



Flexible neuromorphic transistors for neuromorphic computing and perception application

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Received: 9 May 2024 / Revised: 9 July 2024 / Accepted: 15 July 2024
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Abstract

Emulating brain functionality with neuromorphic devices is an emerging field of research. It is extensively considered as the first step to overcome the limitations of conventional von Neumann systems and build artificial intelligent systems. Currently, most neuromorphic transistors are manufactured on rigid substrates, which are difficult to bend and cannot closely fit soft human skin, limiting their application scope. The emergence and evolution of flexible electronic devices address a plethora of application and scenario demands. Particularly, the introduction of flexible neuromorphic transistors injects fresh vitality into neuromorphic computing and perception, symbolizing a significant step towards overcoming the limitations of conventional computational models and fostering the development of more intelligent wearable devices. Herein, the recent developments in flexible neuromorphic transistors are summarized and their applications in neuromorphic computing and artificial perception systems are highlighted. The future prospects and challenges of flexible neuromorphic transistors are also discussed. We believe developments in flexible neuromorphic transistors will shed light on future advances in wearable artificial intelligent systems, humanoid robotics and neural repair technology.

Keywords Neuromorphic device · Flexible neuromorphic transistor · Neuromorphic computing · Artificial perception system

1 Introduction

With the relentless progression of transistor technology towards its physical limits and the growing demand for computational power, conventional computing architecture faces significant challenges. The breakdown of Moore's Law and the emergence of the von Neumann bottleneck highlight the urgent need for breakthroughs in computational methodologies [1–10]. Neuromorphic computing, which simulates and draws inspiration from biological neural systems, is gaining traction owing to its efficiency, low power consumption, high parallelism, and flexibility. This makes it a focal point for overcoming computational bottlenecks and enhancing energy efficiency [11–14]. Neuromorphic devices are essential components in achieving neuromorphic computing and

perception. They aim to replicate the structure and function of the brain. Additionally, they seek to exceed the performance constraints of traditional computers [15–17]. Specifically, flexible neuromorphic transistors, as a newly emerging device type, exhibit characteristics like plasticity, high flexibility, and strong adaptability. These traits offer innovative possibilities for the future advancement of neuromorphic computing.

Neuromorphic devices can be broadly categorized into two types: two-terminal devices and three-terminal devices. Two-terminal devices include memristor [18–21], phase-change memory [22–24], and atomic switch [25–27], while three-terminal devices comprise electrolyte-gated transistor [28–32], floating-gate transistor [33–35], ferroelectric-gate transistor [36, 37], and optoelectronic neuromorphic transistor [38, 39]. These devices have demonstrated various synaptic plasticity or neuron functionalities, showcasing significant potential application value in neuromorphic computing or perception [39–44]. Particularly, neuromorphic transistors, with their capabilities for parallel processing and storage, are more suitable for constructing large-scale

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complex neuron networks compared to traditional computing software solutions [15–17, 45–50]. Additionally, their low power consumption is significant for applications in mobile devices, embedded systems, or energy-constrained environments. While substantial research has focused on neuromorphic transistors, the majority are still fabricated on rigid substrates [51], limiting their application scope and scenarios. Therefore, research on flexible neuromorphic devices becomes imperative. Flexible neuromorphic devices offer diverse potential advantages for future neuromorphic computing and perception applications, such as high plasticity and adaptability. Their soft design allows better conformity to biological surfaces, providing extensive opportunities for brain-machine interfaces and wearable devices. The high flexibility and reliability enable these devices to be deployed and operated in complex environments, such as in soft robots and biomedical fields [52–54]. Expected to drive innovative developments in neuromorphic computing and perception technology, flexible neuromorphic devices hold enormous application prospects in various fields, including healthcare, wearable technology, human–machine interaction, and artificial intelligence.

This review focuses on presenting the latest advances in the field of neuromorphic computing and perception based on flexible neuromorphic transistors. The review begins with a brief introduction to biological synapses and their characteristics. Subsequently, it elucidates the working mechanism of flexible neuromorphic transistors, followed by a discussion on the applications of neuromorphic computing and artificial perception systems based on these. Finally, conclusions and a brief outlook are given. An overview of this article is displayed in Fig. 1. By delving into the recent progress and technical features of flexible neuromorphic transistors, we aim to provide valuable references for researchers interested in this field.

2 Biological synapse and synaptic properties

Our brain controls various neural activities such as learning, computing and memory. These neural activities are based on a complicated neural network which contains a lot of neurons and synapses (see Fig. 2a). The information transmission from one neuron to another is accomplished by synapses in the neural networks [55, 56]. The synapse is mainly composed of the presynaptic terminal, postsynaptic terminal and synaptic gap. When a stimulus arrives at the presynaptic terminal, calcium ions flow in, stimulating the presynaptic terminal to release neurotransmitters into the synaptic gap. The neurotransmitters diffuse to the postsynaptic terminal and bind to the receptors at the postsynaptic terminal, causing a postsynaptic potential response. As a special connection

point between the adjacent neurons, synapse can change its connection strength (synaptic weight) with the historical neuron activities, which is known as synaptic plasticity [11, 57, 58]. In general, synaptic plasticity can be divided by the retention time into short-term plasticity (STP) (see Fig. 2b) and long-term plasticity (LTP) (see Fig. 2c). Short-term plasticity is a transient change of synaptic weight and it usually occurs from milliseconds to a few minutes, which is critical for the recognition and processing of the input information [59, 60]. In contrast, long-term plasticity is induced by intense or repetitive stimulus and the change of synaptic weight lasts for a long time (minutes to several weeks). It is widely believed that the long-term plasticity is related to the learning, memorizing, and forgetting in our brain [61, 62]. Actually, short-term plasticity can be gradually converted into long-term plasticity by repetitive trains [63]. It can be easily comprehended from human experience: you can form the memory of an object if you observe it repeatedly.

In biological synapses, the update of synaptic weights depends on the neural activities of presynaptic terminal and postsynaptic terminal. Spike-timing dependent plasticity (STDP) and spike-rate dependent plasticity (SRDP) are the two major influence factors for the change of synaptic weight [64, 65]. STDP, a form of Hebbian synaptic learning rules, refers to that the change of synaptic weight is connection with the time interval and sequential order of presynaptic and postsynaptic action potentials [66, 67]. For example, if the postsynaptic peak is triggered a few milliseconds after the pre-synaptic peak, the synaptic connection will become stronger, resulting in long-term potentiation. Conversely, if the chronological order is reversed, synaptic transmission becomes less efficient, resulting in long-term depression. Different forms of STDP show different time dependences on the temporal order of presynaptic and postsynaptic peaks (see Fig. 2d). SRDP is another form of Hebbian synaptic learning rules, which is the basic mechanism of the brain to realize the function of storage and memory. SRDP describes the relationship of synaptic weight update with the frequency of presynaptic action potentials [68]. High-frequency presynaptic spikes will lead to long-term potentiation, and low-frequency pre-synaptic spikes will result in long-term depression.

3 Flexible neuromorphic transistors for artificial synapse application

3.1 Mechanisms

In the past few years, many flexible neuromorphic transistors have been used to emulate the various types of synaptic behaviors by the scientists around the world [52, 69–75]. Generally, the flexible neuromorphic transistor is constituted

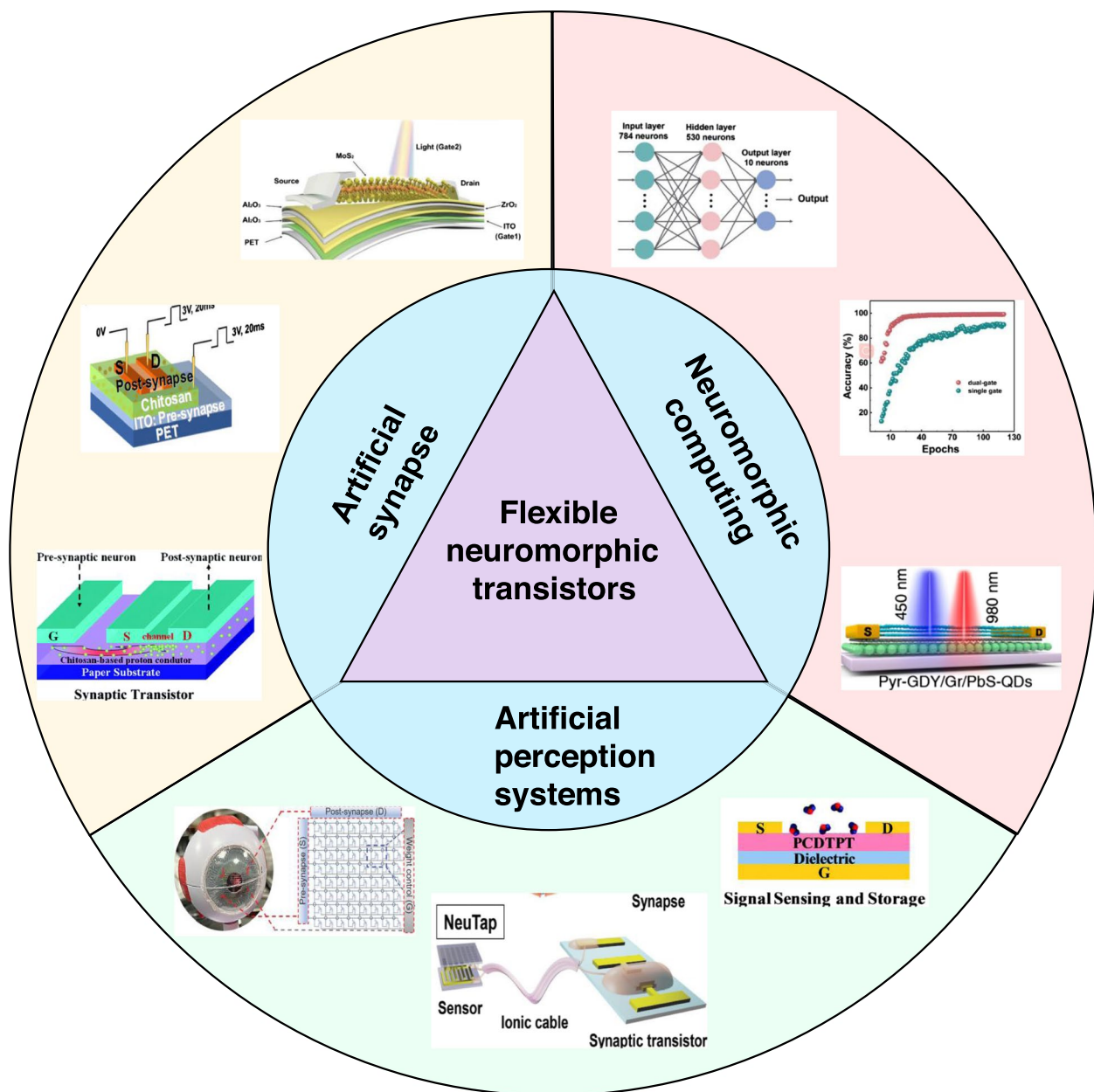


Fig. 1 Overview of flexible neuromorphic transistors used for artificial synapse, neuromorphic computing and artificial perception systems

by a gate dielectric layer, a semiconductor layer (channel), and gate/source/drain electrodes. In order to emulate the synaptic behaviors, the gate voltage pulses (V_G) (or light pulses applied on the channel) and the channel current (I_{DS}) of the flexible neuromorphic transistor are regarded as the presynaptic stimuli and the postsynaptic responses, respectively. And also the channel conductance is deemed as the synaptic weight. The flexible neuromorphic transistors can be categorized as electrolyte gate transistor, floating gate transistor, ferroelectric gate transistor, photoelectric neuromorphic transistor according to the operation mechanisms [50], as shown in Fig. 3.

3.1.1 Electrolyte gate transistor

Electrolyte gate transistors (EGTs) have aroused wide attention due to their low operating voltage and the working mode which is analogous to a synapse [16, 76]. Figure 3a shows the schematic illustration of the electrolyte gate transistor. We can find that the structure of the EGTs are similar with the traditional field-effect transistor, only the gate dielectric layer is replaced by the electrolyte material which is proton-conductive while electron-insulative. There are two basic working mechanism of EGTs: electric-double-layer (EDL) and electrochemical doping/de-doping

Fig. 2 Schematic illustration of **a** biological neuron and synapse; **b** short-term plasticity; **c** long-term plasticity; **d** four types of spike-timing dependent plasticity

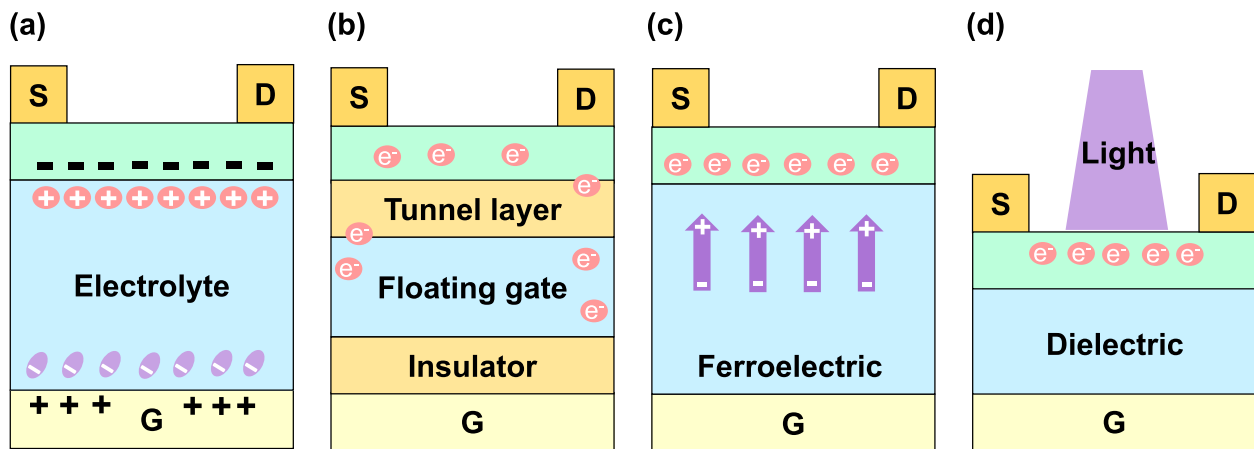
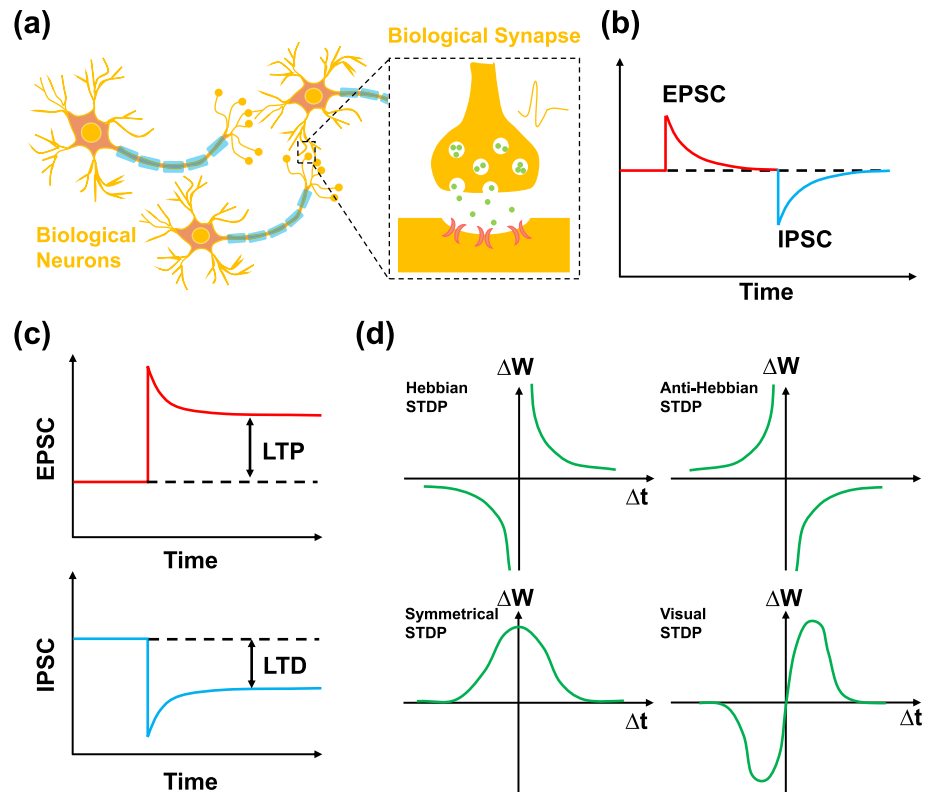


Fig. 3 Schematic illustration of **a** electrolyte gate transistor; **b** floating gate transistor; **c** ferroelectric gate transistor; **d** photoelectric neuromorphic transistor

[15, 77]. The EDL effect refers: The protons in the electrolyte film will move and accumulate at the electrolyte/channel interface under an external electric field according to the Grotthuss mechanism. These protons will induce the electrons of the channel, leading to a large EDL capacitance. Therefore, the EDL transistors can work at a low voltage [17, 29, 78]. However, if the voltage of external electric field is high enough, the protons will penetrate

the interface of electrolyte/channel and enter the channel, directly altering the channel conductance. This is so-called electrochemical doping [79, 80]. Conversely, reverse voltage results in the electrochemical de-doping process. For synaptic plasticity emulation, the EDL effect transistors and the electrochemical doping/de-doping transistors are suitable to emulate STP and LTP, respectively.

3.1.2 Floating gate transistor

Floating gate transistors (FGTs) which also have the analogous device structure with the field-effect transistor are one of the earliest neuromorphic devices [81, 82]. The schematic illustration of the FGT is shown in Fig. 3b. An additional FG is inserted in the dielectric of the FGTs compared with field-effect transistor. When the gate voltage is high enough and the tunnel layer is thin enough, charges will be injected into the FG through the quantum tunnelling effect and thermal emission effect. These charges also can be retained in the FG layer due to the existence of the charge blocking and tunneling layer. The gate voltage pulses can accurately regulate the amount of trapped charges in the FG layer. Thus, the channel conductance can be controlled by the gate voltage pulses [83, 84]. For synaptic plasticity emulation, FGTs are suitable to emulate modulation of synaptic weight.

3.1.3 Ferroelectric gate transistor

Figure 3c shows the schematic illustration of the ferroelectric gate transistors (FEGTs). Ferroelectric material (dielectric layer) is the most important component of the FEGTs. The working mechanism of the FEGTs is as follow: Ferroelectric materials have the characteristic of spontaneous polarization and can switch between two polarization states with the conversion of electric field. Due to the coulomb interaction between ferroelectric polarization and carriers, the polarization state of ferroelectric gate can be controlled by applying gate voltages, which further modulate the channel conductance [85–87]. Therefore, the FEGTs can be used to emulate the biological synapses and are suitable to emulate modulation of synaptic weight.

3.1.4 Photoelectric neuromorphic transistor

Recently, photoelectric neuromorphic transistors (PNTs) (see Fig. 3d) have attracted extensive interest in emulating the highly efficient operations of a brain [39, 50]. Compared to the electronic neuromorphic transistors, photoelectric neuromorphic transistors using light pulses as the input signal have several advantages, for example, low crosstalk, wide bandwidth, low power consumption and high speed [88–90]. Photosensitive semiconductor channel is the key of the PNTs and generates photogenerated charge carriers under the light illumination. Therefore, the channel conductance of the PNTs will increase. After the light illumination, the photogenerated charge carriers will slowly recombine and the channel conductance will decrease gradually. The light signals are converted to electrical signals by the PNTs, this process is consistent with visual synapse [38, 91, 92]. Particularly, semiconductor 2D materials have proven to be suitable to fabricate

photoelectric neuromorphic transistor. For example, Seo et al. [93] presented an optogenetics-inspired flexible 2D materials optoelectronic synapse and builds a convolutional neural network based on this device, demonstrating the feasibility of applying artificial synapses to optogenetics-inspired intelligent systems.

3.2 Emulation of synaptic plasticity

3.2.1 STP

STP plays an important role in information transmission and processing. Common STP contains excitatory/inhibitory postsynaptic current (EPSC/IPSC), paired pulse facilitation/depression (PPF/PPD). PPF is a behaviour that the EPSC amplitude induced by the second stimulus is higher than the EPSC amplitude induced by the first stimulus when the second stimulus closely follows the first stimulus. On the contrary, PPD refers to the behaviour that the EPSC amplitude induced by the second stimulus is lower than the EPSC amplitude induced by the first stimulus. In 2013, Zhou et al. [94] reported a flexible oxide based neuromorphic transistor fabricated on a plastic substrate. The P-doped porous-SiO₂ electrolyte is utilized as the dielectric layer. EPSC and PPF functions are realized by such a neuromorphic transistor. Wu et al. [95] first time fabricated a flexible neuromorphic transistor on paper substrate. This transistor adopts a lateral-gate structure, greatly reducing the difficulty of fabrication, as shown in Fig. 4a. EPSC can be triggered when a lateral-gate voltage pulse was applied (see Fig. 4b). The protons in the electrolyte laterally move and accumulate at the electrolyte/channel interface under a lateral-gate voltage pulse, attracting the free electrons in the channel. These protons gradually drift back to the initial state after the gate voltage. Figure 4c shows the PPF behaviour of a biological synapse were emulated by such transistor. Protons triggered by the first voltage pulse have not enough time to drift back to the initial state before the second voltage pulse arriving. Thus, there is a larger second EPSC than the first one. Compared with excitatory synapse, the emulation of inhibitory synapses has been less reported. Wang et al. [96] designed a flexible MoS₂-based neuromorphic transistor which has a floating gate structure (see Fig. 4d). In order to fabricate such flexible transistor, a one-step mechanical exfoliation method and a low temperature atomic layer deposition (ALD) technology which is compatible with flexible substrate are proposed. Such transistor displays good mechanical stability and reliable memory characteristics. Particularly, IPSC and PPD can be mimicked. This work opens a new path for complicated neuromorphic systems.

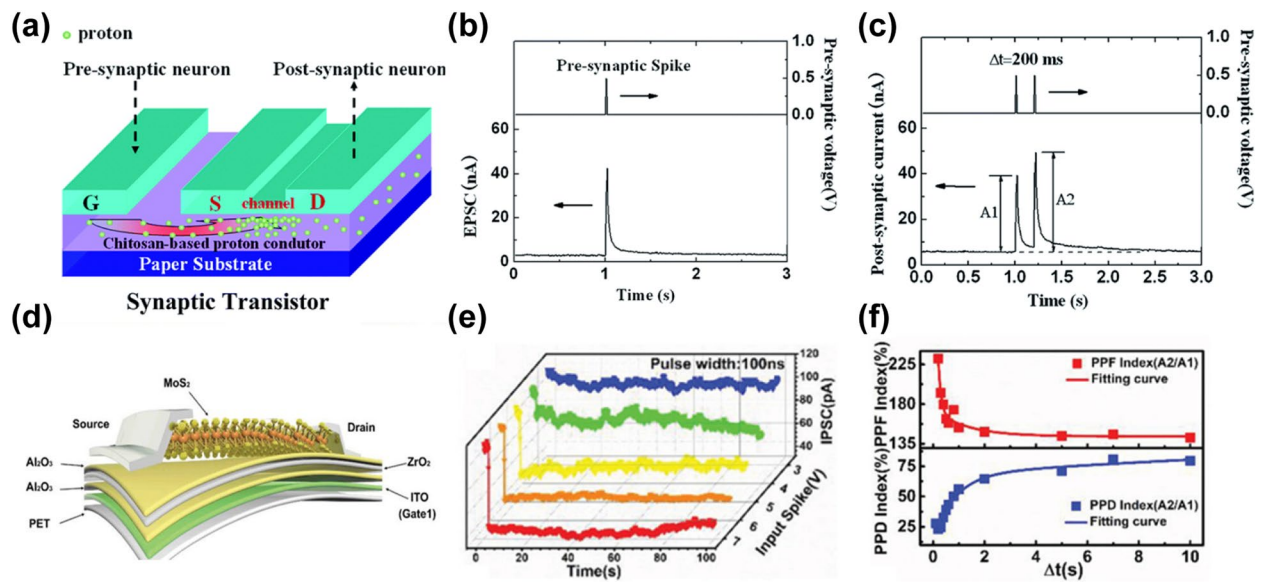


Fig. 4 **a** Schematic diagram of the flexible neuromorphic lateral-gate transistor on paper substrate; **b** typical EPSC triggered by a gate voltage; **c** PPF triggered by two continuous voltage pulses. Reproduced with permission [95]; Copyright 2014, The Royal Society of Chemis-

try; **d** schematic diagram of flexible MoS₂-based neuromorphic transistor; **e** IPSC triggered by different voltage; **f** PPF and PPD rate with different interval time. Reproduced with permission [96]; Copyright 2020, Wiley–VCH

3.2.2 LTP

LTP, including the long-term potentiation and depression, is deemed to be a foundation of learning and memory. Liu et al. demonstrated an organic flexible electrochemical neuromorphic transistor which is fabricated by a low-cost and scalable screen-printing technology [97]. The long-term potentiation and depression can be realized by such a transistor, as shown in Fig. 5a. A series of 100 negative voltage pulses following a series of 100 positive voltage pulses are applied on the transistor gate electrode. The channel conductance gradually increases with the number of positive voltage pulses, and it recovers the initial conductance state after the 100 negative voltage pulses. It demonstrated that this transistor has 100 distinct conductance states. The stability of long-term potentiation and depression process is also tested, as shown in Fig. 5b. The organic flexible electrochemical neuromorphic transistor exhibited good repeatability of the potentiation/depression behaviour after 100 bending cyclic.

In fact, STP can be converted into LTP with sufficient training. Yu et al. [98] reported a polysaccharide-gated flexible neuromorphic transistor based on polyethylene terephthalate substrate. Such transistor has well mechanical reliability. A transition of STP to LTP was mimicked, as shown in Fig. 5c. It is clearly that EPSC decays back to an initial state when value of the gate voltage pulse is 2 V. However, when the voltage value is 5 V, the EPSC maintains for a long time. These phenomena can be understood: there is a formation of EDL layer at the electrolyte/channel interface

when the gate voltage is relatively low. And if the gate voltage is relatively high, the EPSC response is related to the electrochemical doping. Therefore, the STP converts into LTP with the voltage increasing. In addition, this transistor can be dissolved in de-ionized water, implying potential applications in environmental protection device.

3.2.3 STDP

In the late 1990s, STDP learning rules were proposed by Hebbian. STDP, which describes the behaviour of synapses to change synaptic weights based on the time interval between the presynaptic pulse and the postsynaptic pulse, is widely regarded as the fundamental mechanism of unsupervised learning in biological neural networks. At present, four types of STDP has been reported [66]. Yu et al. [99] introduced a restickable ITO-based neuromorphic transistor on polyimide tape substrate. Four types of STDP, containing Hebbian STDP (see Fig. 5d), anti-Hebbian STDP (see Fig. 5e), symmetrical STDP (see Fig. 5f), and visual STDP (see Fig. 5g), were successfully realized by the restickable ITO-based neuromorphic transistor. The realization mechanism is based on the electrochemical doping and dedoping process of proton in the chitosan electrolyte. Furthermore, this transistor is pasted on steel semicylinder and paper holder. It is interesting that well transistor features and STDP learning rules are still observed. These results indicate that such a transistor has potential applications in flexible neuromorphic electronics.

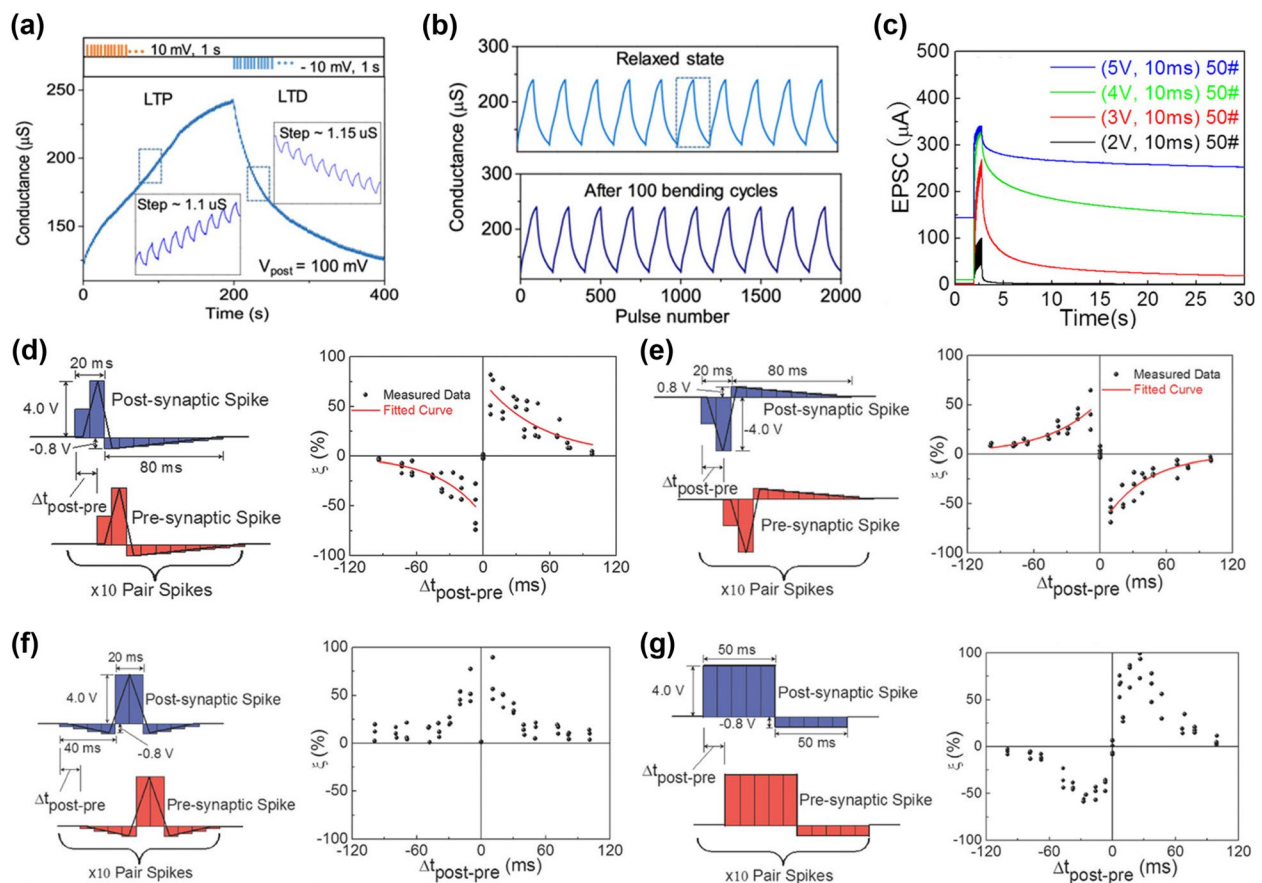


Fig. 5 **a** Long-term potentiation and depression emulated by the organic flexible electrochemical neuromorphic transistor; **b** long-term potentiation and depression cycling stress tests. Reproduced with permission [97]; Copyright 2019, American Chemical Society; **c** EPSC responses with different pluses amplitudes, mimicking the transition

of STP to LTP. Reproduced with permission [98]; Copyright 2018, American Chemical Society; **d** Hebbian STDP; **e** Anti-Hebbian STDP; **f** Symmetrical STDP; **g** Visual STDP; realized by the restickable neuromorphic transistor. Reproduced with permission [99]; Copyright 2018, Wiley-VCH

4 Flexible neuromorphic transistors for neuromorphic computing

4.1 Associative learning

Associative learning refers to the learning process that is realized by the connection between two central excitations caused by two kinds of stimuli in the brain. Pavlovian dog conditioned reflex (also called classical conditioning reflex) is a classic form of associative learning [100]. Classical conditioning reflex consists of the neutral stimulus (NS) and the unconditioned stimulus (US). An unconditioned stimulus can produce an unconditioned response (UR) without any learning. Whereas a neutral stimulus can become a conditioned stimulus (CS) after repeated learning with an unconditioned stimulus, resulting in a conditioned response (CR). In the Pavlovian dog experiment, the bell ringing, feeding food and salivation are regarded as the NS, US, and UR, respectively. Initially, bell ringing (NS) cannot provoke salivation (UR), and only the feeding food (US) can provoke

salivation. During repetitive training, the feeding food and bell ringing are provided simultaneously. There is an association established between the feeding food and bell ringing. Therefore, the bell ringing alone can cause salivation. At this moment, the bell ringing is changed from NS to CS. And the salivation is transformed to CR. This is the famous Pavlovian dog conditioned reflex experiment.

Guo et al. [101] proposed a multifunctional photoelectric neuromorphic transistor gated by starch electrolyte (see Fig. 6a). This transistor is fabricated on PET substrates. This transistor advantages such as, low processing cost, low working voltage and photoelectric synergic modulation. STP including EPSC and PPF can be mimicked by such a transistor, attributed to the EDL effect. Thanks to the persistent photoconductivity phenomenon of the IGZO channel, long-term memory response behaviours were realized. More interestingly, Pavlovian classical condition is emulated due to photoelectric synergic modulation, as shown in Fig. 6b. In detail, 20 consecutive voltage pulses (0.05 V, 100 ms) are deemed as the bell

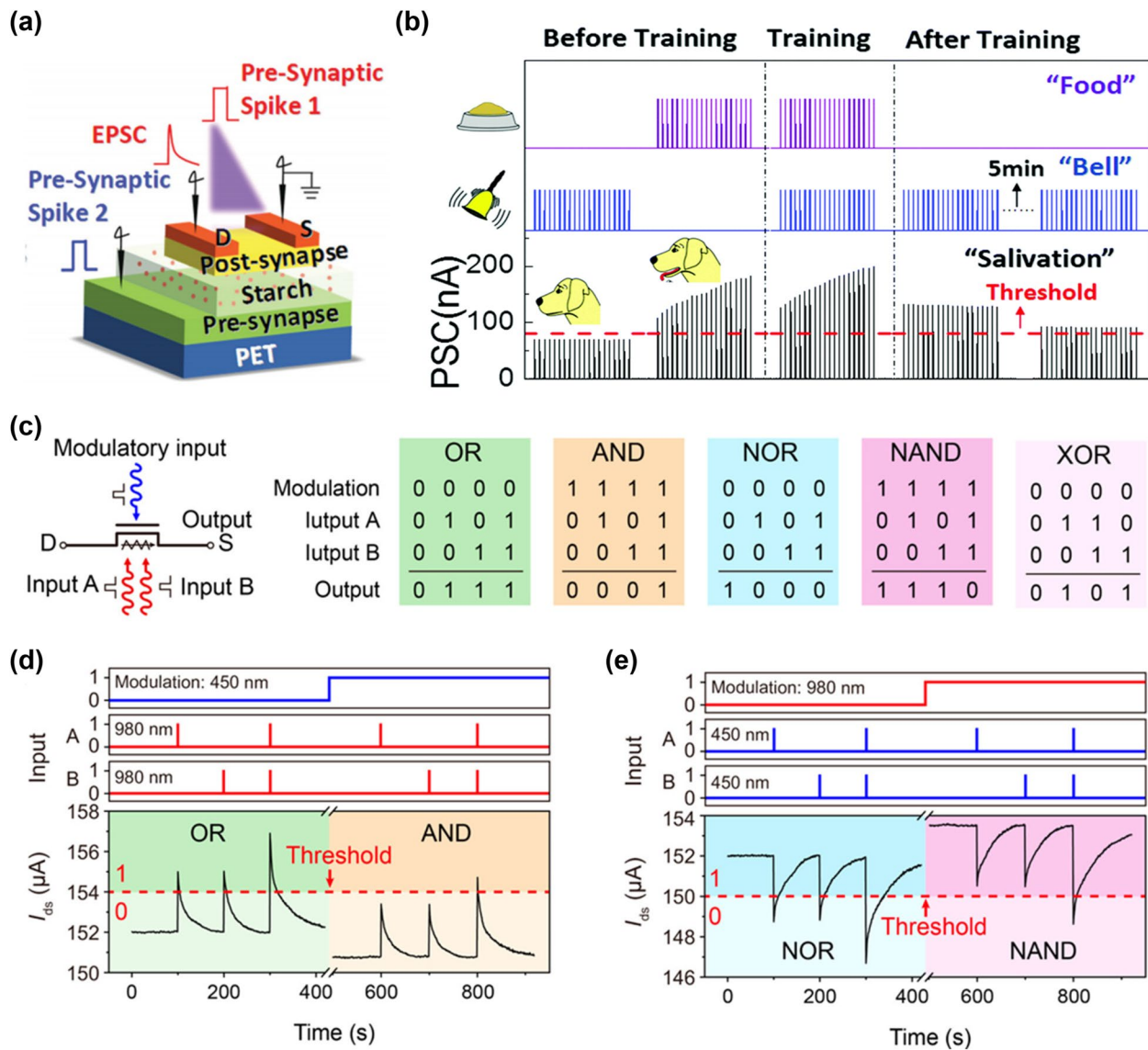


Fig. 6 **a** Schematic diagram of multifunctional photoelectric neuromorphic transistor; **b** Pavlovian classical condition emulated by photoelectric neuromorphic transistor. Reproduced with permission [101]; Copyright 2020, The Royal Society of Chemistry; **c** schematic diagram of logic operations in the optical synapse; **d** "OR"

and "AND" logic operations emulated by utilizing two 980 nm signals as inputs and 450 nm signals as regulation signal; **e** "NOR" and "NAND" logic operations emulated by utilizing two 450 nm signals as inputs and 980 nm signals as regulation signal. Reproduced with permission [102]; Copyright 2020, American Chemical Society

ringing. It is obviously that EPSC triggered by these pulses cannot exceed the "salivation" threshold. 20 consecutive light spike pulses (3.5 mW/cm^2 , 100 ms) are deemed as feeding food, and EPSC responses are significantly higher than the "salivation" threshold. The authors applied the voltage pulses on the gate and the light pulses on the channel simultaneously. During the repeated training, the 20 consecutive voltage pulses also were above the "salivation" threshold. These consequences manifest that the flexible multifunctional photoelectric neuromorphic

transistor have potential values for associative learning system researches.

4.2 Spiking logic operation

Spiking logic operation function is an essential component of the neuromorphic computing systems [9, 103, 104]. Because it can obviously improve the information processing capability of the neuromorphic computing systems. The spiking logic operation has been demonstrated by flexible multiple-input-terminal neuromorphic transistor. Such

structures are beneficial to the emulation of synaptic dendrite integration. Synaptic dendrite integration is the key of spiking logic operation. Liu et al. [105] reported a freestanding IZO-based EDL neuromorphic transistor with multiple-input-terminal for spiking logic operation emulation. Here, due to the excellent mechanical support of the chitosan, it is easily peeled off from the glass platform. Therefore, it is not only the gate dielectric of the transistor, but also is the substrate. And the structure of this transistor is multiple gate input (G_1 , G_2 , G_M). When the positive pulse (0.1 V, 20 ms) is applied on the G_M , the “OR” logic is realized. At this moment, the input voltage of any G_1 or G_2 can trigger the EPSC. The “AND” logic is mimicked when the negative pulse (-0.5 V, 20 ms) is applied on the G_M . EPSC can be observed when G_1 and G_2 are applied input voltage simultaneously. The above consequences are interesting for neuromorphic computing.

Recently, innovative logic gates using photoelectric synapses have been proposed for advanced neuromorphic computing. Hou et al. [102] exploit optical logic gate using the large-scale flexible pyrenyl graphdiyne/graphene/PbS quantum dot heterostructure optical synapse with bipolar optical synaptic plasticity. Such device can emulate EPSC and IPSC by optical signal. When V_g is 0 V, EPSC and IPSC were induced by light pulse with wavelengths of 980 nm and 450 nm, respectively. More importantly, a series of optical logic gates have been demonstrated by the optical synapses. Figure 6c displays the schematic diagram of logic operations in the optical synapse. There are two optical inputs terminal and one optical modulatory terminal in the optical synapse. As shown in Fig. 6d, the light pulse with wavelengths of 980 nm is as the input and illumination at 450 nm is as the modulatory terminal. When the modulatory terminal is closed, either EPSCs induced by input A and B can exceed the threshold value, indicating the “OR” operation. On the contrary, the “AND” operation will be mimicked if the modulatory terminal is opened. Analogously, when the light pulse with wavelengths of 450 nm serves as the input and illumination at 980 nm serves as the modulatory terminal, the logic operation “NOR” and “NAND” have been demonstrated, as shown in Fig. 6e. These optical logic operations will accomplish together more complicated tasks with external controlling the input light signals. This work is an important step toward the development of photoelectric neuromorphic computing systems.

4.3 Artificial neural networks

In biological neural network, neurons join each other by synapses that have different connection strengths (synaptic weight). These connection strengths respond differently to various stimuli. This is the basis of learning [106, 107]. A traditional artificial neural network which is built by

neuromorphic device with modulation conductance updating can emulate the brain architecture and realize its learning capacity [36, 108, 109]. The flexible neuromorphic transistor with variable conductance could be regarded as a promising candidate for the traditional artificial neural network. Currently, many researches have reported the traditional artificial neural network constructed by flexible neuromorphic transistor [110–113].

Zhong et al. [114] designed a flexible neuromorphic FEGT based on mica substrate, it includes a $\text{PbZr}_{0.2}\text{Ti}_{0.8}\text{O}_3$ ferroelectric dielectric layer and a semiconducting indium zinc oxide channel. Such a FEGT exhibits excellent conductance updating regulated by electrical signals. An optimized artificial neural network has been used for the application of Modified National Institute of Standards and Technology (MNIST) database handwritten digits recognition. The structure of the artificial neural network consists of 784 inputs neurons that correspond to the image version (28×28 pixels) of MNIST, 100 hidden neurons and 10 outputs neurons that correspond to the ten digits (from 0 to 9). During the 10 times training, the MNIST recognition rate is up to 94.4%. Moreover, to demonstrate the robustness of the flexible neuromorphic FEGT, the bending cycle tests of the long-term potentiation and depression have been provided. The experimental results show that the influence of bending on MNIST recognition rate is negligible. Due to this transistor is all-inorganic, it has well high temperature reliability. These results provide a realistic routine for highly efficient neuromorphic computing.

Recently, Liu et al. experimentally demonstrate a flexible dual-gate neuromorphic transistor with ion-gel electrolyte and P3HT organic channel based on PET substrate (see Fig. 7a) [110]. This device is capable of computing and storing the spatiotemporal signals from the dual-gates. Importantly, a non-volatile conductance modulation effect was observed in the device after the dual-gate applied pulses simultaneously. The phenomenon can be explained by electrochemical doping effect. More importantly, the authors established an artificial neural network (784×28) using the flexible dual-gate neuromorphic transistor for MNIST handwritten digits recognition, as shown in Fig. 7b. During the training, the two gates are regarded as the presynaptic input terminals of the same neuron to transmit signals. Meanwhile, random noises were generated and superimposed with the signal transmission by each presynaptic input terminal (see Fig. 7c). The simulation results indicate that random noises can be effectively filter by such an artificial neural network built with the flexible dual-gate neuromorphic transistor. Therefore, accurate and stable memory have been formed. The recognition accuracy (MNIST handwritten digits) of dual-gate transistor based artificial neural network is improved from 89.3% to 99.0% compared to the single-gate transistor, as shown in

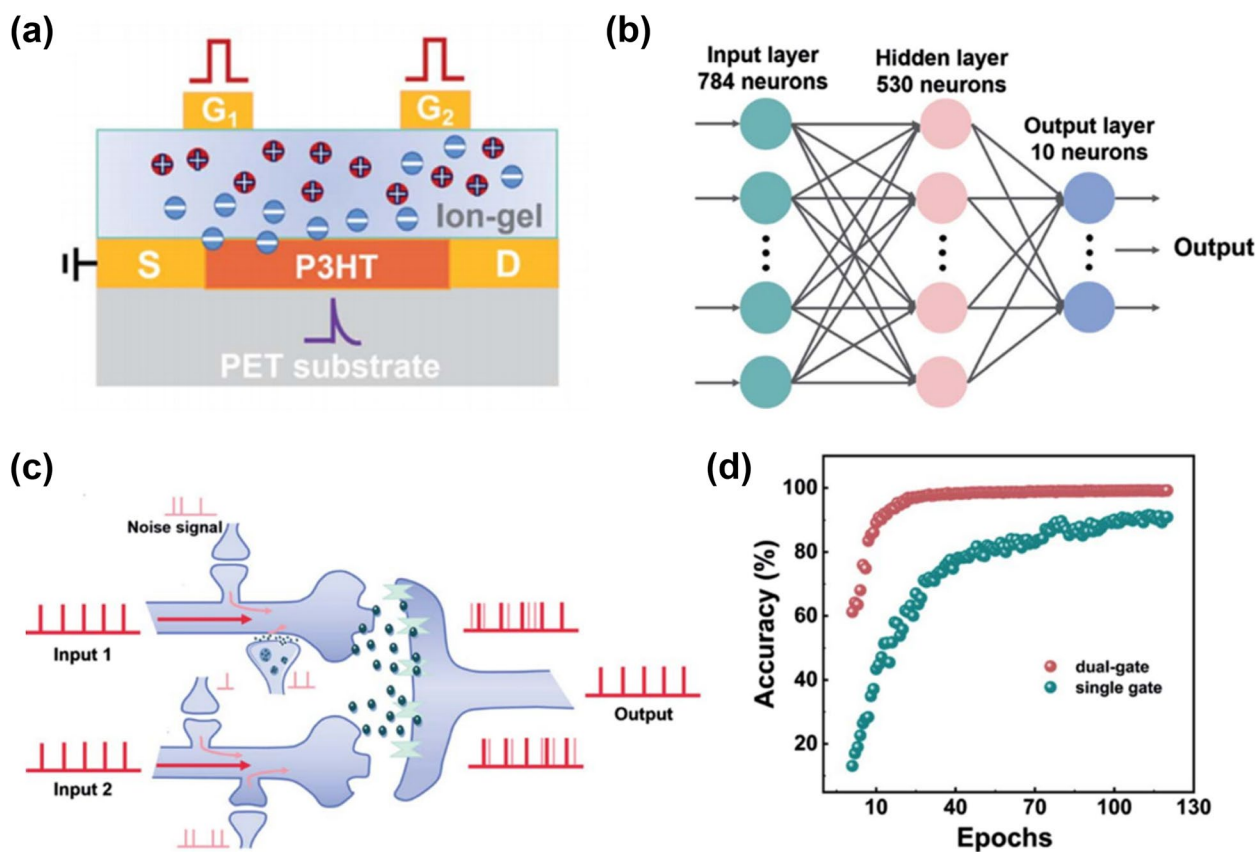


Fig. 7 **a** Schematic of the flexible dual-gate neuromorphic transistor; **b** structure diagram of the artificial neural network; **c** schematic diagram of introducing noise signal; **d** comparison of the classifica-

tion accuracy for the networks based on the dual-gate hetero-synaptic transistor and the single-gate homo-synaptic transistor [110]; Copyright 2022, The Royal Society of Chemistry

Fig. 7d. These consequences certify that dual-gate neuromorphic transistors are more tolerant to noise disturbances than the single-gate neuromorphic transistors and open new avenues for building complex artificial neural network.

5 Flexible neuromorphic transistors for artificial perception systems

5.1 Artificial visual systems

The human visual system plays an important role in exploring real world. Over 70% information that humans receive from the external environment is derived visually [115]. Visual pathway mainly consists of eye, optic nerves, and visual cortex of the brain [116]. The visual system begins with the eye. At back of the eye is the retina, which is light-sensitive layer and contains a mass of photoreceptor cells. There are two basic types of photoreceptor cells in the retina: rods and cones [117]. The rods and cones can capture visual perception and convert light to physiological electrical signals

that transferred into optic nerve by other retinal neurons. Finally, these physiological electrical signals travel through optic nerve to reach the visual cortex [9]. Therefore, to mimic the visual systems, conventional artificial visual systems are consisted of photoelectric sensors, processing and memory units [8]. However, these systems result in high energy consumption, attributing to the issue of complex circuit. Photoelectric neuromorphic devices can integrate the optical detection, processing and storage functions in a single device, simplifying the circuit structure and reducing the energy consumption [118, 119]. As one of photoelectric neuromorphic devices, flexible photoelectric neuromorphic transistors have aroused a wide range interests to constitute flexible artificial visual systems [54].

Li et al. [120] proposed a flexible artificial visual system based on high-quality lead-free metal halide ($\text{Cs}_3\text{Bi}_2\text{I}_9$) nanocrystals transistor array. Figure 8a shows the schematic diagram of the transistor. $\text{Cs}_3\text{Bi}_2\text{I}_9$ nanocrystals-PMMA/DPPDTT organic semiconductor and the Al_2O_3 layers are as the channel and dielectric materials of the transistor, respectively. The transistor exhibits charge trapping induced by light and the electrical-mediated charge de-trapping

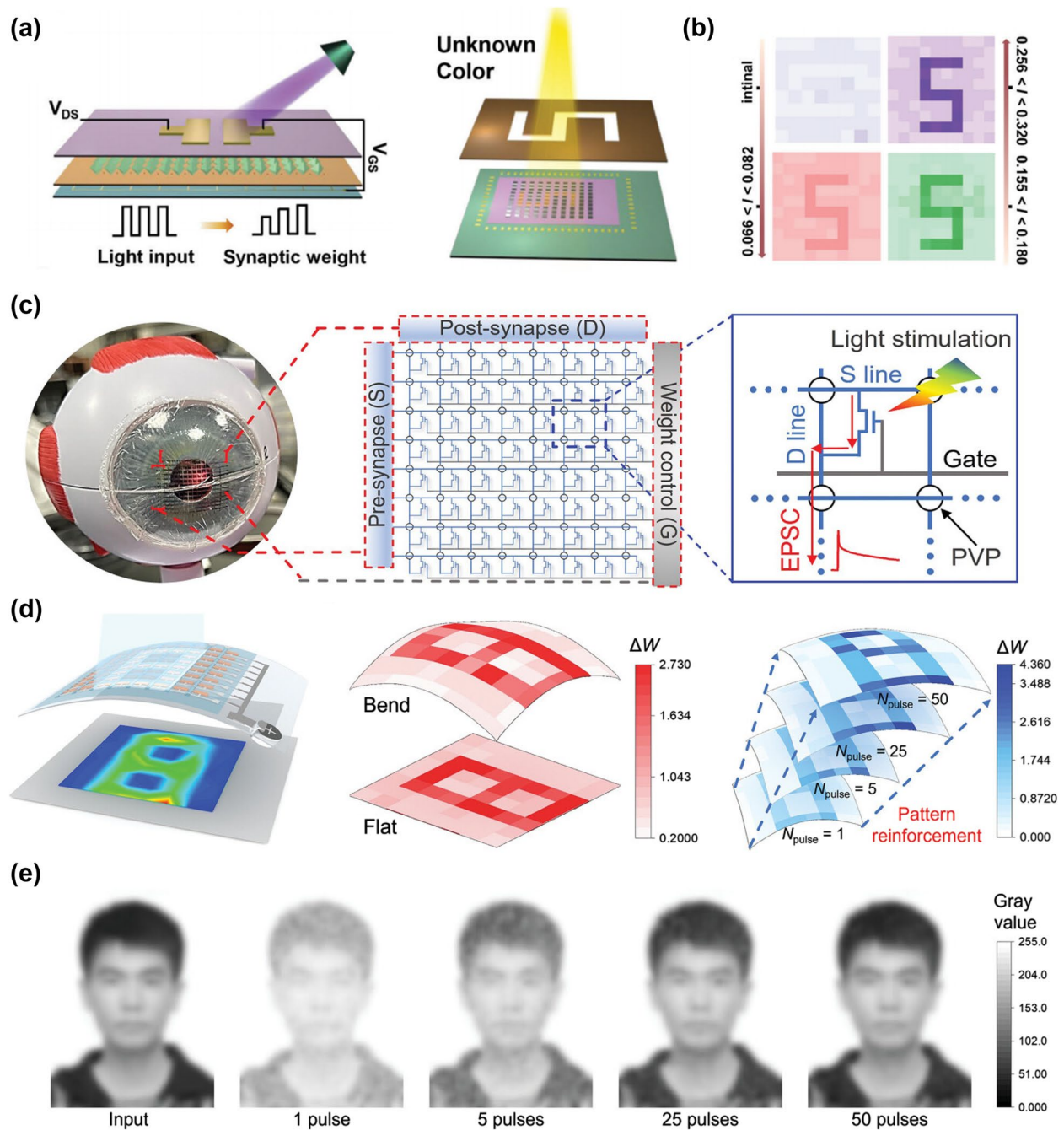


Fig. 8 **a** schematic diagram of the high-quality lead-free metal halide ($\text{Cs}_3\text{Bi}_2\text{I}_9$) nanocrystals transistor; **b** recognition results in the dark condition and light illumination at 405, 532, and 635 nm. Reproduced with permission [120]; Copyright 2022, Wiley–VCH; **c** schematic

diagram of the flexible solution-printed photoelectric neuromorphic transistor array; **d** measured results of a digit “8” pattern; **e** Simulated learning consequences of a human face. Reproduced with permission [121]; Copyright 2022, Wiley–VCH

features, because of the carrier confinement caused by the band mismatching between the DPPDTT organic semiconductor layer and the $\text{Cs}_3\text{Bi}_2\text{I}_9$ nanocrystals-PMMA layer. Based on above-mentioned effects, the light-induced visual synaptic behaviours including EPSC, PPF, the transition of STP to LTP and “learning-forgetting” were performed in such a transistor. Moreover, the transistor array has strong

stability and reliability after bending 1000 times. The flexible artificial visual system based on the transistor array can successfully realize visual perception and visual memory. More importantly, colour recognition functions (different colours of light such as 405, 532, and 635 nm) are effectively implemented by such system, as shown in Fig. 8b. To explore the potential of the flexible artificial visual system

in the field of neuromorphic computing, an artificial neural network is established for the MNIST handwritten digit recognition tasks. High-precision recognition rate of digit images (exceeding 80%) is obtained when the noise ratio is 30%. These results drive the practical progress of metal halide transistor array for artificial visual system.

Besides, Shi et al. [121] fabricated a flexible solution-printed photoelectric neuromorphic transistor on PET substrate for artificial visual neural networks application. The working mechanism of this transistor is distinct from conventional devices. It introduced a source Schottky barrier to modulate the charge-carrier injection. Due to the source Schottky barrier introduced, this transistor operates at a low voltage range, effectively reducing the energy consumption. Meanwhile, such transistor shows extraordinary light signal perception capability like a human eye. Therefore, it successfully realized the visual synaptic responses to light signal stimuli. Importantly, there is an ultralow energy consumption of 0.07–34 fJ per spike in STP and 0.41–19.87 fJ per spike in LTP emulations. As is meaningful for the developments in artificial visual systems with ultralow energy consumption. What's more, an 8×8 transistor array is fabricated on a flexible substrate to emulate artificial optical neural network, as shown in Fig. 8c. It is interestingly that the transistors can be attached on an eyeball model. Figure 8d exhibits the reconstructed images of digit “8” under a flat state and a bending state. Both the images can be clearly identified. The image reinforcement learning of human vision also been realized by the transistor array, as shown in Fig. 8e. It could find that the human face images became sharper and sharper with the training light pulses increasing. The flexible solution-printed photoelectric neuromorphic transistors may pave a promising way for low-cost and low-power-consumption artificial visual neural networks.

5.2 Artificial tactile system

Physiologically, skin, covering the entire body of human, is the largest sense organ. It is the beginning of the tactile system. There are a lot of sensory neurons embedded in the skin. Receptors on these sensory neurons can detect external touch/press signals and convert them into electrical signals. Then, these spike signals are transmitted to the terminal somatosensory cortex, and finally the tactile sensation is formed [119, 122, 123]. As a result, hardware implementation of the artificial tactile system will provide the perceptual learning capability to humanoid robots and help them interact with the external surroundings [124, 125]. To achieve this, sensors with tactile perception functions and neuromorphic devices with synaptic functions are needed. In recent years, the integration of tactile sensors and flexible neuromorphic transistors to establish flexible artificial tactile system has been widely reported [70, 123, 126–128].

Wan et al. [126] designed a “NeuTap” (neuromorphic tactile processing system) to emulate the tactile perceptual sensory neuron. The “NeuTap” is consisted of a resistive pressure sensor (pressure signals generation and collection unit), a soft ionic conductor cable (signals transmission unit), and a flexible EGT-based neuromorphic transistor (signals processing unit), as shown in Fig. 9a. In detail, the resistive pressure sensor can translate the pressure stimuli into electrical signals, which are transmitted to the neuromorphic transistor via a soft ionic conductor cable. The design advantage avoids the crosstalk of the two elements, due to the separation of sensing unit and the processing unit. At the same time, as the signals processing unit, the neuromorphic transistor with two input gates has good spatiotemporal information integration capabilities. By using the characteristics, the NeuTap can recognize tactile patterns by extracting the spatiotemporal correlated tactile feature. Figure 9b, c displays the responses of the “NeuTap” to various spatiotemporally correlated tactile patterns. After a training session, the “NeuTap” exhibits a 44% error rate. Furthermore, the error rate can be improved and dramatically reduced to 0.4% with repeated training. This work demonstrates a neuromorphic tactile processing system that can integrate and distinguish the spatiotemporal correlated tactile feature, is great significance to the practical application of artificial limbs and humanoid robots.

Chen et al. [128] developed a piezotronic graphene artificial sensory synapse on PET substrate, containing a piezoelectric nanogenerator and an ion-gel gate neuromorphic transistor. Figure 9d shows the schematic diagram of the piezotronic graphene artificial sensory synapse. The piezoelectric potential of the piezoelectric nanogenerator can efficiently drive the neuromorphic transistor compared with conventional artificial sensory synapse, due to the formation of EDL at the interface of ion-gel/graphene. Therefore, the channel conductance (synaptic weights) can be readily regulated by the pressure pulses. Representative synaptic properties such as EPSC, IPSC, PPF and STDP are achieved. Moreover, the dynamic modulation based on dual perceptual presynaptic inputs is also demonstrated, as shown in Fig. 9e. The piezotronic graphene artificial sensory synapse can spatiotemporally correlated pressure signals, enabling parallel pressure signals recognition and processing. This report provides a new insight into developing flexible artificial sensory synapse.

Jiang et al. [127] presented a flexible artificial sensory nerve using for neuromorphic tactile recognition without relying on algorithms or computing resources. Such a flexible artificial sensory nerve (see Fig. 9f) is constituted by a flexible tactile sensor with linear response and high sensitivity and a flexible neuromorphic transistor exhibiting synaptic facilitation. Notably, an interfacial self-assembly technique is used for the fabrication of the

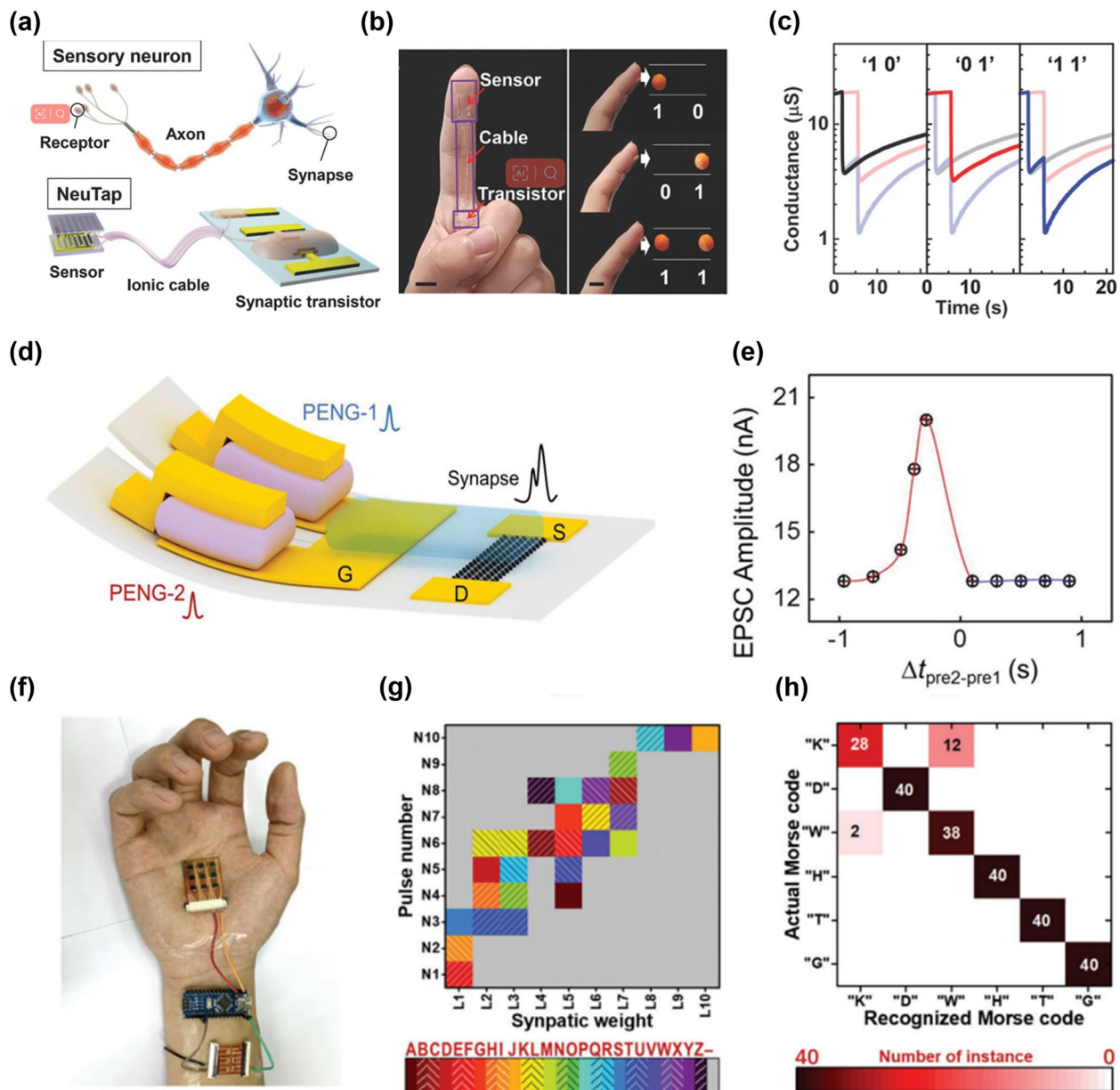


Fig. 9 **a** Schematic diagram of the “NeuTap” (neuromorphic tactile processing system); **b** “NeuTap” on a finger (left) and the schematic illustrating the touch with different two-bit binary code labels (right); **c** responses of the “NeuTap” to different types of pattern pairs. Reproduced with permission [126]; Copyright 2018, Wiley-VCH; **d** schematic diagram of the piezotronic graphene artificial sensory synapses; **e** dynamic responses with dual perceptual presynaptic

inputs. Reproduced with permission [128]; Copyright 2019, Wiley-VCH; **f** photograph of the flexible artificial sensory nerve; **g** colour mapping of the 26 letters from “A” to “Z” for recognizing Morse code; **h** recognition results of Morse code tapping patterns by reading the device output. Reproduced with permission [127]; Copyright 2022, Wiley-VCH

flexible neuromorphic transistor, which allows large-scale and facile transfer to flexible substrates. In the process of tactile recognition, no algorithms or computing resources are needed. It is only directly reading the outputs of the flexible neuromorphic transistor. Also, the device does not require state resetting or memory erasing operations, simplifying the structure of the flexible artificial sensory nerve

and improving the perception capabilities. More importantly, identification of material hardness during robotic grasping and recognition of Mores code tapping patterns during tactile interaction (see Fig. 9g, h) are realized by this system. These results provide a guideline for developing next-generation flexible artificial tactile systems and interactive electronic skin.

5.3 Artificial auditory system

Auditory system is one of the most essential perception systems of human. It can detect, recognize and process the sound signals, making human communicate efficiently and directly. Sound propagation is a complicated process in the human auditory system. In short, the auricle collects the external sound signals and these signals are transferred to perilymph of inner ear. At this moment, the external sound signals are converted into electric signals. Subsequently, the central nervous system will receive the electric signals transmitted by the afferent fiber of the cochlea. Finally, these electric signals are processed and stored, resulting in the generation of the action potentials [129, 130]. Similarly, the artificial auditory system requires the devices not only to recognize and collect the sound information but also to analyse and process these massive information [131]. At present, the research related to the artificial auditory systems is still in its infancy. Therefore, there is few report on the flexible artificial auditory system, especially compared with the flexible artificial visual or tactile systems.

Wan et al. [132] realized a flexible artificial auditory system based on a flexible polypropylene ferroelectret nanogenerator (FENG) and a flexible carbon nanotube neuromorphic

transistor, as shown in Fig. 10a. Here, the FENG acts as the receptor in ear, converting external sound wave into electrical signals. And the flexible carbon nanotube neuromorphic transistor is regard as the information processing unit. When the sound wave reaches the interface of the FENG, the perturbations caused by the sound wave lead to a change of internal dipole moments of the FENG. The electric field distribution within the film changes, creating a free charge at the surface electrodes, which ultimately produces an output electrical signals. Figure 10b shows the output voltages of the FENG at different sound intensity levels. These electrical signals are applied on the gate electrode of the flexible carbon nanotube neuromorphic transistor after a regulating circuit. Finally, the typical EPSC, IPSC, LTP, LTD and synaptic weight update behaviours are demonstrated by the flexible artificial auditory system under different sound intensity levels, as shown in Fig. 10c, d. This work lays a foundation for the development of the flexible artificial auditory system.

5.4 Artificial olfactory system

Biological olfactory system (see Fig. 11a) which is another essential sensory system is of great significance for human to evaluate food intake, sense surrounding environments and

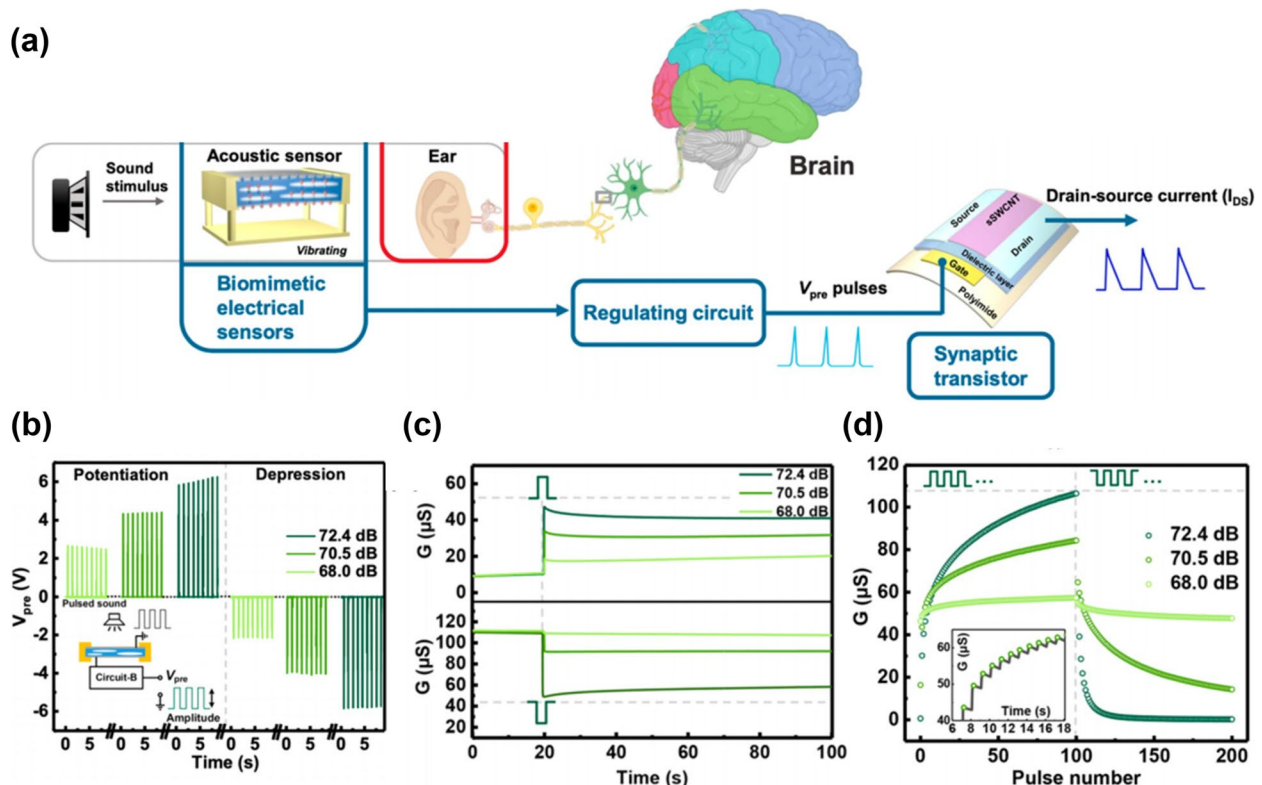


Fig. 10 **a** Schematic diagram of the flexible artificial auditory system; **b** output voltage of the FENG with different sound intensity levels; **c** EPSC and IPSC responses with different sound intensity levels; **d**

synaptic weight update with different sound intensity levels. Reproduced with permission [132]; Copyright 2021, American Chemical Society

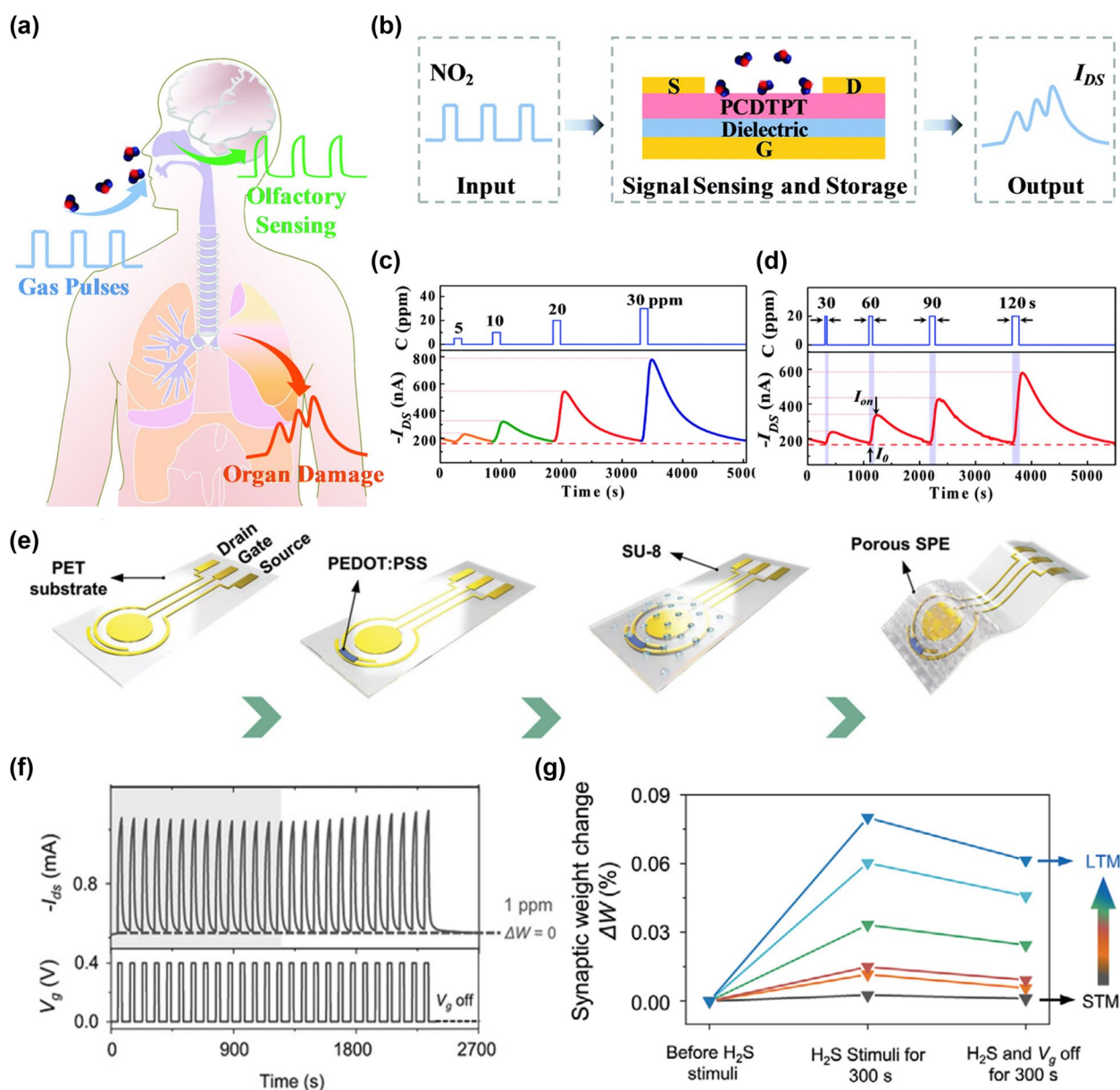


Fig. 11 **a** Schematic of the biological olfactory system; **b** schematic of the flexible artificial olfactory system; **c** EPSC responses of the device to gas pulses with different concentrations; **d** EPSC responses of the device to gas pulses with different pulse widths. Reproduced with permission [137]; Copyright 2019, The Royal Society of Chem-

istry; **e** fabrication process of the porous solid electrolyte OEET; **f** short-term memory of the OEET; **g** transition from short-term memory to long-term memory emulated by the OEET. Reproduced with permission [138]; Copyright 2023, Wiley-VCH

potential dangers [133]. It can recognize multitudinous odor molecules. When these odor molecules enter the nose, chemical interactions occur with olfactory receptors in peripheral sensory neurons of the olfactory epithelium [134]. Chemical signals are converted into electrical signals. Before these resulting electrical signals transmitted to olfactory cortex, they need to be pre-encoded by the neighboring neurons of the main olfactory bulb [135]. The olfactory bulb shows neural plasticity, which plays an important role in olfactory learning and memorizing. Inspired by this mechanism,

scientists have proposed some artificial olfactory systems [136]. However, similar to the artificial auditory system, the development of artificial olfactory systems is also at the early stage, probably because of the complexity of olfactory sensing. Therefore, the reports of flexible artificial olfactory systems are also relatively few.

Song et al. [137] reported a flexible artificial olfactory system based on a single organic neuromorphic transistor which was fabricated on a freestanding PVA substrate, as shown in Fig. 11b. It simplifies the manufacturing

technology and increases integration. Such an organic neuromorphic transistor can sense gas, process and store information, which benefits from the PCDTPT organic semiconductor channel. When the device is exposed to a NO_2 gas pulse, NO_2 molecules are captured and retained on the organic semiconductor surface, acting as an electron capture site. At present, the holes in the semiconductor channel will increase, resulting in the increasing of the current. When the gas is stopped, the current will be maintained because it takes time for the gas molecules trapped in the semiconductor channel to be de-doped from it. The synaptic fundamental features can be mimicked by such a transistor using gas pulses, as shown in Fig. 11c, d. More interestingly, such device exhibits PPF memory behaviour. Based on the behaviour, the flexible artificial olfactory system can emulate the inhalation, metabolism and cumulative of organ damage in the human body during a dangerous gas leakage. Such a flexible artificial olfactory system has a potential value for the future medical monitoring platforms featuring portable.

Recently, Deng et al. [138] designed a flexible artificial olfactory system with gasotransmitter-mediated plasticity based on an organic electrochemical transistor (OECT). Figure 11e shows the fabrication process of OECT. A breath-figure derived porous solid polymer electrolyte is used as the gate dielectric layer, and PEDOT:PSS material serves as the channel layer. The porous solid polymer electrolyte can capture H_2S molecules from the environment, regulating the doping state of PEDOT:PSS channel. The OECT exhibits excellent sensitivity toward H_2S gas molecules with a ppb-level response limit, and realizes excessive concentration detection of H_2S from rotten eggs by coupled with a wireless system. Typical synaptic plasticity induced by H_2S gas including short-term memory, long-term memory, transition from short-term memory to long-term memory are emulated by the OECT, as shown in Fig. 11f, g. This work opens new routes toward advanced next-generation flexible artificial olfactory system and sets an important foundation for intelligent healthcare.

5.5 Artificial multisensory integration neural system

In biological neural system, multisensory integration is defined as a process that integrates the inputs from different sensory perception systems into a comprehensive awareness. Multisensory integration is universal in brain and benefits for humans or animals to realize high-level perceptive and cognitive processes [139–141]. When multiple sensory stimuli are present at the same time, humans exhibit greater sensitivity than an isolated single pattern, because it allows brain to decrease the uncertainty in external environment [142]. The highly complicated emulation of multisensory

integration using emerging electrical devices is of great significance, as the combination of multiples senses in AI will be able to perform more complex recognition tasks [143]. Recently, several artificial multisensory integration systems have been demonstrated based on flexible neuromorphic transistors.

Wan et al. [144] reported a bimodal artificial sensory neuron (BASE) which is fabricated on flexible PET substrate to realize visual-haptic fusion processes, as shown in Fig. 12a, b. Such a BASE is constituted by four core unit, including a perovskite photodetector, a resistive pressure sensor, an ionic cable and a neuromorphic transistor. The resistive pressure sensor and the perovskite photodetector can transform external pressure and optic information into electrical signals, respectively. Then, these electrical signals are transmitted to the neuromorphic transistor via the ionic cable for integration and conversion to EPSC. By synchronizing the two type sensory signals, BASE can be triggered at multiple levels, allowing them to manipulate skeletal muscle tubes and robotic arms, as shown in Fig. 12c. If a tennis ball located near the manipulator can transmit visual or tactile feedback to trigger the manipulator to grasp the ball, it is marked as “yes” and visual and tactile feedback are used to distinguish between “yes” or “no” on the “z” and “y” axes, respectively. The ball can only be grasped when it is in the “yes” position in both directions. The fusion sense can make a more appropriate action than the single sense. More interestingly, BASE also is used for recognition of multi-transparency alphabetic patterns, confirming enhanced recognition ability achieved on the fusion of visual/haptic cues. These results have profound implications for building a highly integrated perception system.

Jiang et al. [145] proposed a bioinspired motion-cognition nerve based on a flexible neuromorphic transistor for multisensory integration applications, as shown in Fig. 12e. A fast, scalable, and solution-processed method is used for the fabrication of nanoparticle-doped two-dimensional-nanoflakes which is as the semiconductor channel of the flexible neuromorphic transistor. Benefited from the charge-trapping effect of the two-dimensional materials, this flexible neuromorphic transistor exhibits superior synaptic features, stable linear modulation and good spatiotemporal integration ability. These device characteristics are beneficial to the parallel and efficient processes of multisensory inputs. Human activity recognition and drone flight-mode recognition tasks (see Fig. 12f–j) can be achieved by the bioinspired motion-cognition nerve utilizing hardware outputs. And the recognition rates reach 0.94 and 0.95, respectively. Moreover, visual-vestibular integration and vibrotactile-vestibular integration also fulfilled in such device. This work provides a new paradigm for sensory robotics and human-interactive intelligent devices.

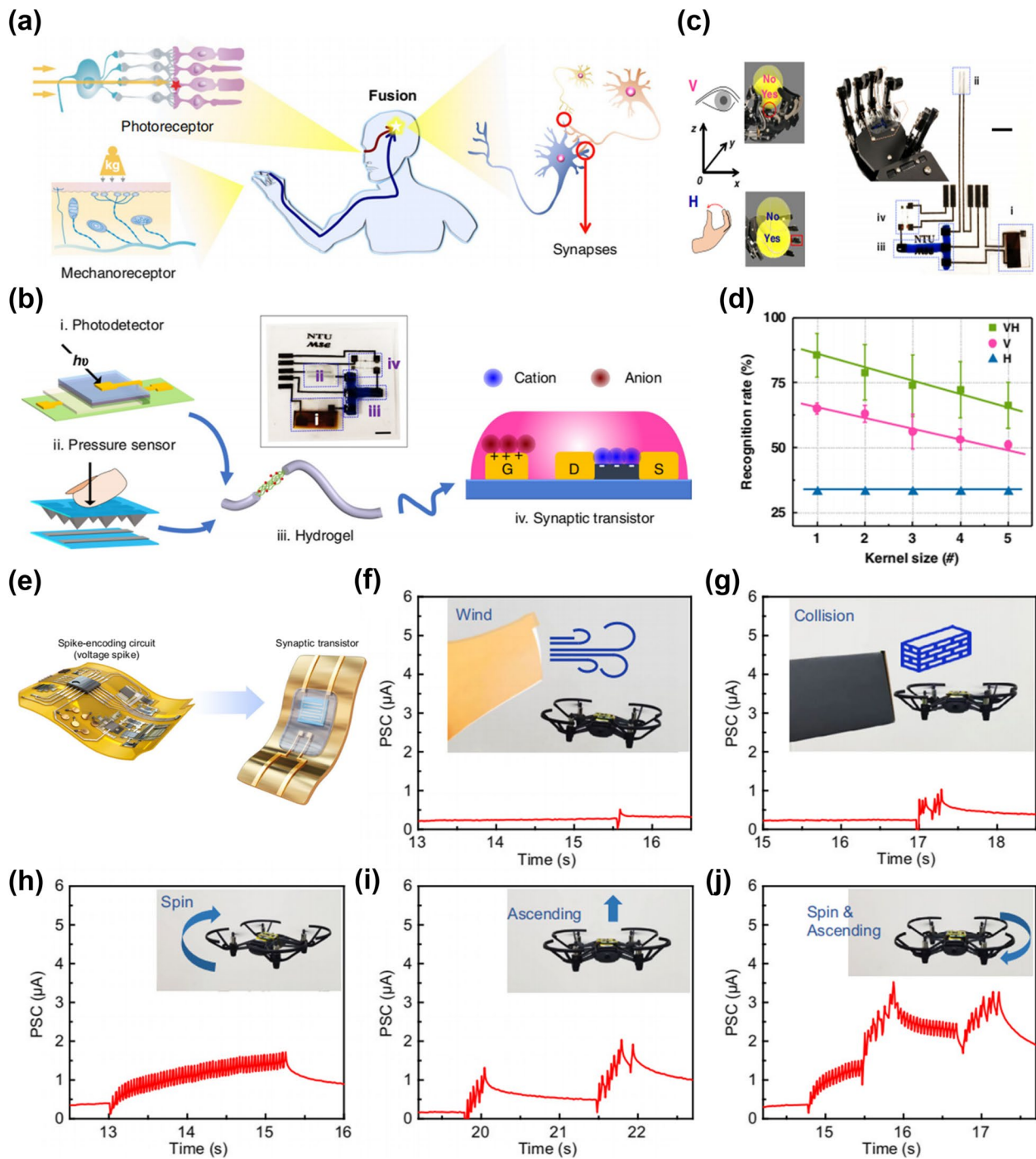


Fig. 12 **a** Visual-haptic fusion processes in biology; **b** schematic diagram of bimodal artificial sensory neuron (BASE); **c** the strategy of integrating visual-haptic feedback to realize the motion control of the robot; **d** the recognition rates for the mapping of unimodal and bimodal modes. Reproduced with permission [144]; Copyright 2020,

Springer Nature; **e** schematic diagram of flexible multisensory neuromorphic device; ESCP generated, when the drone was operated in five modes: **f** wind stabilization, **g** collision stabilization, **h** spinning, **i** ascending, and **j** spin-ascending. Reproduced with permission [145]; Copyright 2023, Springer Nature

6 Conclusions and outlook

Traditional computing models encounter bottlenecks when dealing with large-scale computing and complex perception

tasks. The development of new concept devices with biological synaptic/neuronal functions from the bottom level is of great significance to the construction of neuromorphic systems to break through the von Neumann bottleneck of

traditional computers, and has attracted widespread attention from governments, enterprises and universities all over the world. In the past decade, transistor-based neuromorphic devices have become increasingly prominent because of their good stability, relatively controllable test parameters and clear operating mechanism. Compared with two-terminal synaptic devices, neuromorphic transistors can build more complex neural networks. This is because neuromorphic transistors have the advantage of multiple inputs, enabling devices to perform concurrent learning, parallel data processing, and spatiotemporal dynamic logic functions. At the same time, the proliferation of intelligent wearable devices and flexible electronic products underscores the growing demand for highly flexible and bendable electronic devices. The appearance of flexible neuromorphic transistors not only broadens the design scope of electronic devices but also injects new vitality into the field of neuromorphic computing and perception.

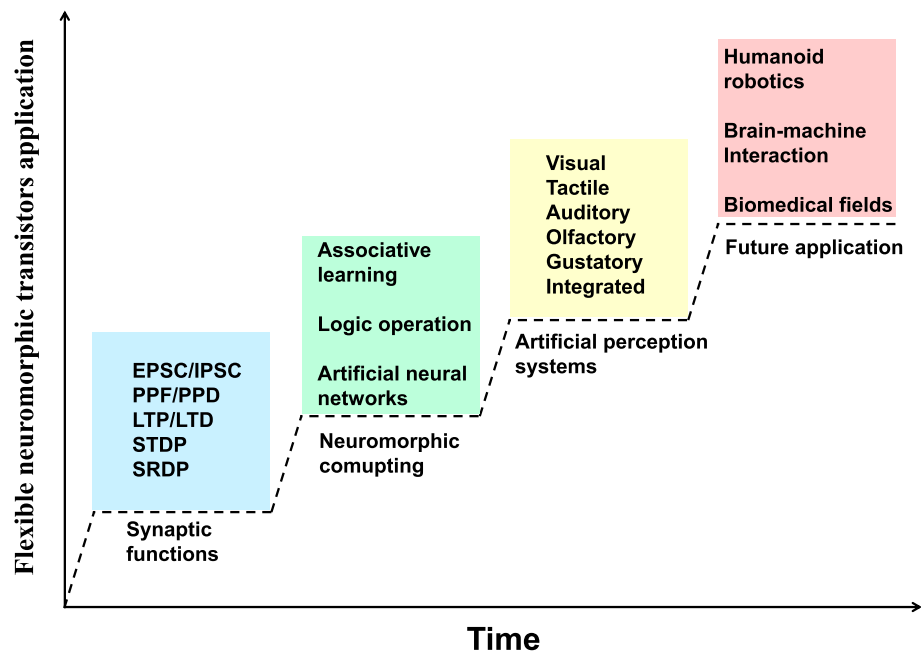
In the recent years, flexible neuromorphic transistors and artificial neural systems based on different structures and mechanisms have made significant progress. Here, this article reviews the research progress of flexible neuromorphic transistors. First, we briefly introduce biological synapses and synaptic characteristics. Then, we discuss the mechanisms of different types of flexible neuromorphic transistors, including electrolyte gate transistors, floating gate transistors, ferroelectric gate transistors, and photoelectric neuromorphic transistors. Subsequently, we focus on the applications of flexible neuromorphic transistors in neuromorphic computing and artificial perception systems. Figure 13 shows the development of flexible neuromorphic transistors application scenarios over time. Flexible

neuromorphic devices offer several potential advantages for future neuromorphic computing and perception applications, such as high plasticity and adaptability. Their soft design allows better conformity to biological surfaces, providing a wide range of opportunities for brain-machine interfaces and wearable devices. The high flexibility and reliability enable these devices to be deployed and operated in complex environments, such as in soft robots and biomedical fields. Flexible neuromorphic devices are expected to promote the innovative development of neuromorphic computing and perception technology, and have great application prospects in various fields such as healthcare, wearable technology, brain-machine interaction and artificial intelligence.

Unfortunately, the technology surrounding flexible neuromorphic transistors is still in its infancy and far from practical application. The research status of flexible neuromorphic transistors is full of many limitations and challenges. This section outlines the main obstacles and suggests potential avenues for future exploration.

- (i) Limited functional scope: While artificial visual and tactile systems based on flexible neuromorphic transistors have received a lot of attention, artificial auditory, olfactory, and taste systems are significantly under-reported. Addressing this imbalance is critical to the development of comprehensive artificial perception systems that can simulate the complexity of human perception systems.
- (ii) Stability and reliability issues: The stability and reliability of flexible neuromorphic transistors are critical to achieving high performance. At present, most of the research focuses on the proof of concept of new devices,

Fig. 13 Application trend of flexible neuromorphic transistors over time



and pays less attention to the stability and reliability of new devices. For the practical application of these transistors, stability and reliability are essential.

- (iii) **Integration challenges:** Various manufacturing techniques have been employed for flexible neuromorphic transistors, but some approaches, such as solution-based approaches, present challenges for integration with existing silicon-based integrated circuit manufacturing techniques. Overcoming these integration challenges is essential for the development of large-scale flexible neuromorphic transistor arrays or chips.
- (iv) **Interconnection complexity:** The three-dimensional arrangement of biological neurons and synapses presents a significant challenge for the interconnection of flexible neuromorphic transistors. Achieving effective interconnection in large numbers, like biological systems, is a difficult task that demands innovative solutions.
- (v) **Algorithm-transistor integration:** While advanced neural network algorithms, including machine learning and deep learning, have been proposed for neuromorphic computing, their execution is still tied to the traditional von Neumann computer architecture. The ideal scenario involves fully embedding these algorithms into neural networks constructed from flexible neuromorphic transistors, enabling ultra-low-energy computing and more closely mirroring the efficiency of the human brain.

In conclusion, despite the current difficulties in the development of flexible neuromorphic transistors, we remain optimistic that collaborative efforts across disciplines such as microelectronics science, materials science, computer science, and brain science will pave the way for these transistors to become the building blocks of the next generation of artificial intelligence. This collective pursuit promises to overcome existing challenges and realize the full potential of flexible neuromorphic transistor technology.

Acknowledgements We would like to thank all authors for their valuable contributions to this research.

Authors' contributions Shuo Ke and Yinxin Zhu are contributed equally to this work. Shuo Ke: Writing-original draft. Yixin Zhu: Writing-original draft. Chuanyu Fu: Methodology. Huiwu Mao: Methodology. Kailu Shi: Validation. Lesheng Qiao: Validation. Qing Wan: Methodology; Supervision; Writing-review & editing.

Funding This study was supported by National Natural Science Foundation of China (Grant no. 62074075).

Availability of data and materials Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate This manuscript does not involve human or animal research.

Competing interests Author Qing Wan is an editorial board member.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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