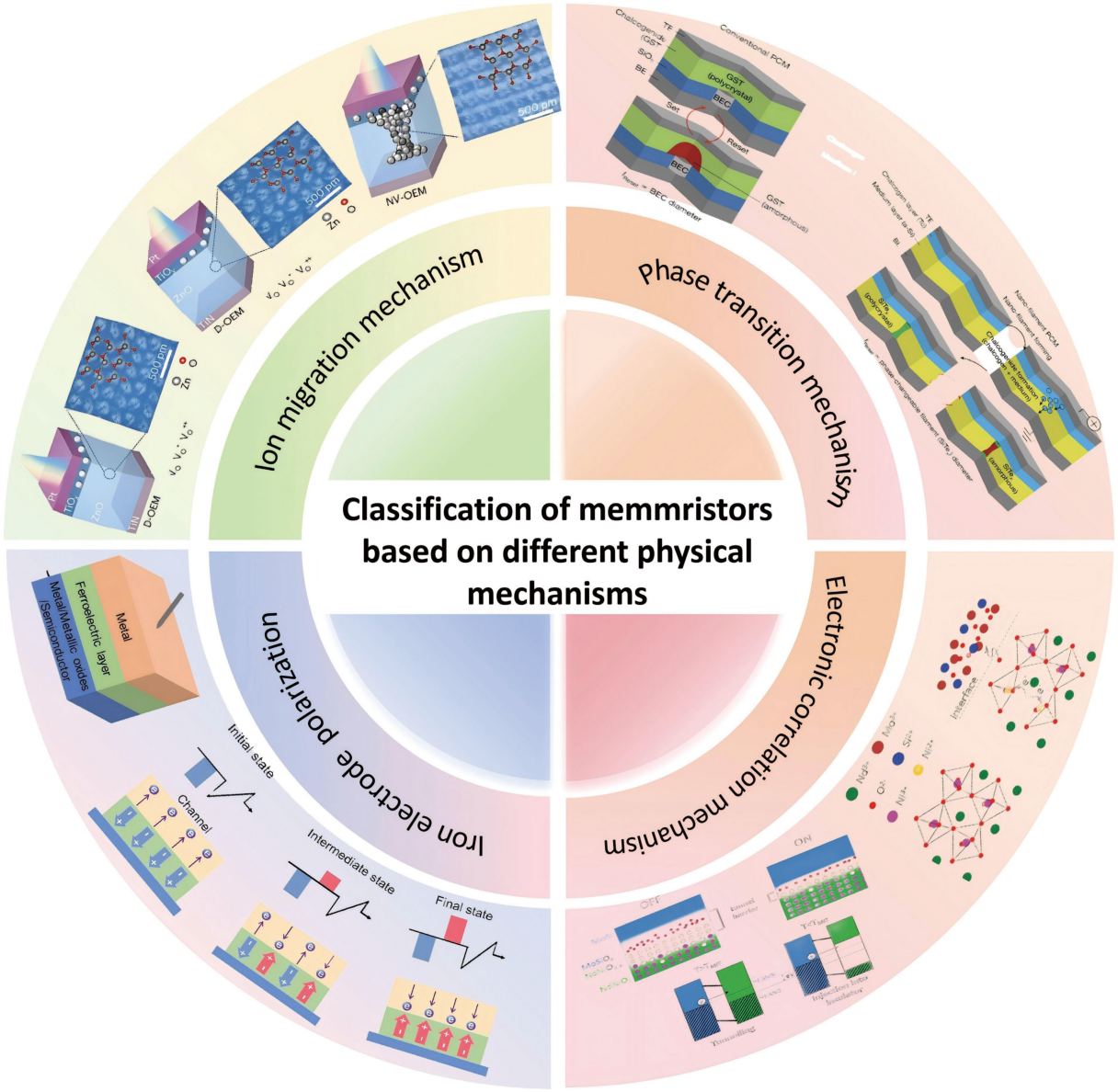

Fig. 2. (Color online) Classification of memristors based on different physical mechanisms[30, 43, 47]. Copyright 2024, American Institute of Physics. Copyright 2024, Springer Nature. Copyright 2022, Wiley.

nonlinear modulation[52]. Deep exploration and utilization of multiphysical coupling effects in ferroelectric systems represent a critical pathway. This pathway advances memristors from single-purpose storage to high-efficiency neuromorphic computing and nonlinear information processing.

Current research indicates that there does not exist a "universal" memristor capable of simultaneously meeting all requirements of tactile brain-inspired systems. Fig. 2 summarizes the currently mainstream memristors based on various physical mechanisms. The ion migration mechanism demonstrates inherent advantages in simulating biological synaptic plasticity. This makes it particularly suitable for temporal learning and memory of tactile information. Phase transition mechanisms prove essential for accelerating complex neural networks requiring high-precision weight calculations. The strong electron correlation mechanism achieves ultra-fast threshold switching through Mott phase transitions. It perfectly replicates the "all-or-none" firing behavior of biological neurons. It also replicates the threshold-triggering characteristics of nociceptors. This mechanism offers unique advantages in neuromorphic device design. Meanwhile, ferroelectric polarization mechanisms enable non-volatile storage through polarization reversal of ferroelectric domains. Their high linear weight update capability and low power consumption make them indispensable for constructing edge devices integrating sensing, storage, and computing functions. Future research will focus on heterogeneous integration strategies based on application requirements. Memristors with different mechanisms will be synergistically deployed across various levels, including tactile perception, processing, and feedback. The goal is to construct brain-inspired tactile systems that achieve comprehensive optimization in performance, power consumption, and reliability.

3. Application of memristors in brain-inspired tactile sensing

3.1. Artificial neuron

Artificial neurons are the core of neuromorphic computing. Their function mimics the dynamic behavior of biological neurons, which is characterized by an "integration-threshold-firing" process. Among various neuronal models, such as

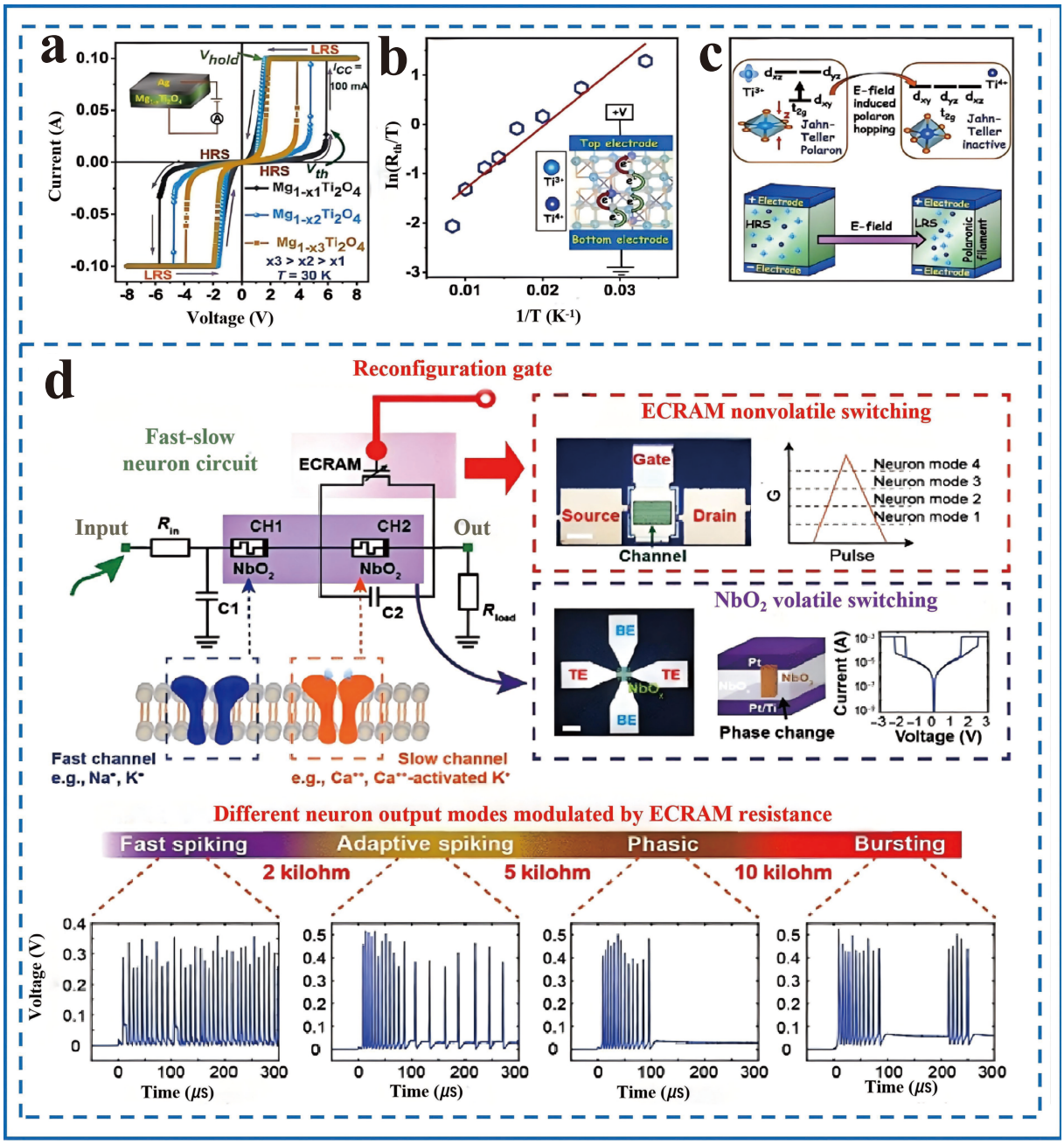

Fig. 3. (Color online) LIF neuron model with time encoding mechanism. (a)–(c) Realization of single-device LIF neuronal functionality in the $MgTi_2O_4$ system[45]. Copyright 2026, Wiley. (a) Threshold-driven resistance switching at different magnesium vacancy concentrations. (b) Schematic diagram of the driving mechanism for resistance transition phenomena. (c) Electric field-induced Jahn–Teller polarons jumping from Ti^{3+} sites to Ti^{4+} sites, followed by polarization filament formation along the electric field direction, resulting in resistance switching. (d) Spike-element neural systems with reconfigurable properties[59]. Copyright 2026, Wiley.

the MP and H–H models, the leaky-integrate-fire (LIF) model has become the mainstream choice for constructing spiking neural networks (SNNs). This is due to its precise representation of the bioelectrical activity cycle: leakage, integration, firing, and reset[53, 54]. Hardware implementation based on the LIF model can convert analog signals into spike frequencies, enabling the replication of adaptive characteristics in biological systems where frequency varies with stimulus intensity[55]. As a core component of neuromorphic computing, the information encoding mechanism of memristors directly determines the efficiency and performance of brain-inspired systems. In memristor systems, rate coding typically manifests as controlling the average conductance state of memristors by adjusting input pulse frequency. In contrast, time coding leverages the temporal fine structure of memristor dynamic responses—such as the precise timing of conductance transitions, pulse arrival intervals, or state transition delays—to carry information[56]. This time encoding is based on the precise timing of individual spikes. It achieves millisecond-level rapid response and offers higher information capacity compared to traditional rate encoding, which relies on statistical averaging[57]. The efficiency of time coding stems from its event-driven nature. However, it imposes extremely stringent requirements on hardware precision. The validity of spike-timing-dependent plasticity is based on precise spike timing before and after synapses, whereas inherent variations in analog circuits can lead to significant temporal distortions[58]. Therefore, exploring the temporal regulation and encoding

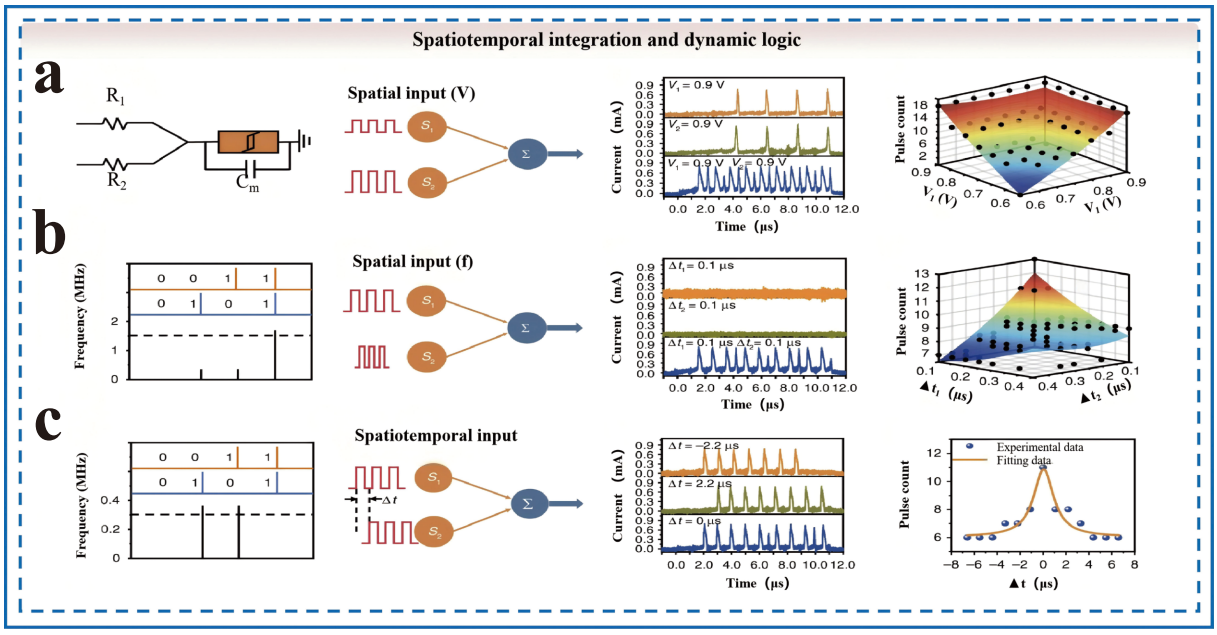

Fig. 4. (Color online) LIF neuron model with spatiotemporal encoding mechanism[60]. (a) Spatial summation. (b) AND logic and temporal regulation of spatial summation. (c) XOR logic and spatiotemporal summation. Copyright 2020, Springer Nature.

capabilities of memristors is key to achieving highly robust brain-inspired computing.

Currently, the temporal encoding mechanisms in spike neural networks (SNNs) are evolving from simple pulse frequency encoding to more efficient and complex temporal dynamics, largely driven by breakthroughs in memristor technology. Fig. 3 illustrates the research progress of time-encoded memristors in two major directions: energy efficiency breakthrough and functional evolution. Figs. 3(a)–3(c) demonstrates how to maximize the potential of time-encoded energy consumption and latency while enhancing device precision[45]. This hole-doped memristor achieves a threshold electric field as low as 60 V/cm, which is two orders of magnitude lower than that of other Mott insulator systems. This allows peak generation through minimal energy consumption via insulator–metal phase transition. Such performance makes it ideal for constructing neuromorphic chips with high energy efficiency ratios, thereby enabling physically feasible large-scale time-encoded computations. Fig. 3(d) demonstrates how the high integration of devices drives time encoding to evolve from a single "time point" to complex dynamics encompassing "time processes"[59]. By using memristors to simulate voltage-gated ion channels (such as Na^+, K^+, and Ca^{2+} channels) in biological neurons, fast-slow kinetics similar to biological neurons can be achieved. By adjusting the resistance of ECMAR, various biologically rational firing modes can be flexibly achieved, including rapid firing, adaptive firing, staged firing, and burst firing. This collaborative working mechanism overcomes the functional limitations of traditional LIF (leaky integrate-and-fire) neuron models, endowing spike neurons with reconfigurable properties and enabling support for multitasking tactile processing.

With the deepening research on neural information processing mechanisms, single temporal encoding has demonstrated limitations in terms of biological authenticity and the processing of complex spatiotemporal information. To address this issue, researchers have shifted their focus to spatiotemporal encoding mechanisms that can simultaneously integrate temporal and spatial information. At the hardware neuron level, Duan and his colleagues successfully constructed an artificial spiking neuron with spatiotemporal integration capability using NbO_x threshold-switching memristors[60], in Fig. 4 This neuron realized threshold-driven firing consistent with the classic leaky integrate-and-fire (LIF) model, and also achieved synchronous integration of spatial and temporal pulses. For the first time, it implemented linearly inseparable XOR logic and gain modulation in a single memristor neuron. Based on this neuron, the researchers further built a 4×4 all-memristor spiking neural network, demonstrated online pattern recognition and coincidence detection, and validated the feasibility of spatiotemporal encoding at the hardware level. At the system implementation level, available research have presented a viable architecture for a reservoir computing system (MESN) based on multifunctional memristors[61]. The system employs a reconfigurable $Ta/HfO_2/RuO_2$ memristor to achieve three distinct switching modes. Unlike traditional reservoir computation that relies on delay feedback, MESN leverages the parallel computing capability of memristor arrays. It achieves synchronous processing of spatiotemporal data through a 1T1R high-integration architecture. This enables diverse tasks ranging from deterministic prediction to non-deterministic multivariate time series classification. This system-level advancement lays the foundation for large-scale hardware deployment of spatiotemporal coding neuronal models.

3.2. Artificial synapse

In neuromorphic computing, memristors achieve electrical conductance modulation by applying spikes to electrodes, which trigger conductive filaments to release and transmit through dielectric or semiconductor layers. The magnitude of conductance changes is regarded as synaptic weight[62]. This process closely aligns with the biological synapse mechanism. In biological systems, stimuli are received at the synaptic cleft, and neurotransmitters are released to alter the postsynaptic neuronal potential. This simi-

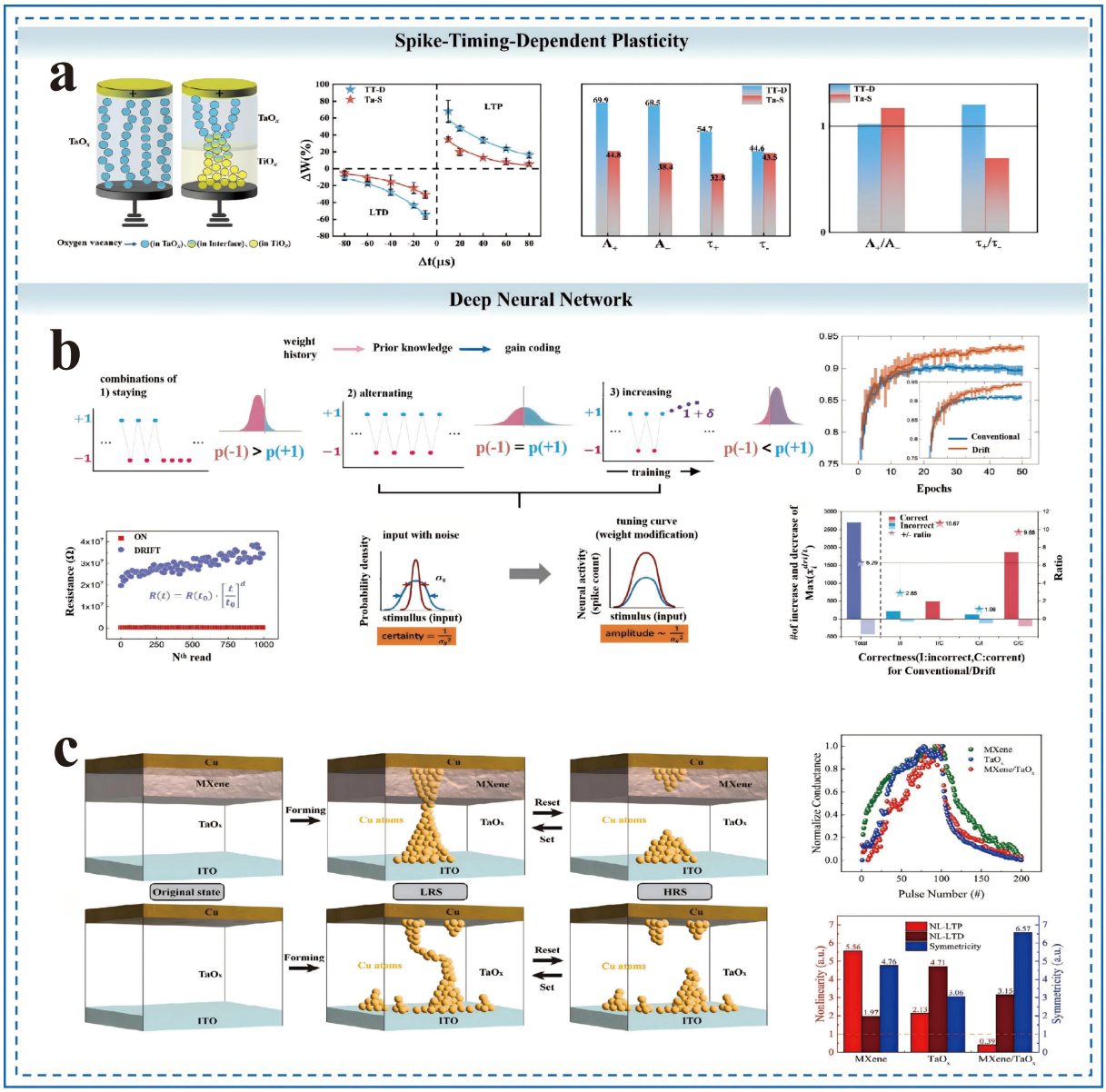

Fig. 5. (Color online) (a) Memristive synapses dependent on local learning rules such as spike-timing-dependent plasticity (STDP). Pulse-time-varying plasticity of Ta-S and TT-D devices; fitting parameters of STDP for Ta-S and TT-D devices; ratio of STDP fitting parameters for Ta-S and TT-D devices[65]. Copyright 2026, Royal Society of Chemistry. (b) and (c) Memristive synapses via backpropagation algorithm. (b) Utilizing PCM resistance drift as a learning mechanism to enhance supervised learning performance[37]. Comparison of classification accuracy between traditional neural networks and drifting neural networks. Copyright 2021, Springer Nature. (c) Enhancing synaptic plasticity of memristors in supervised learning tasks through interface modification. The conductivity gradients of the three devices under bipolar pulse sequences and the nonlinearity and symmetry of LTP/LTD curves were compared. Copyright 2026, Elsevier.

larity makes memristors an ideal candidate for use as "artificial synapses". The core functions of artificial synapses include input-driven weight updating and time-driven weight decay. In the input-driven dimension, current research can be categorized into two primary technical approaches. The spiking neural network (SNN) approach relies on spike-timing-dependent plasticity (STDP) to achieve local learning rules. In contrast, the deep neural network (DNN) approach optimizes device conductance through gradient descent using backpropagation algorithms. In the time-driven dimension, both types of trajectories can achieve spontaneous weight decay by leveraging the intrinsic volatility characteristics of the device.

STDP is a bio-inspired learning mechanism that adjusts synaptic weights based on the spike time difference between presynaptic and postsynaptic neurons, thereby enabling learning and memory functions[63]. Implementing STDP typically requires precise control over the amplitude, width, and timing of write pulses[64]. Fig. 5(a), Liu discovered that the three-level oxygen defect concentration distribution in TaO_x/TiO_x-based memristive synapses is the primary factor influencing STDP performance optimization. They proposed a device structure and fabrication process capable of effectively regulating the bidirectional conductance update characteristics of STDP in oxide memristors, which has contributed to the development of high-performance neuromorphic devices[65]. Another mainstream approach involves hardware acceleration of deep neural networks (DNNs) trained via backpropagation. In this approach, weight updates are optimized through gradient descent rather than relying on impulse timing sequences.

Achieving high linearity and high symmetry in conductance modulation remains a critical challenge for artificial synaptic devices. These properties directly impact recognition accuracy in neural network inference tasks[66]. Therefore, researchers have enhanced synaptic plasticity performance of memristors in supervised learning tasks through strategies, including material engineering, interface modification, and structural design. Fig. 5(b), researchers have employed PCM resistance drift as a learning mechanism. In this approach, the device's non-ideal characteristics are transformed into a Bayesian inference advantage, significantly enhancing the recognition capability of ambiguous samples in MNIST classification[37]. Compared with traditional training and testing accuracy, drift exhibits smaller deviations in later epochs but larger deviations in earlier epochs. The final accuracy rates for routine testing and drift testing were 89.6% and 93.2%, respectively. This demonstrates the selectivity of output correction. The overall mean was 6.29. When the drifting neural network made correct predictions, this ratio increased to 10.67 (for test images where conventional neural networks made incorrect predictions) and 9.68 (for test images where traditional neural networks made correct predictions). In contrast, when the drifting neural network makes prediction errors, this ratio is significantly lower than the average value. Improving memristor performance through heterogeneous interface engineering addresses several issues, in Fig. 5(c). These include narrow switching window and susceptibility to short circuits caused by MXene's high conductivity. Additionally, this approach significantly enhances device stability, durability, linearity, and neuromorphic simulation capabilities through synergistic physical–chemical interactions at the interface[25]. However, SNNs exhibit lower efficiency when training complex tasks. In contrast, DNNs are constrained by their energy efficiency requirements and necessitating large amounts of labeled data for training. Once forgetting occurs, the damage to the entire system becomes irreversible[63]. To overcome these limitations, researchers have begun exploring the applications of meta-learning. Meta-learning aims to enable models to "learn how to learn", allowing rapid adaptation to new tasks with minimal sample input. This capability is crucial for addressing the issues of low training efficiency and insufficient generalization capacity in existing neural networks[67]. Inspired by the hippocampus-neocortex learning and memory mechanisms in humans, one study proposed a Hebbian learning-driven meta-learning framework[68]. This framework enables rapid, efficient, and continuous learning in brain-inspired spiking neural networks, thereby addressing the limitations of SNNs in handling complex tasks. Primary plasticity refers to the ability of neurons to generate synaptic plasticity, which is regulated by their activity history[69]. Meta-plasticity-based artificial synapses can mitigate catastrophic forgetting in artificial neural networks, thereby enabling multi-task persistent learning capabilities[70]. By introducing graphene quantum dot interface modulation to achieve asymmetric conductive pathways, metaplasticity was realized for the first time at the single-device level. This approach replicates classical synaptic plasticity and enables direct and dynamic modulation of long-term memory and sustained learning capabilities.

The completeness of synaptic function depends not only on event-driven weight update rules but also on time-driven weight evolution dynamics. In biological systems, the strength of synaptic connections is regulated by impulse timing and also exhibits spontaneous decay over time. This property is known as plasticity[71]. Volatility describes the spontaneous evolution trajectory of synaptic weights under no-stimulus conditions. In memristors, this dynamic behavior originates from passive diffusion processes within the material, including charge trapping and untrapping, ion concentration gradient relaxation, and oxygen vacancy redistribution. Ephemeral memristive devices spontaneously revert to a high-resistance state. Due to their inherent nonlinear and transient memory characteristics, they are highly suitable for simulating short-term plasticity (STP) and short-term depression (STD)[72]. These properties enable rapid response and information filtering, forming the foundation for processing priority and short-term memory in neural computing. The core mechanism underlying volatility is strain energy-driven bidirectional diffusion. Conductive filaments tend to grow along paths of minimum strain energy, while low-strain-energy pathways also facilitate reverse atomic diffusion[73]. As a result, the conductive filament forms quickly and fractures rapidly, exhibiting pronounced volatility. Figs. 6(a)–6(c), Weilenmann and colleagues overcame a key limitation of traditional memristors, which were only applicable to spiking neural networks (SNNs)[74]. They demonstrated, for the first time, multifunctional memristor hardware synapses compatible with backpropagation (BP) training algorithms. Through DNN training combined with the inherent volatility of the device itself, the STPN network achieves short-term plasticity and metaplasticity. This non-filamentary memristor based on $SrTiO_3$ (STO) can simultaneously simulate six functions of biological synapses in a single device. It has been successfully applied to deep reinforcement learning tasks. This hardware acceleration solution achieves training accuracy comparable to software. Additionally, it eliminates the von Neumann bottleneck through an in-memory computing architecture. This reduces data transfer energy consumption during DNN training and inference processes by over 98%. Experimental results demonstrate that, compared to equivalent GPU implementations, the memristor-based DNN hardware accelerator achieves over 96-fold energy efficiency improvement. Importantly, it maintains compatibility with backpropagation training. This breakthrough provides critical hardware support for constructing large-scale, low-power, and trainable neuromorphic computing systems. In contrast, non-volatile devices can maintain low-resistance states without continuous stimulation, making them more suitable for simulating long-term plasticity[75](LTP and LTD). Non-volatile resistors maintain stable weights but lack inherent dynamics, whereas volatile resistors exhibit dynamics but cannot retain weights. Therefore, connecting volatile and non-volatile memristors in series to achieve complementary functions represents an excellent solution. This approach enables the formation of a complete neuromorphic computing architecture spanning from artificial neurons to artificial synapses. Building on this methodology, recent studies have addressed the core challenges of neuromorphic computing through two key dimensions: high-efficiency single-pulse inference and noise-resistant online learning. Fig. 6(d), we designed and implemented a fully hardware-based single-pulse neuromorphic system using memristors. The system constructs neurons using high-consistency

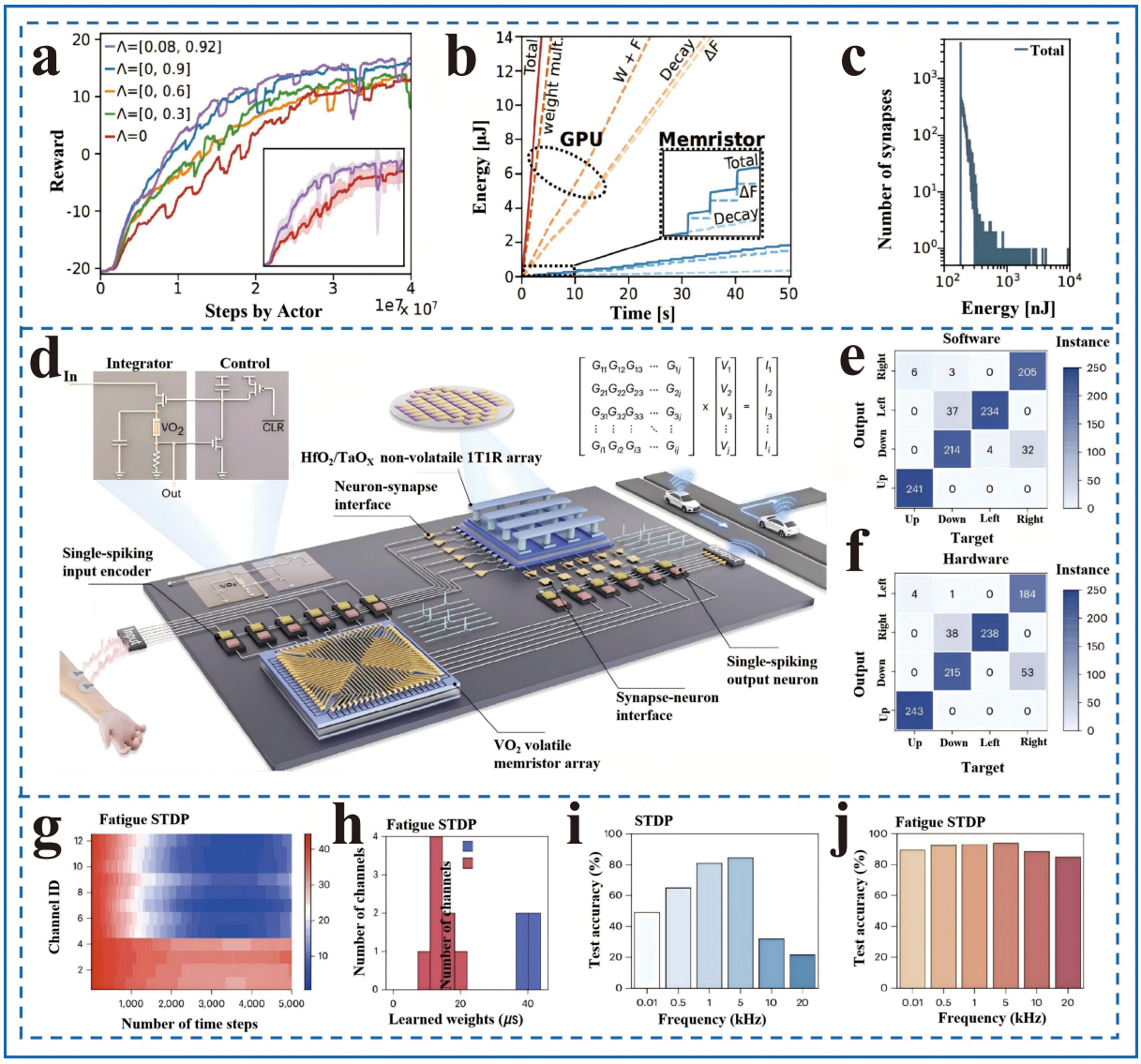

Fig. 6. (Color online) (a)–(c) Exploits the short-term (volatile) plasticity of the device to enhance the performance of deep neural networks in dynamic environments[74]. Copyright 2024, Springer Nature. (a) The average reward curve under different parameter ranges (Λ). (b) Comparison of synaptic energy consumption, cumulative energy consumption curves for pure GPU implementation versus the memristor-based implementation described in this paper. (c) Total energy histogram. (d)–(f) Achieving ultra-high energy efficiency and low latency in end-to-end systems through high-precision encoding of volatile devices and high-reliability computation of non-volatile devices[76]. Copyright 2026, Springer Nature. (d) Conceptual diagram of all-memory-resistive single-pulse HMI. (e) Confusion matrix based on software-based classification. (f) Confusion matrix of hardware-based classification, demonstrating the minimal accuracy degradation. (g)–(j) Enhancing the learning capability of SNNs in complex spatiotemporal information through fatigue dynamics of volatile devices[77]. Copyright 2026, Springer Nature. (g) Displaying the evolution of resistance weight (*W*) for presynaptic spikes. (h) Fatigue STDP can clearly separate correlated and uncorrelated synapses, enhancing the former while inhibiting the latter. The comparison between the accuracy of (i) STDP testing and (j) fatigue STDP learning at input frequencies ranging from 10 Hz to 500 kHz demonstrates that traditional STDP exhibits frequency sensitivity, whereas fatigue STDP remains stable.

VO_2 volatile memristors and employs low-relaxation HfO_2/TaO_x non-volatile memristors as synapses. This system achieves software-level accuracy in electromyographic signal processing tasks and enables efficient single-pulse inference[76]. The biological brain possesses a synaptic fatigue mechanism, where neurotransmitter depletion under high-frequency stimulation leads to a temporary decline in synaptic transmission efficiency, functioning as a natural band-pass filter. By leveraging the fatigue dynamics of volatile devices, the study enhances the learning capability of SNNs in complex spatiotemporal information in Figs. 6(g)–6(j). This approach directly implements noise-resistant fatigue-based STDP learning rules at the hardware level[77]. Although the serial integration of volatile and nonvolatile devices can simultaneously emulate short-term and long-term plasticity at the hardware level, enabling dynamic filtering, transient retention, and long-term memory conversion of tactile information[78], its application in large-scale tactile arrays still faces challenges related to hardware overhead, control complexity, and integration scalability. Such serial architectures generally require the integration of multiple functional devices and auxiliary selector/current-limiting components within a single unit, thereby increasing cell area, interconnect density, and fabrication complexity[79]. Meanwhile, differences in threshold voltage, response time, retention characteristics, and cycling stability between volatile and nonvolatile devices make unified

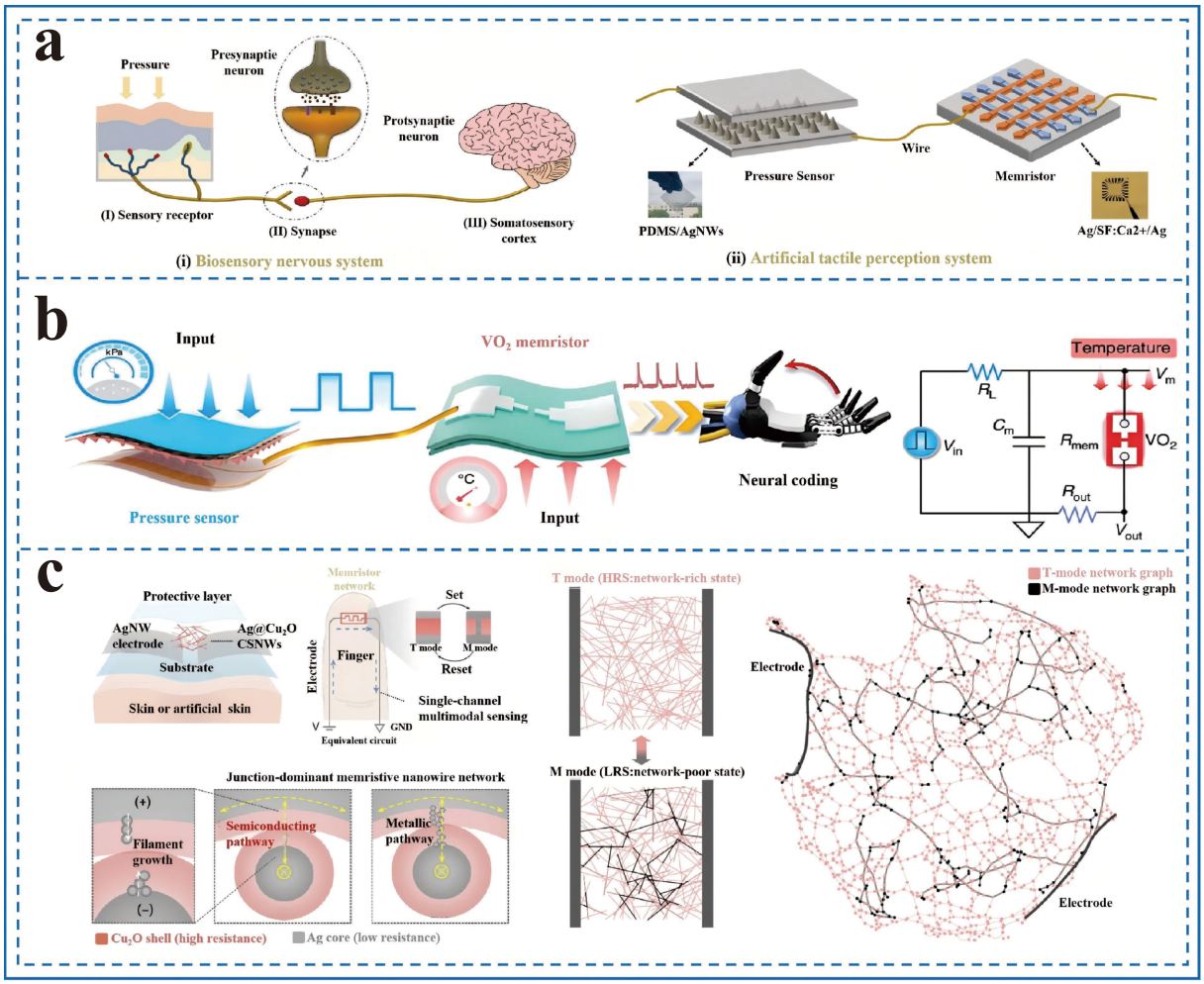

Fig. 7. (Color online) (a) A piezoresistive pressure sensor and silk fibroin-based composite memristor are connected in series to simulate the human tactile system[85]. Copyright 2024, Science China Press. (b) Schematic diagram of neural encoding and feedback artificial CSSN within multimodal sensors, along with a circuit diagram of artificial peak temperature sensing neurons[86]. Copyright 2024, Springer Nature. (c) Dynamic switching of sensing modes for single-material systems. Multimodal receptors and hierarchical assembly of core-shell nanowires (CSNWs). The equivalent circuit representation enables the acquisition of multimodal information through a single-channel architecture[87]. Copyright 2025, Springer Nature.

pulse modulation and read/write strategy design more difficult. When extended to flexible tactile arrays, device variability, crosstalk, parasitic effects, read/write disturbance, and performance drift induced by mechanical deformation may further affect the acquisition, storage, and recognition accuracy of multipoint tactile signals[80]. Therefore, future studies should quantitatively evaluate cell area, energy consumption, read/write margin, device uniformity, flexible substrate compatibility, and peripheral circuit overhead at the array level to clarify the integration advantages and bottlenecks of this hybrid scheme in neuromorphic tactile systems.

Most existing reports are based on first-order memristors, which fail to simulate all biological characteristics. Recent studies have demonstrated that the conduction mechanism of memristors is influenced by multiple internal state variables, enabling them to function as higher-order memristors and exhibit more complex dynamic behaviors[81]. In his review, Chaurasiya systematically organized the significant advantages and highlights of higher-order memristors in mimicking biological synapses and neuronal functions[81]. To simulate artificial synapses inherently possessing habituation and sensitization properties, a memristor device with third-order switching complexity was introduced[82]. The application of this memristor in robotic arms endows robots with bio-inspired "experience-dependent response" capabilities. This enables automatic filtering of irrelevant stimuli and threat event focusing without processor intervention, thereby significantly enhancing energy efficiency and intelligence. It is noteworthy that the weight updating and decay of artificial synapses are not physically independent in essence. The multi-state variable model of high-order memristors reveals that Joule heat accumulation induced by ion migration affects not only the time constant of STDP but also determines the relaxation time of volatility[81, 83]. Thermodynamics serves as both the physical origin of peak timing dependence and the fundamental driving force behind transient temporal evolution. This insight provides a novel paradigm for the co-design of "learning-forgetting" mechanisms in artificial synapses.

3.3. Membrane-sensing and computing integrated material

Materials that integrate sensing, storage, and computing can regulate signals and perform local computation while sensing deformation. They can directly output event-driven pulses or compressed feature values. This in-memory comput-

ing characteristic offers two key advantages. On one hand, it can eliminate the latency caused by data movement. This enables extremely low-latency closed-loop control, thereby meeting the real-time requirements of interaction. On the other hand, preliminary processing of the signal can reduce energy consumption. This extends the battery life of portable and wearable electronic devices operating under miniature batteries[84].

Early exploratory work involved the simple series connection of silk fibroin-based biological memristors and piezoresistive pressure sensors[85]. This approach initially achieved the synergy of sensing, memory, and computing functions. It also verified the feasibility of constructing memristor-based sensing systems. However, the sensor and memristor remained independent of each other, in Fig. 7(a). To simplify system complexity and achieve more efficient in-sensor computing, the sensing function was further embedded into neuromorphic circuits. Li and colleagues used VO_2 memristors in an in-sensor computing system to construct cross-modal sensory neurons, encoding pressure and temperature bimodal information into spikes[86], in Fig. 7(b). By utilizing the inherent temperature-dependent phase transition of VO_2 memristors in the LIF circuit, a temperature-sensing spiking neuron circuit was designed. Simultaneously, an artificial spiking pressure-sensing neuron circuit was developed by integrating a flexible piezoresistive sensor with the LIF circuit. This implementation demonstrated the potential of memristive devices in developing biomimetic sensing systems capable of multimodal information processing and efficient in-sensor computing. The sensing, memory, and computing systems are not only simply connected in series but also achieve circuit-level functional integration. Although significant progress has been made in the above circuit-level integration, the combination of multiple devices or materials still limits the system's spatial resolution and response speed. The latest research explores achieving multimodal sensing within a single material, further breaking this limitation. Fig. 7(c), Kim and colleagues used a memristive nanowire network switch and a cross-coding system to enable a single sensory element to detect mechanical and thermal stimuli simultaneously[87]. During the T-to-M mode switching process in memristive nanowire networks, the network geometry undergoes structural changes. In M-mode, the electrodes at both ends exhibit poor network connectivity and demonstrate computational results of switching dynamics in memristive nanowire networks, revealing differences in network density between T-mode and M-mode configurations. By combining sensing, storage, and computing functions within a single device platform, this approach holds promise for fundamentally overcoming the latency and energy bottlenecks inherent in traditional "sensing-transmission-processing" separated architecture. Nevertheless, the field still faces multiple bottlenecks spanning materials, manufacturing, and system levels, and a considerable gap remains before practical applications can be realized. At the materials level, multifunctional material systems that simultaneously exhibit high-sensitivity sensing response and stable memristive characteristics are still scarce. The direct physical coupling mechanism between sensory signals and memristive behavior remains poorly understood, and critical issues such as poor device-to-device uniformity, long-term stability, and fabrication yield control urgently need to be addressed[88]. At the integration and manufacturing level, sense-storage-computation integrated systems inherently involve heterogeneous integration of sensing materials, memristive dielectrics, and electrode materials, which often conflict in terms of process temperature windows and chemical compatibility. This challenge becomes particularly acute for flexible tactile applications, where the low thermal budget of flexible substrates sharply contradicts the high-temperature annealing processes required for certain oxide-based memristors[89]. At the system architecture level, scaling sense-storage-computation units into large-scale crossbar arrays introduces severe read margin degradation due to sneak path currents, parasitic effects, and read/write disturbances. Furthermore, the cross-level speed mismatch-sensor response time on the millisecond scale, memristor switching speed on the nanosecond scale, and the processing speed of computing cores-substantially complicates system timing coordination and power management. Addressing these bottlenecks is therefore essential for realizing major breakthroughs and enabling widespread applications in areas such as wearable electronics, medical diagnostics, human-machine interaction, and beyond in the future[90].

4. Summary and prospects

In conclusion, memristors demonstrate significant application potential in the field of tactile sensing. With their unique physical mechanisms and structural advantages, memristors can simulate the working mode of biological tactile nervous systems at the underlying hardware level. They integrate three major functions—perception, storage, and computation—into a unified system. This provides a novel approach to overcoming the von Neumann bottleneck and constructing active tactile sensing systems with high energy efficiency and low latency. In artificial neurons, the inherent threshold characteristics of memristors can accurately simulate the "all-or-none" neural electrical signal excitation mechanism, thereby enabling event-driven perception. In artificial synapses, their continuously adjustable electrical conductivity properties can mimic synaptic plasticity, supporting both short-term and long-term learning and memory functions. Meanwhile, memristors feature a simple structure and ease of three-dimensional stacking. They can also be fabricated on flexible substrates. These advantages demonstrate potential for constructing high spatial resolution, large-scale flexible tactile arrays. Based on distinct physical mechanisms, memristors exhibit unique characteristics that can meet diverse bionic sensing requirements. Therefore, sensing-memory-computing integrated materials with the aforementioned biological characteristics represent a significant direction for future tactile sensing systems. This field still offers vast potential for research and innovation.

However, despite the promising prospects of memristors in tactile sensing applications, they remain constrained by three core challenges: insufficient device reliability, poor environmental adaptability, and difficulties in controlling uniformity for large-scale arrays. First, device consistency and stability represent the core barriers to large-scale application. The switching voltage and high/low resistance ratio of memristors exhibit significant fluctuations between cycles and across

devices. This heterogeneity leads to nonlinear and asymmetric updates of simulated synaptic weights, severely compromising the accuracy of neuromorphic computing. In crossbar array architectures, the variability of individual devices is further amplified. This makes it challenging for matrix-vector multiplication (MVM) to achieve the computational precision required for high-precision applications. Second, challenges such as interface matching and signal crosstalk remain during system integration. Although self-rectifying memristors can suppress sneak path currents through built-in rectification functionality, they significantly increase the complexity of material and process design. The global memristor field is currently experiencing a surge of breakthroughs. These span fundamental theoretical advancements, critical industrialization challenges at the chip system level, and novel applications across industries. These achievements collectively demonstrate the full picture of this cutting-edge technology transitioning from laboratory research to commercialization. Of course, we must also clearly recognize that memristor technology is still primarily in the laboratory research and development stage, and there remains a significant gap from industrial-scale production and system-level applications.

Looking ahead, to address the above pain points, future research on memristor-based tactile sensing should focus on the following directions. First, improving device reliability and uniformity is the most urgent task. This includes developing new materials and device structures to reduce cycle-to-cycle and device-to-device variability, as well as establishing standardized characterization and testing protocols. Second, enhancing environmental adaptability should be pursued, such as improving device stability under mechanical bending, temperature variation, and humidity changes, which is especially critical for flexible tactile sensing applications. Third, developing large-scale array integration techniques is essential, including solutions for sneak path currents without excessively increasing process complexity, and effective compensation algorithms for device non-idealities. Regarding system architecture, two complementary technical pathways can advance the field. Near-sensor computing represents a more feasible development direction in the short term. It enables signal processing at the sensing end to reduce data transmission latency and energy consumption. Meanwhile, sensor-memory-computing integrated materials and devices represent a longer-term, more disruptive goal. This approach has the potential to achieve true neuromorphic computing. Currently, material defects and non-ideal device characteristics in sensing-memory-computing integrated materials remain critical bottlenecks that must be overcome. Future research should focus on developing high-performance, highly consistent sensing-memory-computing integrated materials and sensor arrays. It should also integrate near-sensor computing architectures for advanced global information processing. This approach aims to achieve coordinated optimization from underlying devices to upper-layer systems, driving tactile sensing systems toward higher-order, more intelligent neuromorphic computing.

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Xintong Liu received her BE degree from South-West JiaoTong University in 2025. She is currently pursuing her M.S. degree at Beihang University. Her research focuses on flexible sensors, flexible electronics and intelligent sensing systems.



Rongrong Bao graduated with a Ph.D. from the Institute of Physical Chemistry and Chemical Technology, Chinese Academy of Sciences in 2012. She is currently a professor at the Institute of Atomic Manufacturing, Beihang University. She has long been engaged in research on multimodal flexible sensing materials and devices, flexible electronics, and wearable electronics.