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RESEARCH ARTICLE

A review of transforming neuromorphic computing with 2D material memtransistors

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ABSTRACT

In the pursuit of advancing neuromorphic computing, 2D material-based memtransistors have emerged as a promising avenue. These memtransistors offer a unique blend of attributes, including tiny dimensions, compactness, and low-power operation, making them ideal candidates to mimic human brain functionality for artificial intelligence applications. This review focuses on various 2D materials such as MoS_2, WSe_2, h-BN, and In_2Se_3, and their suitability for bio-synapse applications, highlighting their advantages over other synaptic devices. Additionally, the review suggests the development of multi-terminal memtransistor-based synaptic devices with innovative operational principles for in-memory computing applications. Finally, concludes by discussing both the current state of development and the prospects and challenges that lie ahead, aiming to inspire further progress in information storage and neuromorphic computing.

Keywords: 2D materials; memtransistor; synaptic devices; CMOS technology; neuromorphic computing and artificial intelligence

1. Introduction

In the context of artificial intelligence (AI) applications, conventional computer hardware adhering to the serial Von Neumann architecture encounters significant challenges related to performance and energy efficiency [1]. This is primarily attributed to the extensive data transfer requirements between processing and memory units [2]. To address this critical issue, a promising approach involves the integration of principles from computational neuroscience and neuromorphic engineering [3,4]. This integration aims to establish computing systems that operate in a parallelized, spike-based fashion, offering a potential solution to alleviate the well-known von Neumann bottleneck [5,6]. The goal is to pave the way for the next generation of neuromorphic computing systems that are energy-efficient and capable of mimicking the sophisticated cognitive functions of the human brain [7].

The memtransistor, a groundbreaking electronic device at the intersection of memristors and transistors, represents a pivotal advancement in electronics [8,9]. This innovative device holds the potential to revolutionize

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how we process and store information by seamlessly merging memory and logic functions within a single unit[10]. Unlike traditional transistors, which predominantly focus on logic operations, memtransistors possess a unique ability to retain and process data simultaneously [6,11]. This dual functionality has profound implications for various fields, from neuromorphic computing, where it mimics the behavior of biological synapses, to in-memory computing, which enhances data processing speed and energy efficiency[10,12,13]. Several groups of researchers are actively exploring the potential of 2D material-based memtransistors to replicate the complex behaviors of biological synapses [6,14–18]. Taking advantage of 2D material-based memtransistors has emerged as an exciting frontier in electronic devices in the quest to improve computing power and energy efficiency [19,20]. In contrast to traditional semiconductor devices, these memtransistors are constructed from atomically thin 2D materials offering unique capabilities that promise to have a wide range of applications. A key to this technology lies in the extraordinary properties of 2D materials such as molybdenum disulfide (MoS_2)[21,22], tungsten selenide (WSe_2) [23], hexagonal boron nitride (h-BN) [24,25], and indium selenide (In_2Se_3)[26]. These materials are characterized by their remarkable electrical conductivity, flexibility, and compatibility with nanoscale fabrication processes. Such attributes make them ideal candidates for revolutionizing electronic devices and, in particular, memtransistors.

Here, we will delve into the specifics of 2D material memtransistors, their applications in neuromorphic computing, the challenges they face, and the prospects they hold for shaping the future of information storage and neuromorphic intelligence. This article will walk you through the unique features of MoS_2, WSe_2, h-BN, and In_2Se_3 to help you better understand how they contribute to the evolution of 2D material based memtransistor technology. The review concludes by assessing the current progress and future challenges, aiming to inspire advancements in information storage and neuromorphic computing.

2. Introduction to the artificial synapses and neurons based 2D materials

Artificial synapses and neurons are essential for neuromorphic computing, an innovative field aiming to replicate the brains neural networks for more efficient and intelligent systems[9]. These artificial elements simulate the functions of biological neurons and synapses, enabling advanced information processing and communication [5]. Two-dimensional (2D) materials have emerged as critical components in this technology[27]. Due to their unique properties including high surface area, excellent electrical conductivity, and mechanical flexibility, 2D materials significantly enhance the performance and efficiency of artificial neurons and synapses[28,29]. By integrating 2D materials, researchers can create neuromorphic devices that operate at lower power, respond faster, and are more compact[30]. These advancements promise to revolutionize computing, making it possible to develop highly efficient, scalable, and versatile systems[30]. The ongoing research and development in this field are paving the way for future breakthroughs in artificial intelligence, flexible electronics, and beyond[19,31].

2.1. Artificial synapses

Artificial synapses are critical components in the development of neuromorphic computing systems, which aim to replicate the brains neural architecture to achieve more efficient and intelligent computational capabilities[17]. These artificial synapses emulate the function of biological synapses, enabling complex signal processing and communication between artificial neurons[32]. Incorporating 2D materials into artificial synapses not only enhances their functionality but also opens up new possibilities for flexible and wearable neuromorphic systems[33]. Further, explores the integration of 2D materials in artificial synapses, examining their potential to revolutionize neuromorphic computing and advance the development of next-generation computing technologies[34].

2.2. Artificial neurons

Artificial neurons are fundamental building blocks in the realm of neuromorphic computing, designed to mimic the information-processing capabilities of biological neurons[35]. By replicating the intricate functionalities of the human brain, these artificial neurons aim to enable more efficient and intelligent computational systems[36]. Recent advancements in materials science have brought 2D materials, offering unprecedented opportunities for enhancing the performance and capabilities of artificial neurons. 2D materials are characterized by their atomic thinness, high surface area, exceptional electrical properties, and mechanical flexibility[18]. These unique features make them ideal candidates for developing high-performance artificial neurons[37]. The high surface area of 2D materials allows for greater interaction with other materials and components, thereby enhancing the efficiency and responsiveness of neural processing. Their excellent electrical conductivity and mobility facilitate faster and more energy-efficient signal transmission, which is essential for real-time processing in neuromorphic systems. Additionally, the mechanical flexibility of 2D materials supports the creation of flexible and wearable electronic devices, paving the way for innovative applications in healthcare, robotics, and beyond [26].

3. 2D material based memtransistors for artificial synapses

Memtransistors, or memory transistors, are devices that combine the functions of both memory and transistors [38]. They have the potential to play a crucial role in the development of neuromorphic computing, which aims to mimic the way the human brain works. Artificial synapses, on the other hand, are components that replicate the functionality of biological synapses in the nervous system, allowing for the transmission of signals between artificial neurons. **Figure 1** Summarizes the various 2D materials structures are MoS_2, WSe_2, h-BN, and In_2Se_3. To fabricate artificial synaptic devices, a variety of 2D materials has been utilized as a memristive layer, which is the first step in creating an exceptionally energy-efficient artificial neural network[11]. These materials possess unique electrical and optical properties that make them ideal for applications in next-generation electronics [9,39]. The exceptional features of 2D materials, such as high surface area, tunable electronic properties, flexibility, and low power consumption, offer substantial advantages over traditional bulk materials. In the context of neuromorphic computing, 2D materials-based synaptic devices provide several key benefits. Their atomic thinness allows for tight electrostatic control and reduced leakage currents, enabling low-power operation essential for energy-efficient computing. Furthermore, the tunability of 2D materials' electronic properties facilitates the precise emulation of various synaptic functions, including short-term plasticity (STP)[40], long-term plasticity (LTP)[40], paired-pulse facilitation (PPF)[41], and spike-timing-dependent plasticity (STDP)[42]. These functionalities are crucial for developing hardware that can support complex neural network behaviors and learning processes.

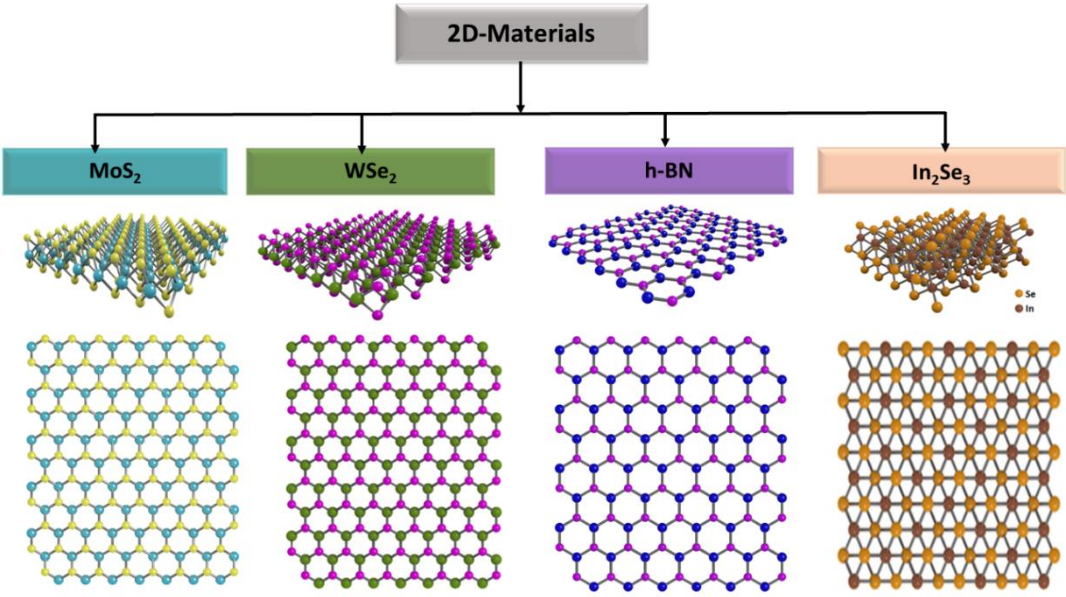

Figure 1. Schematic illustration of various 2D materials such as MoS_2, WSe_2, h-BN, and In_2Se_3.

3.1. MoS_2-based memtransistor devices

Molybdenum disulfide (MoS_2) is a two-dimensional (2D) semiconductor material with unique electronic properties that make it promising for building synaptic devices [43]. In MoS_2-based memtransistors, MoS_2 serves as the active channel material. The device typically consists of layers of MoS_2 sandwiched between two electrodes, forming a transistor-like configuration. By applying voltage pulses, the conductance of the MoS_2 layer can be modulated, allowing the device to emulate synaptic behavior. Key advantages of MoS_2-based memtransistor devices include their high carrier mobility, scalability, and compatibility with existing semiconductor fabrication processes [44,45]. For example, Dual-gated MoS_2 memtransistors were fabricated on polycrystalline monolayer MoS_2 grown by chemical vapor deposition (CVD). The devices use a global bottom gate and a local top gate as shown in **Figure 2a**. Specifically, polycrystalline monolayer MoS_2 was grown by CVD on doped Si substrates coated with 300 nm thick thermal oxide serving as the bottom gate dielectric. **Figure 2b** shows the bipolar resistive switching characteristics of the dual-gated MoS_2 memtransistor at different bottom gate biases (V_{BG}) with a floating top gate. The device channel dimensions of all individual and crossbar devices are identical (channel length, L = 0.9 μm; channel width, W = 0.7 μm). The device is initially in a low resistance state (LRS) and switches to a high resistance state (HRS) at forward bias (drain voltage $V_D > 0$). This RESET process (i.e., switching from LRS to HRS) occurs during both sweeps 1 and 2 in **Figure 2b**. In contrast, the device undergoes a SET process (i.e., switching from HRS to LRS) at reverse bias ($V_D < 0$). It should be noted that SET and RESET do not require an electroforming process. As a result, dual-gated memtransistors show a pinched hysteresis loop in the clockwise direction at forward bias, in contrast to the counter-clockwise loops for single-gated MoS_2 memtransistors (bottom gate or top gate). The dual-gated MoS_2 memtransistors show excellent cycle-to-cycle endurance, as shown by the tight distribution of switching characteristics for 250 bias sweeps (**Figure 2c**). The I–V characteristics do not pass through $V_D = I_D = 0$ in **Figures 2b and 2c,** which is a result of a mem-capacitive effect that is known to induce a pinched hysteresis loop in the charge–voltage plot as opposed to the current-voltage plot. This mem-capacitive effect is expected near the metal contacts as has been previously observed in MoS_2 memristors and single-gated MoS_2 memtransistors. The two gate terminals in dual-gated memtransistors provide electrostatic control over synaptic learning behavior. As shown in **Figure 2d**, tunable learning is achieved in long-term potentiation (LTP) and long-term depression (LTD) for dual-gated memtransistors, where V_D pulses of 1 ms period are applied and the postsynaptic current ($I_{PSC} = I_D$) is measured between pulses. For simplicity, the top gate is grounded in all measurements, while the bottom gate voltage is controlled during the reading and writing operations. The artificial neural network (ANN) is trained to classify MNIST (Modified National Institute of Standards and Technology) database handwritten digits using backpropagation showed in Figure 2e. Each input neuron corresponds to a distinct pixel in the image. For representing each synaptic weight (w) between fully connected neurons in the input, hidden, and output layers, a pair of dual-gated MoS2 memtransistors is employed.

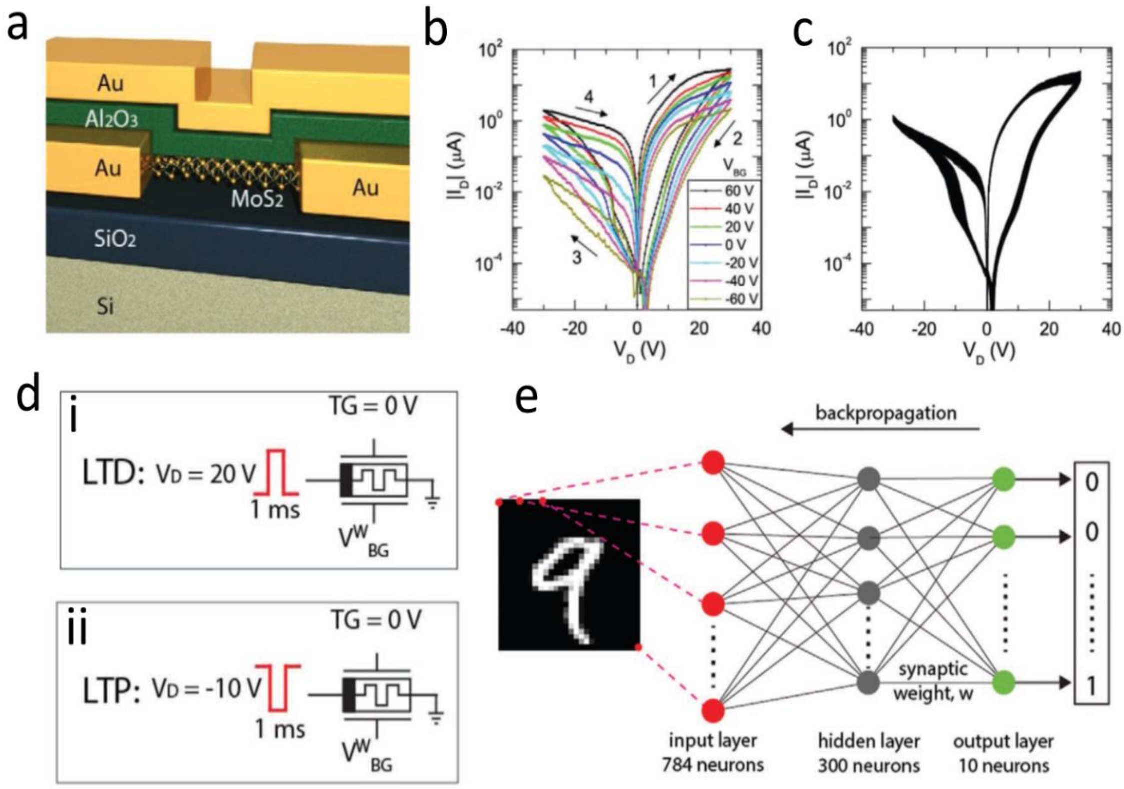

Figure 2 a) Schematic of the dual-gated MoS_2 memtransistor structure. The Si substrate acts as a global bottom gate and patterned Au acts as a local top gated). (b) Gate-tunable memristive switching (V_D = -+ 30) at various bottom gate biases (V_{BG}) from −60 to 60 V with the top gate floating (L = 0.9 µm, W = 0.7 µm). The black arrow and number indicate the bias sweep sequence (clockwise switching). c) A plot of 250 full switching cycles at V_{BG} = 0 V and V_{TG} = 0 V. (d) Tunable long-term potentiation and depression of MoS_2 dual-gated memtransistors. (i) Pulsing scheme for long-term depression (LTD) at various V_{BG} values during the writing operation (V_W B_G). The device was read at V_D = 1 V and various V_{BG} values during the reading operation (V_R B_G). (ii) Pulsing scheme for long-term potentiation (LTP) at VW BG during the writing operation. (e) The ANN is trained to perform the classification of Modified National Institute of Standards and Technology database (MNIST) handwritten digits using backpropagation. Reproduced with permission [58]. Copyright 2020, Advance Functional

3.2. WSe_2-based memtransistor synaptic devices

WSe_2-based memtransistor synaptic devices represent a cutting-edge approach to neuromorphic computing, inspired by the brain's synaptic connections. These devices leverage WSe_2, a 2D semiconductor material with unique properties, as the active channel material. For example, **Figure 3a** presents a schematic illustration and a circuit diagram of the synaptic barristor. This three-terminal device can be considered a gate-tunable memristor composed of a WO_3–x resistive memory and a WSe_2/graphene barristor. The WSe_2/graphene heterojunction, which is formed by van der Walls (vdW) assembly of the mechanically exfoliated WSe_2 layers on graphene, acts as a variable-barrier Schottky diode owing to the electrostatically tuned work function of graphene. Unlike typical memristors based on metal/oxide/metal structures, it is critical to have the layered semiconducting WSe_2 in our synaptic barristor because its vdW surface enables to form the variable-barrier contact with the graphene without Fermi-level pinning [46,47]. This bottom barrister component enables electrical regulation the total current flow through the entire device by controlling the gate voltage; hence, the switching states in the vertically integrated memristor can be actively tuned. The current-voltage (I_D–V_D) characteristics of the 2D heterostructure device are drastically altered by the presence of the intermediate $WO_{3–x}$ layer, as shown in Figure 3b. The device composed of Ag/WO_3–x/WSe_2/graphene heterostructures exhibits a typical resistive switching hysteresis loop in the I_D–V_D curve upon sweeping the source-drain voltage (V_D) at the zero-gate voltage (V_G). Based on the existence of an interfacial oxide layer between Ag (or Ti) and $WO_{3–x}$ and the bipolar switching with the negative SET voltage, the switching behavior may be attributed to the migration of oxygen vacancies and electrochemical redox reactions at the Ag (or Ti)/$WO_{3–x}$ interface. Meanwhile, we believe that forming a metallic filament by diffusion of the top Ag cations may not be the dominant switching mechanism because of the low current level ($\approx 10^{-8}$ A for LRS) measured in our controlled devices including Ag/$WO_{3–x}$/WSe2/graphene (**Figure 3b**).

Our monolithic memristor can emulate two neuronal-based synaptic functions even without the application of gate voltages. As shown in **Figure 3c**, here, we define the top metal electrode (drain) and the bottom electrode (source) as pre- and post-neurons, respectively. The synaptic weight represented by the degree of connectivity between the pre-and post-neurons is simply described by the postsynaptic current (PSC) magnitude when the input spikes stimulate the synapse [48]. The ability to control and retain the synaptic weight over time is defined as synaptic plasticity, classified into two forms: short-term plasticity (STP) and long-term plasticity [48–50]. **Figure 3d** demonstrates that synaptic plasticity, such as LTP and LTD, is further accelerated by applying a larger negative V_G, corresponding to the consolidation of long-term memory. This behavior originates from the effective electric field across the $WO_{3–x}$ layer strengthening as the Schottky barrier at the WSe_2/graphene junction decreases, resulting in an increasing dynamic variation range of the PSC. Utilizing this capability achieved by electrostatic gating, we could even modify the intrinsic type of the synaptic plasticity. As shown in **Figure 3e**, the PSC gradually increases by adjusting the V_G to −30 V (right panel), while the application of the same input spikes (V_A = −1 V, V_W = 10 ms, and Δt = 1 s) did not cause a noticeable increase in the PSC at V_G = 0 V (left panel). This result implies the conversion from STP to LTP, mimicking the essential role of a neuromodulator. Notably, gate-induced tuning of the synaptic functionality is controlled electrostatically, while considerable electrical power is inevitably consumed to achieve weight tuning by amplifying the potential and/or frequency of input spikes from neurons. Furthermore, the ability to accelerate the modulation of the synaptic weight can offer potential advantages to improve recognition accuracy and reduce the learning time of pattern recognition [51].

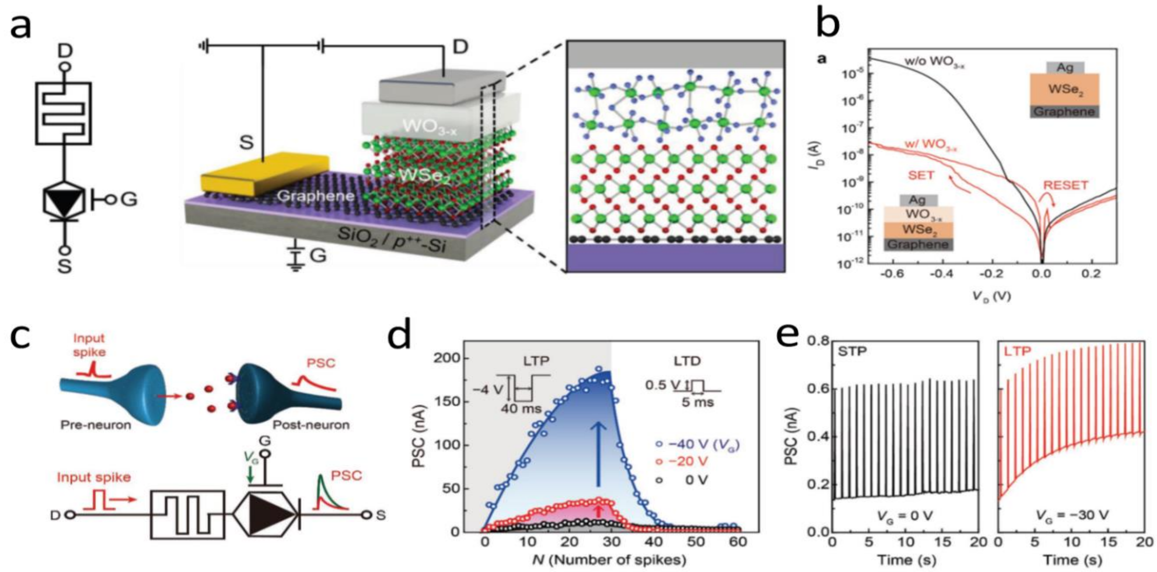

Figure 3a. Circuit and schematic representation of diagrams of the synaptic barristor consisting of a vertically integrated WO_{3-x} memristor and WSe_2/graphene barristor. (b) Gate-tunable-resistive switching characteristics. I_D–V_D curves of the devices with (red line) and without a WO_{3-x} layer (black line). Insets show a schematic representation of the diagrams of the devices. The "SET" and "RESET" processes are indicated by the up and down arrows, respectively. (c) Gate-tunable synaptic characteristics. d) Schematic illustration of the synaptic barristor and the corresponding circuit diagram of the synaptic barristor. e) Plots of PSC as a function of the number of input spikes while consecutively applying a series of potentiating spikes ($V_A = -4$ V, $V_W = 40$ ms, and N = 30) and depressing spikes ($V_A = 0.5$ V, $V_W = 5$ ms, and N = 30) at various V_G values of 0, −20, and −40 V. e) Plots of PSC as a function of time while applying spikes ($V_A = -1.0$ V, $V_W = 10$ ms, and $\Delta t = 1$ s) at $V_G = 0$ V (left panel) and $V_G = -30$ V (right panel). All PSCs are measured at $V_D = -0.1$ V. Reproduced with permission[17],.Copyright 2020, Advanced Materials.

3.3. h-BN based memtransistor synaptic devices

Hexagonal boron nitride (h-BN) based memtransistor synaptic devices are another intriguing avenue in the realm of neuromorphic computing. h-BN, similar to WSe_2, is a 2D material with a hexagonal lattice structure. It exhibits excellent insulating properties and thermal stability, making it a promising candidate for various electronic applications, including synaptic devices. For example, **Figure 4a**, show the schematic image of the vdW heterostructure monolithic memtransistor. The electronic synapses of the h-BN-based memristor were characterized by applying bias voltage to the Ti/Au top electrode (TE) with the MLG bottom electrode (BE) grounded. **Figure 4b** represents the first (red curve) and successive (gray curves) resistive switching (RS) characteristics of the memristor with a 10 nm thick h-BN RS layer. The compliance current (ICOMP) was set as 500 µA during the memristive set process to avoid irreversible electrical breakdown of the device. In our experiments, an electroforming process was needed in order to initiate the RS, as shown in the inset of **Figure 4b**, which indicates that the electrical breakdown of the grain boundary-free h-BN memristor triggers the RS. This behavior is different from that of the CVD h-BN-based devices that require no electroforming process and show grain boundary-mediated RS behavior [52,53]. All devices with h-BN layers with thicknesses below 30 nm showed electroforming and RS characteristics, where the electroforming electric field (EEF) decreased with increased thickness of h-BN similar to those of SiO_2, polyimide [54–56]. The h-BN memristor showed a stable RS characteristic over 40 cycles, and the resistance memory window between HRS and LRS maintains approximately three orders of magnitude (**Figure 4c**). Note that a higher HRS/LRS ratio can be achieved by setting higher ICOMP during the set process. **Figure 4d** shows the cumulative probability of HRS and LRS resistance, showing acceptable resistance variation. The electroforming, hysteretic current–voltage (*I*–*V*), and LRS and HRS distributions of a h-BN memristor, in which Pt was used as TE, showed completely different behaviors from those of a device with Ti contacts. This strongly indicates that the RS of the exfoliated h-BN is dependent on the metallic ions diffused from the electrode through the h-BN layer by the applied electrical bias. Our novel architecture can provide a higher order of functionality to both logic and memory devices as an atomically thin configuration, and thereby be the basis for energy-efficient neuromorphic computing.

3.4. In_2Se_3 based memtransistor synaptic devices

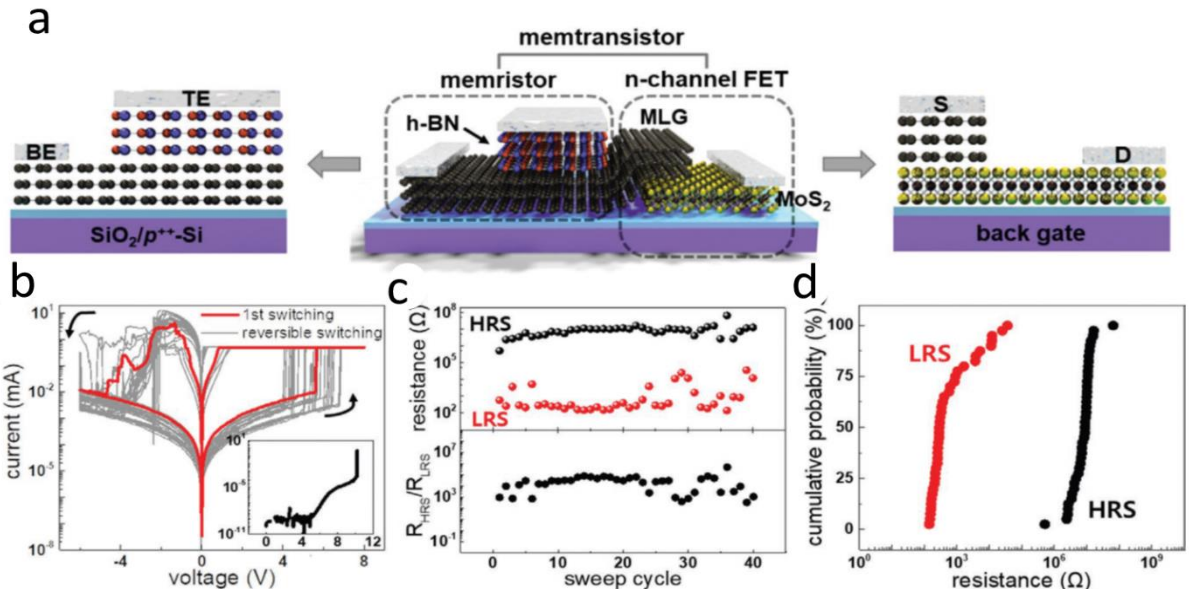

Figure 4a) Schematic of a MoS_2/Multilayer Graphene (MLG)/h-BN programmable memtransistor consisting of memristor (left) and transistor (right). b) Typical bipolar resistive switching (RS) curves of first (red curve) and successive (gray) cycles. The inset image is the I–V curve that shows the electroforming process. c) Variation of the memristor resistance at HRS and LRS (top), and the RHRS/RLRS (bottom) from the initial to multiple programming/erasing cycles. d) Cumulative distribution of the LRS and HRS resistance. Reproduced with permission [20]. Copyright 2020, Advanced Electronic Materials.

Indium selenide (In_2Se_3) based memtransistor synaptic devices represent a fascinating frontier in neuromorphic computing. In_2Se_3 is a semiconductor material with unique properties that make it suitable for building synaptic devices. In_2Se_3 ability to undergo phase changes under external stimuli, such as electrical pulses, enables the device to exhibit plasticity, akin to the synaptic plasticity observed in biological synapses. This plasticity allows for the modification of synaptic weights, crucial for learning and memory functions in neuromorphic computing systems. In this context [57], the α-In_2Se_3 ferroelectric Semiconductor (FES) memtransistor configurable multilevel conductance states enable the emulation of the diverse synaptic plasticity observed in biological counterparts (**Figure 5a**). Both $_{VGS}$ and V_{DS} pulses are utilized to mimic presynaptic inputs, while I_{DS} is monitored as the postsynaptic current (PSC). Given the significance of linearity and symmetry in synaptic weight updates for achieving high accuracy in neural network simulations, we investigated these characteristics of the α-In_2Se_3 FES memtransistor under various V_{GS} and V_{DS} presynaptic pulse schemes. Additionally, we assessed the endurance performance of the α-In_2Se_3 memtransistor by extracting LRS and HRS values at V_{DS} = -1 V from the I_{DS}-V_{DS} curves in **Figure 5b**. To delve into the nonvolatile resistance switching performance of the α-In_2Se_3 memtransistor, we further examined retention and endurance. This involved applying set (pulse amplitude: V_{GS} = +2 V, V_{DS} = -1 V, pulse width: 20 s) and reset (pulse amplitude: V_{GS} = -2 V, V_{DS} = -1 V, pulse width: 20 s) voltage pulses, and then reading the LRS and HRS currents at V_{DS} = -0.1 V and V_{GS} = 0 V, respectively (**Figure 5c**). It is noted that the HRS and LRS values show similar temporary decays, thus the $I_{On/Off}$ remains relatively unchanged for 500 s. As illustrated in **Figure 5d**, we compared our proposed FES synaptic memtransistor to documented artificial synapses based on the number of conductance states and the asymmetry value of synaptic weight updates. Our device achieved an asymmetry value of 0.004, outperforming both two-terminal and three-terminal synaptic counterparts. Additionally, simulations using an electronic synapse under an amplitude-modulated positive V_{DS} pulse scheme demonstrated optimal near-ideal linear and symmetrical conductance parameters (**Figure 5e**). Consequently, ANNs incorporating the artificial synapse achieved impressive accuracies of 93.67%, 96.16%, and 97.76% after 40 training epochs for the file type, University of California Irvine (UCI), and Modified National Institute of Standards and Technology database (MNIST) datasets, respectively. These findings highlight the advantages of α-In_2Se_3 memtransistor-based synaptic devices in neural networks, offering more configurable near-ideal linearity and symmetry, multilevel conductance states, and minimal conductance response variability due to ferroelectric (FE) polarization switching in the FES channel.

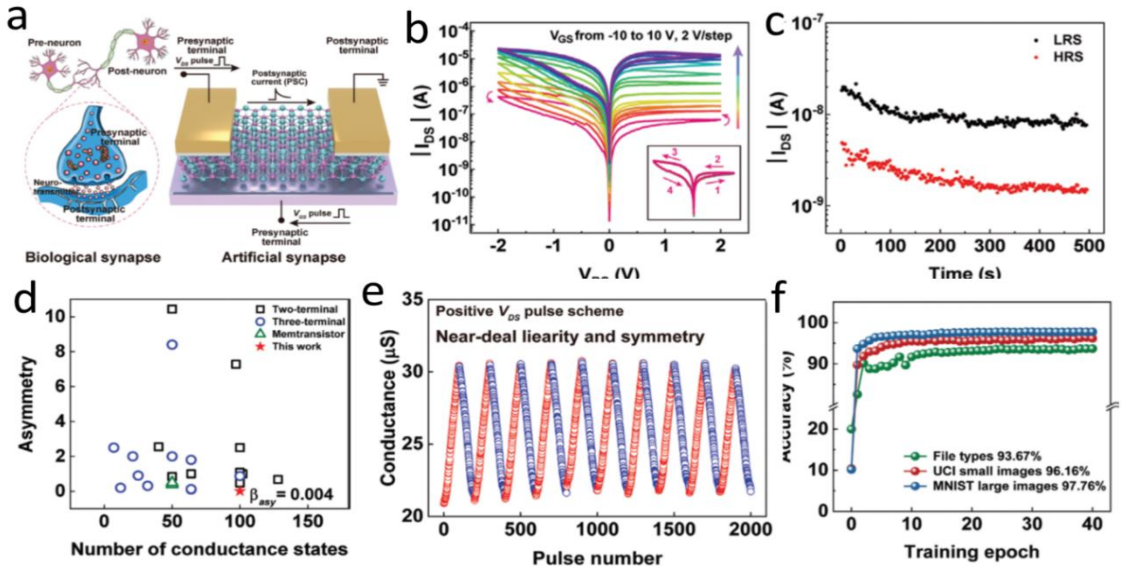

Figure 5(a) Schematic illustration of biological neurons and synapses (left) and the α-In_2Se_3 memtransistor-based artificial synapse (right). The electrical pulses at gate or drain. b) I_{DS} − V_{DS} curves of α-In_2Se_3 memtransistor with consecutive measurements over a V_{DS} range of −2 to 2 V, at different V_{GS} bias from −10 to 10 V with 2 V step−1, exhibiting wide gate tunable conductance states. The inset shows I_{DS} − V_{DS} curves of 30 consecutive VDS sweep cycles measured at V_{GS} = 0 V. The direction of V_{DS} sweeps is indicated by arrows and numbers. c) Retention of the high resistance state (HRS) (after V_{GS} pulse = −2 V, V_{DS} pulse = −1 V, 20 s) and low resistance state (LRS; after V_{GS} pulse = +2 V, V_{DS} pulse = −1 V, 20 s) currents. The HRS and LRS current values were read at V_{DS} = −0.1 V and V_{GS} = 0 V. d) Comparison of asymmetry values of synaptic weight update and number of conductance states of α-In2Se3 memtransistor-based synapse with reported counterparts. Asymmetry value of 0 indicates perfect symmetric characteristic. e) Cycle-to-cycle variations of programmed conductance states in P/D curves for 10 cycles with nonidentical positive VDS pulse scheme. f) The accuracy of α-In_2Se_3 synapses for different pattern recognition based on the conductance parameters in (e). The accuracies after 40 training epochs were presented. Reproduced with permission[57]. Copyright 2020, Small.

4. Prospects and challenges

Two-dimensional (2D) materials like MoS_2, WSe_2, h-BN, and In_2Se_3 are at the forefront of advanced material science, offering unique prospects and facing substantial challenges. These materials are promising for applications in electronics and optoelectronics due to their high electron mobility, tunable bandgaps, and mechanical flexibility, enabling the development of ultra-thin, flexible, and high-performance devices. Table shows the comparison of advantages and disadvantages of MoS_2, WSe_2, h-BN, and In_2Se_3. In the realm of energy, 2D materials are being explored for battery electrodes and solar cells, capitalizing on their high surface area and strong light-matter interaction. Additionally, their exceptional properties open new avenues in quantum computing and spintronics, particularly with materials like WSe_2 that exhibit strong spin-orbit coupling. Hexagonal boron nitride stands out as an excellent insulator and dielectric, making it ideal for protective coatings and electronic substrates.

However, these exciting opportunities come with significant challenges. The scalable and consistent synthesis of high-quality 2D materials is still a major hurdle, with issues related to contamination and defects during production. Integrating these materials with existing silicon-based technologies requires overcoming compatibility and fabrication challenges, while ensuring the environmental stability and long-term reliability of 2D material-based devices is essential for their commercial viability. Additionally, a deeper understanding of the fundamental properties and interlayer interactions within 2D material heterostructures is necessary to fully exploit their potential. Addressing these challenges through continued research and technological advancements will be crucial in harnessing the full capabilities of 2D materials for transformative applications across various fields.

The field of 2D material-based neuromorphic computing faces several challenges and holds promising prospects. Key challenges include producing high-quality, uniform 2D materials at scale, integrating these materials with traditional semiconductor technologies, and ensuring consistent layer control. Creating reliable memristors and synaptic devices with stable switching and plasticity using 2D materials remains complex. Additionally, efficient thermal management in densely packed neuromorphic circuits is crucial, and ensuring long-term durability and consistent performance of these devices is essential. Economic and environmental concerns, such as high production costs and the need for sustainable synthesis and disposal methods, also pose significant issues. These materials exhibit superior electronic properties, such as high carrier mobility and tunable bandgaps, making them suitable for fast and efficient neuromorphic devices. Their ultra-thin, flexible, and scalable nature makes them ideal for dense neuromorphic circuits. They also offer potential for low power consumption and reduced heat generation. Novel device architectures can be developed by stacking 2D materials and leveraging quantum effects. Furthermore, 2D materials can mimic synaptic plasticity and neuronal behavior, enhancing adaptive learning capabilities. Ongoing interdisciplinary collaboration and increased funding are driving rapid advancements in 2D material-based neuromorphic computing, paving the way for innovative solutions that could revolutionize the field.

5. Conclusion

The drive to incorporate advanced synaptic functions into neuromorphic hardware has led to exploration of novel multi-terminal memristive devices. These devices, utilizing metal oxides, nanoparticles, nanowires, and increasingly 2D materials like MoS_2, WSe_2, h-BN, and In_2Se_3, offer rich and tunable synaptic-like behaviors. Their atomic-level thickness and tunable electronic properties promise lower energy consumption and improved synaptic emulation. Despite these advancements bridging software and hardware in neuromorphic engineering, challenges persist in materials, device operation, design, and integration with CMOS technologies. However, the examination of memristor devices utilizing 2D materials reveals their potential as pivotal components in contemporary electronics. Leveraging the exceptional properties of 2D materials such as low power consumption, gate tunability, and compatibility with hetero-integration, they are envisioned as promising elements for artificial synaptic devices, crucial for energy-efficient neuromorphic computing. These materials enable the implementation of essential synaptic functions and advanced features like synaptic learning acceleration and hetero-synaptic cooperation, surpassing the limitations of conventional memristors. Specifically, the utilization of 2D materials facilitates the development of artificial synaptic devices with low power consumption, essential for future neuromorphic electronics. The atomically thin nature of 2D materials reduces operation voltage and leakage current, enhancing energy efficiency. Additionally, the uniform surface and vdW interfaces of layered materials enable low supply voltages and fast switching speeds, further optimizing performance. Despite challenges in meeting synapse requirements, particularly in achieving symmetry and linearity of conductance change, 2D material-based devices offer promising avenues for addressing these obstacles and advancing hardware artificial neural networks.

Competing interests

The author declare no competing interests.

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Table. Comparison of advantages and disadvantages of the 2D materials which includes as MoS_2 , WSe_2 , h-BN, and In_2Se_3 .

Material Properties	**MoS_2**	**WSe_2**	**h-BN**	**In_2Se_3**
Bandgap	Direct(monolayer)	Tunable	Wide	Tunable
Electron Mobility	Moderate	Lower	N/A	Moderate
Photoluminescence	Strong (Monolayer)	Strong (monolayer)	N/A	Moderate
Mechanical Flexibility	High	Moderate	Brittle	Moderate
Thermal conductivity	Moderate	Moderate	High	Low
Chemical Stability	High	Moderate	High	low
Scalability	Challenging	Challenging	Challenging	Challenging
Unique properties	High on/off ratio	Spin-orbit coupling	Insulator, smooth surface	Ferroelectricity