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Artificial Sensory Memory

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Abstract

Sensory memory, formed at the beginning when we perceive and interact with the environment, is considered as one primary source of intelligence. Transferring such biological concept into electronic implementations aims at achieving perceptual intelligence, which would profoundly advance a broad spectrum of applications such as prosthetics, robotics, and cyborg systems. Here, we summarize recent development on design and fabrication of artificial sensory memory devices and highlight their applications in recognition, manipulation, and learning. The emergence of such devices benefits from recent progress on both bioinspired sensing and neuromorphic engineering technologies and also obtains abundant inspirations and benchmarks from an improved understanding of biological sensory processing. Increasing attention on this area would offer unprecedented opportunities toward new hardware architecture of artificial intelligence, which could extend the capabilities of digital systems with emotional/psychological attributes. Pending challenges are also addressed to such aspects as integration level, energy efficiency, and functionality, which would undoubtedly shed light on the future development of translational implementations.

1. Introduction

Intelligence is fundamentally a memory-based process, and the dynamic modification of the memory underlies our learning capability. The memory in biological systems benefits from the natural evolution of neural networks that possess several properties including event-driven operation, in-memory computing architecture, and massive parallel processing. These characteristics allow us to perceive and react appropriately when confronting to the events of the real world in a more robust, plastic, fault tolerant, and energy efficient manners than current digital systems.[1] Although digital systems could acquire, store and access information with high speed and precision, they absolutely rely on the complementary metal-oxide-semiconductor (CMOS) technology and von Neuman scheme, which are struggling with achieving intelligence as the biological systems.[2, 3] To address this problem, new hardware architectures designed to adapt neuromorphic computing paradigm are highly pursued by both academia and industry, such as coherent nanophotonic circuits,[4] quantum neural network,[5, 6] IBM TrueNorth,[1] and Google TPU.[7]

Accessing data is crucial to the success of these systems, and ultimately no level of algorithmic or systematic sophistication would make up for a poor set of data. In biology, the sensory neuron that initiates the sensory memory process could be regarded as the first stage of data access in the neural network of our brain. It collects, integrates, and refines massive sensory data timely for dynamically training the neural network, which greatly shapes our cognition and awareness through modifying the connections between neurons.[8, 9] In that case, electronic implementations with sensory neuron paradigm could serve as the building block for constructing new hardware architectures toward autonomous artificial intelligence, which directly access to sensory data and store them at the same time (**Figure 1**). One step forward is to develop devices that capture the essential properties of the sensory neuron and are able to implement sensory memory. Sensory memory is interpreted as the capability to restore the sensory information after the stimuli gone.[10-14] The stored sensory information can be further processed to form a specific perception, which could serve as the expertise for action/decision.[15-17]

Recently, much effort has been made on the incorporation of advanced bioinspired sensing and neuromorphic engineering technologies. In these works, the integrated devices were endowed with both the receptor-like exquisite sensing capabilities and synapse-like memory/learning behaviors for mimicking the sensory memory processes observed in sensory neurons and/or sensory nervous system. Accordingly, we introduce the concept of artificial sensory memory (ASM) to describe this type of devices. The precise and timely access to the spatiotemporal sensory data is now feasible with the development of bioinspired sensing devices such as electronic skin (E-skin)[18-22], which mimic the essential properties of natural sensory organs or receptors.[23-26] This has aroused profound implications in the development of prosthetics,[27-30] soft-/bio-robotics,[19, 31-35] wearable medical devices,[36-41] and so on. In the meanwhile, the development of neuromorphic engineering has given birth to synaptic devices, which aims at building bio-inspired cognitive adaptive devices to reproduce processing/memory capabilities as the biological synapse.[42, 43] Furthermore, artificial neural networks based on synaptic devices enable the efficient implementation of machine learning algorithms when fulfilling such tasks as pattern classification and feature extraction.[44-47] Therefore, the incorporation of the two attributes (i.e. sensing and memory), in one device is promising and at exactly the right time to propel the development of related artificial intelligence.[48, 49] Studies on the design, fabrication, and application of ASM devices are also critical to the realization of intelligent and humanized systems that directly interact with humans.

Herein, recent advances in ASM devices are discussed with respect to strategies for integrating functional modules to achieve various modalities of sensory memory. We highlight the advantages of combining bioinspired sensors with neuromorphic devices for their applications in robotics and prosthetics. Potential implications on neuromorphic perception have also been discussed, which would improve current technologies in cyborg systems, robotics, and prosthetics, and might endow these systems with emotional/psychological attributes. It is believed that rational integration resembling the biological sensory memory would open a new chapter in artificial intelligence, and the ASM device serves as the building block for constructing systems with perceptual intelligence.

2. Understanding sensory memory

Sensory information (**Figure 2**) could be interpreted as the source that underlies the exteroception (involved in touch, sight, sound, smell, and taste) that enables the awareness of the external, the interoception (involved in pain, hunger, and other homeostatic conditions) that enables the awareness of the inner, and the proprioception (involved in body position, movement, and acceleration) that enables the awareness of motion. Such sensory information could be detected, interpreted, and memorized by our sensory nervous system to provide us with awareness and guidance. The 'multistore model' of human memory was proposed by Atkinson and Shiffrin in 1968.[50] Despite its very simplified form, it is considered as one most accepted model to date. In this model, the memory flow is explained as follow. Firstly, when sensory information is firstly detected, it would enter the sensory memory (SM). If this information is paid enough attention, it enters the short-term memory (STM). Only when the information is rehearsed (i. e. repeated), known as the consolidation, the short-term memory will transform to long-term memory (LTM). The long-term memory store information permanently, which always requires protein synthesis in the nervous system.[51] Otherwise, the information would be forgotten induced by the processes of displacement or decay. Each store is a unitary structure and has its own characteristics in terms of encoding, capacity, and duration.[52] The duration for SM, STM, and LTM could be a quarter to one second, one to dozens of seconds, and unlimited, respectively. Such hierarchical memorial mechanism is intrinsically different from what underlies modern semiconductor memory devices where forgetfulness is never useful. For mammals, forgetfulness is not always a disadvantage, because it allows them to pay attention to more important or more urgent information, which could improve adaptability and save energy for individuals.

In the sensory nervous system, the sensory neuron that serves as the interface between external stimuli and inner memory is responsible for sensory transduction—an important link in sensory processing underlying memory, perception, and action. Sensory neuron could be simplified by three parts including receptor, axon, and synapse, which has provided inspirations and benchmarks for the ASM. Recent progress on ASM has been devoted to integrating the sensing and memory components together (Figure 1) to mimic the sensory memory process. The further developments would also benefit from the more in-depth biological and anatomic understanding the sensory neuron.

2.1 From biological receptors to electronic receptors

In the peripheral nervous system, the sensory information comes from the sensory receptors and is carried by the sensory neuron toward the central nervous system. The sensory memory begins with the comprehensive activities of the sensory neuron, in which the sensory information is converted into action potentials or graded potentials. Generally, the stimulus would induce the open of Na^+ channels, which allow Na^+ to flow into the cell. Then such a process would result in depolarization that causes the Ca^{2+} channels to open, which in turn lead to the release of neurotransmitter into the afferent nerve receptors.[53, 54] Different types of sensory neurons have different sensory receptors that respond to specific kinds of stimulus. Our human beings have several kinds of receptors that enable us to sense iconic, auditory, gustatory, haptic stimuli, and so on. For example, seven kinds of receptors are involved in the formation of tactile sensation including nociceptive receptors, cold receptors, warm receptors, and four mechanoreceptors.[28, 55]

Therefore, mimicking the sensing capability of these receptors and even developing platforms similar to the sense organs might greatly propel the development in the prosthesis, robotics, and artificial intelligence. Recent progress on e-skin devices that resemble the haptic receptors could be regarded as a salutary lesson for the development of electronic receptors with other sense modalities. The e-skin devices are pursued not only exquisite sensing capability as the biological receptors[56] but also other intriguing properties like stretchability,[57-61] self-power,[62-64] and self-healing.[65, 66] To achieve this, specific structures and materials were exploited. For example, a mass of microstructures was utilized such as micropyramidal,[67-70] microdome,[71-74] microcavity,[75-79] microcracks,[80-82] thickness-gradient structures,[57, 83] even metamaterial structure.[84] Biomaterials,[70, 85-88] nanocomposites,[89-94] triboelectric and piezoelectric materials,[95-99] stimuli-responsive polymers,[66, 100] hydrogels,[101-104] and so on, were exploited to enhance the functionalities and to extend the limits owned by traditional silicon-based materials.[105-107] Aforementioned, multiple receptors are involved in the formation of tactile sensation, which has also inspired the design and integration of artificial sensors with versatile sensing capabilities.[36, 72, 82, 108-111]

Furthermore, unlike the electronic sensors modulate signals on direct-current (dc) amplitude, biological receptors exploit oscillating electrical action potentials for signal transmission, which is inherently energy-efficient and tolerant to noise.[27] Thus, implementing such a strategy in electronic receptors would greatly advance the technologies of highly functional prosthetics that directly interact with the human. For an instant, a digital mechanoreceptor was developed based on piezoresistive sensors with microstructure and organic transistors-based ring oscillator that is capable to transduce pressure into digital frequency signals with similar frequency range as the biological counterpart.

2.2 From synapse to electronic synapse

To take benefit of nature evolved memory mechanism which promotes the efficiency and adaptability of individuals to an ever-changing environment, synaptic electronics has been proposed based on the consensus that the synapse is the origin point for learning and memory.[112, 113] The ability to memorize relies on synaptic plasticity, and the memorization events would change the strength of synaptic connections (or weights). To develop electronic analogues (**Figure 3**), a broad spectrum of electronic/ionic hybrid devices have been developed, including atom switch,[43, 114, 115] resistive switching device,[42-44, 116-119] phase change memory,[120-122] electrolyte gated transistor,[123-128] correlated oxide transistor,[129, 130] ferroelectric device,[131-134] electrochemical device,[135-137] Mott insulator.[138, 139] Generally, the conductance of these devices is usually analogous to synaptic weight, which could be tuned by programmed stimuli (e.g voltage, light, and temperature) pulses gradually due to the interactions between electrons and ions. In this case, some essential synaptic plasticity, as well as the memory, computation and even learning behaviors have been mimicked, which would empower the design and implementation of neuromorphic engineered systems. The ultimate aim is to build an electronic brain to empower current computing systems beyond binary logic and von Neumann architecture. Artificial neural networks based on the synaptic devices that represent a step forward this aim have already achieved.[46, 47, 140] These achievements in synaptic devices reveal the possibility for developing a new architecture toward autonomous artificial intelligence, in which the artificial neural network based on synaptic devices could directly be trained by the data from the ASM devices.

Up to now, three kinds of devices have been currently utilized as the memory components to mimic the sensory memory, including the resistive switching memory, threshold switching device, and ionic/electronic hybrid transistor. Resistive switching memory is a kind of nonvolatile memories, which typically applies two-terminal geometry with a metal–insulator–metal (MIM) architecture.[141-144] Such device can be configured between a high resistance state (HRS) and a low resistance state (LRS), inducing the information storage by encoding OFF (0) and an ON (1) states, respectively.[141, 145, 146] Only a voltage that is larger than threshold would induce a transition between HRS to LRS, and the transition in conductance is permanent. While, threshold switching (TS) devices is a kind of volatile memories with a similar structure as the resistive switching memory, which is notable for the spontaneous rupture of conduction channels with a time window from nanoscale seconds to tens of seconds, even minutes.[147-149] Depending on its specific relaxation time, it can be served as diffusive memristor for neuromorphic computing or access device for matrix addressing.[149-151] The electrochemical and diffusive dynamics of the active metals such as Ag and Cu), is regarded as the dominant mechanisms for the conductance evolution.[147] Unlike the resistive memory, the resistance of TS devices recovers back spontaneously when the applied voltage decrease to a low value. The decay process occurs spontaneously due to the metal ions need to merge into minimized interfacial energy state, and the time for such a process is known as the relaxation/retention time. The ionic diffusive process and its dynamics have been demonstrated the capability for mimicking the short term plasticity.[118] Synaptic transistor, unlike the previous two devices, is deemed as another important group of synaptic devices with exclusive three-terminal or multi-terminal structure.[124, 152] Ionic/electronic hybrid transistor is a typical synaptic transistor, in which the electrostatic/electrochemical interactions between ions and electrons at the electrolyte/channel interface are regarded as the general working mechanism.[153-155] In such devices, the swept gate voltage would induce a metal-insulator-transition in the semiconducting channel, and the transfer curves usually show hysteresis, which could be due to the ionic relaxation.[154] An intriguing phenomenon based on the ionic relaxation is that the channel conductance could be temporally retained after a voltage pulse, exhibiting very similar behaviors as short-term plasticity of the biological synapse.

Besides, there are other promising candidates could function as the memory components like the ferroelectric synapses and electrochemical synapse. For example, the ferroelectric synapses are notable for its long-term memory effect, in which the multi-valued modulation of the conductance can be achieved by applying a pulse gate voltage due to the polarization of the ferroelectric materials.[131, 132, 156] All these candidates would enrich and facilitate the development of artificial sensory memory by providing versatile memory forms that closely resemble the biological process.

3. Developing artificial sensory memory

Although much attention has been paid in the collection of information in forms of light, sound, smell, etc., of the vivid world via apparatus for thousands of years, technologies for recording such information were developed rather late. For example, the camera obscura principle has been described by Chinese philosopher Mozi for more than 2000 years, but there was no way to preserve the images before the photographic processes came. The artificial sensory memory could also be deemed as the continuation of such tradition to pursue recording technologies with respect to sensory information by biological wisdom (**Figure 4**). Up to now, researchers have developed several kinds of ASM devices for detecting-recording the stimuli of haptic,[146] iconic,[157] nociceptive,[158] motor[159] aspects, respectively.

3.1 Artificial haptic memory

Haptic memory is used for guiding the grip and interaction with familiar objects in our daily life.[160] The haptic memory could help us with holding a fragile object after several times of broken experience, and tell us how much force is needed for string-pressing of a violin by practice. The fact that we are able to figure out how much force needs to hold most of the common objects without hesitation is also benefited by such kind of memory (**Figure 5**a).[146] The state-of-art robots or brain-computer interfaces might be able to utilize the tactile feedback for detection/manipulation of targets.[30, 161] However, without the addition of haptic memory, these apparatuses would still suffer from stiffness and unintelligence when coming to even familiar objects. In that case, the artificial haptic memory is very necessary, and a step forward is to develop the basic devices to mimic the haptic memory.

A simple method to record the tactile sensation is to integrate sensing and memory elements. For example, Figure 5b and 5c show the haptic memory device based on a resistive pressure sensor and a resistive switching memory device, in which the two devices were connected in series. Such devices take advantage of the amplitude of the pressure sensor signal as a criterion for memory. Such circuit is equivalent to a voltage divider. When the pressure was applied on the sensor, the resistance of the sensor would decrease, which increases the voltage applied on the resistive switch. If the applied voltage is larger than the threshold on the memory device, a long-term change in conductance could be observed. Therefore, such pressure information could be stored in the resistive memory.

In the resistive pressure sensor, the microstructured elastomer film served as a sensitive layer is usually embedded with conducting nanowires (e. g. AgNWs and CNTs) as shown in Figure 5d. The high pressure sensitivity in the low-pressure regime (<1 kPa) is achieved because the microstructure arrays (e. g. pyramidal) could provide large deformation in response to the subtle pressures.[18, 69] The sensitivity of such kind of pressure sensor is defined as $S = dR/dP$, where R is the resistance and P is applied pressure.[146, 162] The sensitivity is generally dependent on:[69] 1) the compressibility of the material used; 2) geometrical shape (e. g. slope) of the structures; 3) spatial arrangement of the structures. In this haptic memory device, the memory component is a SiO_2-based resistive switch with the metal-insulator-metal (MIM) architecture, and the possible switching mechanism should be due to the forming and dissolution of the Ag filaments (Figure 5e).[163, 164] As the two components are connected in series, the partial voltage applied on the memory device is dependent on the pressure applied to the pressure sensor. Only when the pressure is larger than 500 Pa would induce a partial voltage higher than the threshold voltage. In this case, the transition from HRS to LRS in the memory device could be observed, resulting in storage of the pressure information.

To demonstrate the skin-like capability of haptic memory, the array of this haptic memory device was utilized to map and memorize haptic patterns by using the letter molds (Figure 5f). The mapping and recording of external pressure by such device arrays were tested by using different letter molds of "N", "T", and "U". As shown in Figure 5g, only on the top of a device that is covered by the letter molds can be memorized, inducing a discernible current change for mapping the external pressure. In this manner, the nonvolatile conductance change of the resistive switch would also provide long-term storage of the pressure distribution even after the removal of the letter molds. As illustrated in Figure 5h, the arrays can retain the haptic pattern of "T" based on current mapping with slight decay for a week. Moreover, pressure information can be easily erased demonstrating the reprogrammable capability for multicycle usage.

3.2 Artificial iconic memory

Near half of our cerebral cortex is busy with processing visual information,[165] because through vision we could appreciate object's surface in terms of the size, shape, color, and brightness of objects, distance, and location sensation, smoothness, roughness, etc.[166, 167] Iconic memory that refers to the memory of visual stimuli is also an important exteroceptive sensory memory. It could be classified into visual short-term memory (VSTM) and long-term memory (VLTM), and it's believed to be essential for a range of cognitive tasks, from measuring of fluid intelligence to visual search.[168]

The iconic memory begins with the receiving of the image information from the retina and ends with the memory of the impressions of images in the neural network, as illustrated in **Figure 6**a. Inspired by the biological configuration, integrating photodetectors with memory devices in series could directly achieve visual long-term memory (Figure 6b).[157] The In_2O_3 semiconductor micrometer-sized wires (SMWs) were fabricated by a direct-printing system, which was used for detecting the UV light signal. The photocurrents increase with the light intensity because the increase of absorbed photon flux would enhance the photogenerated charge carrier efficiency. As shown in Figure 6c, when being applied with ultraviolet light, the charge carrier in SMWs increases greatly than in dark, inducing more than two magnitudes current increase under the same voltage sweep. The Al_2O_3 based resistive memory was exploited to store the light signals detected by the photodetector, which exhibited good bipolar resistive switching characteristics. As the memristor was connected in series with the image sensor, its switching behavior is controlled by the photoelectric response. The current of the integrated device in dark is very low (<0.1 nA) during the voltage sweep applied to it (Figure 6d). However, when the UV light is on, a dramatic increase (decrease) in current could be observed when the partial voltage applied on the resistive memory is larger than its positive (negative) threshold voltages. Therefore, when the device is exposed in UV light, the transition from HRS to LRS or from LRS to HRS of the whole integrated device could be observed. In other words, such devices could retain or erase light information.

To demonstrate the iconic memory capability, the iconic memory arrays (10 × 10 pixels) were then fabricated for imaging and memorizing the distribution of external visual impression patterned light. The patterned light image is generated through applying UV laser entered in the diffraction optical element (DOE) with a designed pattern (butterfly-like pattern, Figure 6e). Then only the pixels exposed under the patterned light could be programmed when applying a positive voltage sweep from 0 to V_{set} would lead to a transition from HRS to LRS. Thus, after removing the light, each programmed pixel could record the light information, and the whole arrays show a similar image as the original pattern. The butterfly-shaped pattern was imaged and retained in the visual memory arrays for one week with slight attenuation. The arrays are reprogrammable by applying negative voltage sweeping from 0 to V_{reset} to erase the previous image information.

3.3 Artificial nociceptive memory

The humanoid robots seem affectless, and one possible reason is they have no feeling of pain. Pain increases the adaptability for an individual by providing a rapid warning to the nervous system to defense further harm.[169, 170] The pain sensation begins with the trigger of the action potential in nociceptor which is a specific receptor in response to noxious stimuli. The individual can feel the pain sensation only when the intensity of the external stimulus exceeds a threshold value. Unlike most other sensory receptors, no adaptation is observed in the nociceptor. Only the excessively intensive stimulus that could result in tissue damage would increase their sensitivity, known as the sensitization.[171] The sensitization can be characterized by "hyperalgesia" and "allodynia": a normally painful stimulus induced increased pain response and a normally innocuous stimulus induced pain sensation, respectively. In that case, the development of artificial nociceptor would enable the feasibility and simplicity of realizing embodied cognition in artificial intelligence systems. Recently, an artificial thermal-nociceptor has been demonstrated with close properties as the biological counterpart.[158] Artificial nociceptors in response to other types of noxious stimuli are feasible by translating this idea to various sensors.

To develop an artificial nociceptor, a memory component is required for indicating the damage state and level at first. More importantly, the memory component should also respond only to the stimuli higher than the threshold value, similar to what external stimulus does to the sensory receptor (**Figure 7**a). Therefore, the threshold switch could be a perfect candidate (Figure 7b). A SiOx:Ag based diffusive memristor was fabricated with a very thin silver layer (1 nm) inserted between the bottom electrode and the switching layer. Such silver layer as a reservoir of Ag atoms enables the artificial nociceptors to avoid adaptation phenomenon which would result from the Ag depletion during successive stimuli.[158] Partial electroforming process was introduced to indicate different levels of damage through applying voltages several-fold larger than the threshold. The partial electroforming process would induce a lower threshold voltage than the unformed devices. In that case, the forming voltages could be analogous to the level of damages, which affect the response intensity of the devices. After applying a higher forming voltage (severer damage), the higher current response could be observed by applying the same voltage (served as the normally painful stimulus), which could be analogous to the hyperalgesia phenomenon. At the same time, the same level of response could be induced by a lower voltage, which could be analogous to the allodynia phenomenon.

Finally, such devices were connected with a thermoelectric module for mimicking thermal nociceptor (Figure 7c). The thermoelectric module would generate a voltage in response to a thermal stimulus. If this voltage exceeds the threshold value of the threshold switch, the conductance of the threshold switch would greatly decrease and increased voltage would apply on the series resistor. The voltage responses generated by the thermoelectric module under different temperature and the voltage responses measured on the resistor were shown in Figure 7d and 7e, respectively. If the temperature was too low (40 ^{o}C), the generated voltage would lower than the threshold voltage (0.25-0.3 V) of the TS devices, and the system would not trigger any output alarm signal. On the contrary, if the temperature was higher than a certain value, substantial output signals could be observed.

3.4 Artificial motor memory

Motor memory also noted as muscle memory, which could help to improve the smoothness and accuracy of movements by memorizing muscle motions and is necessary for complicated movements.[172] The motor memory that starts from the triggering of the stretch receptors located in the muscles and the joint-supporting ligaments is formed based on the proprioception.[173] Motor memory also underlies proprioception which could provide the brain with information on the movement and relative positions of the parts of the body.[174] Rooted in such sensory-memory cooperated system, animals can simultaneously monitor and memorize the corresponding motion information, and perform these motions later (**Figure 8**a).

The necessity of the motor memory for animals thus inspired the design and integration of motor memory devices for biomimetic/robotic systems as well as wearable applications. One of the major challenges for realizing motor memory devices is to achieve good mechanical tolerance to accommodate deformations of motor systems. The aforementioned sensations that response to pressure, light, and heat, respectively, are not prone to be deformed. However, motor systems are suffered to deformation from time to time. The mechanical deformation from the motor systems would significantly degrade the performance of the functional components with delicate configuration and constituent brittle materials. A possible strategy is to provide a stretchable substrate for those constituent brittle materials and separate the high and low moduli domains of the substrate. (Figure 8b).[159] As a result, physical forces would lead different localized strain on these patterned domains. Therefore, both the stretchable and non-stretchable components can be located on the mechanically compatible parts of the hybrid structure.

By achieving that, a device integrated with a strain sensor and a resistive memory could obtain both mechanical stability and the capability of motion monitoring and memorizing. A LED was connected to the integrated devices for indicating the state of motion as shown in Figure 8c. The LED would be turned on when the integrated device was stretched with the elbow flexion (Figure 8d). It is because the induced strain on the strain sensor could increase the voltage applied to the memory, which in turn switch the memory from HRS to LRS. After the extension of the elbow, the resistance of the memory could be retained and the LED was still lightening, indicating the muscle action has been memorized. Such artificial motor memory can be reprogramed (from LRS to HRS) by applying the reset voltage. As shown in Figure 8e, two motor memory devices were jointly used for monitoring the composite motions of shoulder abduction and elbow flexion, indicating the complex motion could also be stored by the motor memory devices.

4. Exploiting artificial sensory memory for recognition tasks

The sensory memory could be deemed as one fundamental mechanism of intelligence, and it is involved in very essential tasks such as manipulation, recognition, and learning (**Figure 9**). Generally, these tasks can be grouped under three categories: action for perception, perception for action, and reaction.[175, 176] At the same time, these tasks are always interrelated and require integration of multiple sensory modalities. We explore a certain object like an egg, a keyboard, or a piano by observing, listening, as well as touching, grasping and, tapping, which are related to tactile perception. Then we could obtain the features of the object and recognize it. After recognition, we could manipulate them based on our previous experience, which is mainly obtained through repeated perceptual learning.

An important step for robotic systems to achieve perceptual learning capability is to refine and memorize sensory inputs in both short-term and long-term manners. Hence, the development of ASM possesses great potential for artificial intelligence in robotic systems. Summation of recent achievements on achieving intelligent tasks based on ASM devices is briefed and discussed below.

4.1 Artificial sensory memory for differentiating touch speed

The neural coding could be classified into two categories: temporally correlated coding (encoded in input timing) and rate coding (encoded in input rate).[177, 178] These coding strategies have inspired the implementation of synaptic devices to process information beyond the binary paradigm.[124, 135, 179-181] Synaptic transistors possess intriguing advantages in the processing of both timing and rate information. The response of such kind of transistors is not only dependent on the intensity of the stimuli but also dependent on the frequency, numbers and time intervals of the stimuli. Such phenomena have inspired the emulation of some neuronal/synaptic processing power, such as high-pass[152, 182, 183] and low-pass filtering[184, 185]. In biology, increasing or decreasing response to high-frequency synaptic inputs (corresponding to high-pass and low pass filtering, respectively) is achieved based on short-term synaptic facilitation and depression, respectively. For synaptic transistors, the high or low-pass filtering function is realized due to the residual ions in the gate dielectric generated by previous inputs that induce higher or lower electron/hole concentration in the channel.

For most of the e-skin devices in respect to bioinspired tactile sensing, only the amplitude of touch could be measured or mapped. Besides, essential information like the rate or timing of the touch could not be figured out without peripheral equipment. The sensory neuron could integrate multidimensional information as a whole by the receptors and selectively transmit based on a series of interaction and cooperation strategies of synapses/neurons in the neural network (**Figure 10**a). For example, the short-term synaptic depression and/or facilitation enable the synapses to selectively respond to a specific mode of stimuli. Unlike the aforementioned ASM devices that belong to the long-term memory category, these filtering functions are related to short-term memory. Therefore, by introducing short-term memory into artificial sensory devices would be of great significance for collecting and refining massive sensory information rather than passive storage. This inspires the integration of pressure sensor and synaptic devices, especially synaptic transistors for extending the sensing capabilities and exploring the potential of endowing e-skin devices with tactile perception.

A possible approach was proposed based on a dual-organic-transistor-based tactile perception element (DOT-TPE)[186] as shown in Figure 10b and the equivalent circuit shown in Figure 10c. Suspended gate transistors[76] were exploited as a pressure sensitive component for converting the pressure stimuli into electrical signals. The converted signals were transmitted to an organic synaptic transistor through a common electrode. The channel current of the synaptic devices that resembles the excitatory postsynaptic current (EPSC),[112] was used as the output. Such output could be modified by the amplitude, duration, numbers, and time interval (could be equivalent to reciprocal of frequency) of the input spikes. The gate voltage would cause the protons concentration gradient at the gate dielectric/channel interface, which could induce the electrons in the n-type semiconductor through electrostatic interaction. In that case, larger gate voltage would drive more protons to the interface, thereby increasing the electron concentration in the channel. What’s more, the concentration of residual protons at the interface of the dielectric/channel would increase by the successive gate pulses before they diffuse back to the equilibrium state. Therefore, increasing the numbers or reducing the time intervals of the pulses would augment the output current.

Based on these proton/electron electrostatic coupling mechanisms, the tactile signals from the suspended gate transistor-based pressure sensors could be processed by the organic synaptic transistors. The higher pressure applied on the sensors would induce a larger partial voltage (equivalent to gate pulse) applied on the gate of the synaptic transistors, and a larger EPSC could be observed (Figure 10d). More importantly, the speed of the touch could be recognized by such devices based on the short-term facilitation property (Figure 10e). The higher touch speed means less contact time and less time interval between each touch, therefore the lower output amplitude by the first spike (Figure 10f, left panel) and the higher facilitation ratio (Figure 10f, right panel) could be achieved. A 3×3 arrays was used to illustrate the current change by different touch speeds (Figure 10g).

4.2 Artificial sensory memory for recognition tasks

Perceptual learning enhances our ability with respect to vision, hearing, taste, etc. based on what we've experienced.[187] The reason why we can differentiate two musical tones, recognize braille and identify faces, is due to the capability of perceptual learning. At the cellular level, sensory stimuli are detected by receptors of sensory neurons. Signals are sent through the afferent axons to synapses for further process by the postsynaptic neurons. For instance, multilevel features of the touched pattern could be obtained by sensory neurons in skin by integrating and modulating both synchronous and asynchronous signals in an action-perception loop.[188] Our capability to perceive and react with the real-world are further empowered through practice and/or training—a process known as the perceptual. In that case, the endowing the device/system with learning capability is essential for robust and fault-tolerant processing of sensory stimuli. Furthermore, the addition of learning capability would ultimately endow machines/systems with artificial intelligence that enables them to possess "self-awareness" like human.

To implement such capability in biomimetic devices/systems, the first step is to develop a functional device to extract enough features of external stimuli. Almost all sensory data is unstructured, such as face and voice, which is difficult for a digital computer to recognize. ASM devices like the DOT-TPE that can extract both amplitude and timing information of the pressure stimuli has set a good example. However, in order to perform identification and recognition tasks and go beyond just tactile pattern differentiation, there is a need to fabricate devices for implementation of learning capabilities. At the same time, another important issue is to make such devices mechanical tolerant considering the processing unit is prone to breakdown under the ever-changing environment. To meet such challenge as well as to explore the potential of perceptual learning in robotic systems, a neuromorphic tactile processing system (NeuTap) is proposed for mimicking the sensory neuron and implementing perceptual learning. There are three core components including a resistive pressure sensor, a soft ionic cable, and a synaptic transistor to analogous the receptor, axon, and synapse, respectively (**Figure 11**a). The functions of sensing, deciding and acting are usually located in different places and are connected through the afferent/afferent nerves in the animal. The introduction of the ionic cable that resembles the nerve fibers would benefit the design of robotic systems. Because the ionic cable could: 1) separate processing and sensing units to reduce interference; 2) provide ionic/electronic coupling interfaces; 3) endow stretchability to enhance mechanical stability (Figure 11b, left panel).

The information flow in NeuTap could be interpreted as: 1) signal conversion from pressure stimuli to electrical signals by the pressure sensor; 2) ionic fluxes triggering in the ionic cable by the converted electrical signals; 3) the triggering of a transient channel current of the synaptic transistor. By achieving that, a protocol should be addressed in order to apply these specific features for recognition. As a demonstration, four kinds of patterns represented by two-bit binary numbers were used as the object to be recognized (Figure 11b, right panel). Then the response of the NeuTap to the patterns and the corresponding label of the pattern (i.

e. '01') were used as the feature data and label, respectively, for training the model using a supervised machine learning algorithm. After that, new or testing feature data was input, and the trained model would give an inferred label for this data based on previous training. The typical responses to the three nonzero patterns (i. e. '01', '10', and '11') were shown in Figure 11c, the decay properties could be obviously differentiated. However, these specific feature data is unstructured and even user-dependent. One possible reason is due to the variations between every touch process (i. e. contacting with the binary patterns). Thus, the feature data of one pattern could be varied, and the clear criterion for recognizing these patterns seem impossible to be figured out by limited times of training. However, by taken advantage of the machine learning method, these patterns could be classified through several times of training and the error rate of recognition decreases with the training times (Figure 11d).

More recently, an artificial optic-neural synaptic (ONS) device was proposed for color-mixed pattern recognition with notable accuracy and energy efficiency. Such device is fabricated by integrating synaptic and optical-sensing functions together as shown in Figure 11e.[189] Such device could be equivalent to an optic sensor and a synaptic transistor connected in series. The channel conductivity of this synaptic transistor could be modulated based on the trapping or de-trapping of electrons, which is the dominant operation mechanism. The light would decrease the resistance of the optic sensing component, which increases the voltage applied on WSe_2 channel. A shorter wavelength of light induces a larger decrement of the resistance of the optical sensing device. Such operation mechanisms result in differentiable responses with red, green, and blue light as stimuli. The differentiable responses thus provide robust features for recognizing different single-colored numeric pattern images (Figure 11f) and even color-mixed patterns. To demonstrate the advantages of such combination (i. e. optic-sensing device and synaptic device), an optic-neural network (ONN) was built based on the ONS devices as shown in Figure 11g, which shows a better recognition result than conventional neural network (Figure 11h). The synaptic weight values were optimized with the increase of the training epochs, which were reconstructed and visualized as shown in Figure 11i.

4.3 Artificial sensory memory for motion control

To build robotic/biomimetic/prosthetic systems with artificial intelligence, intensive attention has been paid on the movements control that enables exploring and interaction with the external environment. Although by combining software and complex electronic circuits could realize precise movement control, the bioinspired devices could serve as a simplified strategy by replicating the functionality of essential biological components. For example, a digital mechanoreceptor [27] based on organic ring oscillator and resistive pressure sensors that greatly resembles the signal conversion in a biological system, represents a step toward the advanced prosthetic systems with the feedback of neural-integrated touch based on large-area organic electronic skins. However, the lacking of functional components that could integrate and extract features from the converted tactile inputs, would limit the potential for precise and effective control or recognition.

An artificial afferent nerve was developed for collecting data from multiple digital mechanoreceptors, and mimic the encoding of tactile information process as the somatosensory peripheral nerves (**Figure 12**a).[190] The artificial afferent nerve incorporates sensors, organic ring oscillators, and a synaptic transistor (Figure 12b). In such afferent nerve, the information flow is interpreted as follow: 1) external tactile stimuli converted into voltage pulses by pressure sensors and the ring oscillator; 2) integration of multiple electrical signals; 3) triggering of postsynaptic currents by a synaptic transistor. As mentioned before, the amplitude, duration, and frequency of the spike applied on the gate of the synaptic transistor could modulate the response of it, thus the intensity and duration of touch would also tune the response of such afferent nerve. It should be noted that the duration could not be differentiated if without the synaptic transistor.

Based on these mechanisms, an artificial reflex arc is built as shown in Figure 12c. The artificial afferent nerve was exploited to construct a biohybrid monosynaptic reflex arc by connecting to biological efferent nerves in a detached cockroach leg (Figure 12d). The information flow in such hybrid neuromorphic circuit could be described as follow: 1) the pressure stimuli result in the voltage change of the pressure sensor; 2) the voltage change leads to voltage pulses with corresponded frequency through the oscillator; 3) the voltage pulses are integrated by the synaptic transistor to induce EPSC responses; 4) the EPSC signals then are converted and amplified as a voltage to trigger the actuation of the cockroach leg. Because the oscillating signals are robust to noise, therefore these signals exhibited better performance than signals encoded by constant voltages, in terms of elicitation of action potentials from the artificial afferent nerve.[27] Figure 12e shows a typical response of the afferent nerve to touch. The EPSC signals eventually were exploited to program the motion of the cockroach leg by actuating the muscle of tibial extensor. The amplitude and frequency of stimulation signals would increase the activation number of muscle fibers and augment the forces from each fiber, respectively. Such behavior could be well mimicked by the artificial afferent nerve due to the integrating capability of the synaptic transistor (Figure 12f and g).

5. Conclusions and perspectives

Despite its infancy, artificial sensory memory has implicated in a broad range of applications like bionics, prosthetics, robotics, and artificial intelligence. The mimicry of sensory memory involved in exteroception, interoception, and the proprioception has been achieved although not completed. One motivation to develop ASM is the consensus that memory is the basis of intelligence and the sensory memory is the very first step of information encoding from outside. Therefore, the emerging ASM would give rise to perceptual intelligence and even the realization of robotic cognition. In the meanwhile, it can improve these systems by simplifying traditional complex silicon-based circuits, while endowing them with biological characteristics like stretchability and self-healing capability. Recent progress in incorporating such advanced technologies in bioinspired sensing and neuromorphic engineering is impressive, and the next wave of this area is around the corner.

ASMs basically incorporates three main components: the sensor (S), the pathway (P), and the memory device (M), which resembles the biological receptor, axon, and synapse, respectively. Connecting sensors with memory devices in series (named as SM-ASM) could electrically implement in-situ sensory memory. Namely, the sensory stimuli could be memorized where they were activated. A group of ASMs has exploited this architecture to achieve sensory memory, such as haptic memory[146] and iconic memory[157]. However, the sensor unit is herein exposed to the external environment with diverse ever-changing stimuli (e.g., mechanical deformation, humidity, chemical, and light), which would lead to the failure of synaptic devices. Also, the functionality would be very limited by the simple equivalent model. One alternative approach is to introduce a pathway (named as SPM-ASM) that could introduce additional functions or serves as connecting wires with mechanical tolerance. For example, an ionic cable, as a pathway with structural similarity to the afferent axon, blocks the crosstalk between the sensory and memory modules and endows the system with stretchability.[49] Another case is to introduce a ring oscillator for converting the DC signal from the sensory module into AC signal in order to transmit the signal as what the biological neuron does. Compared with information transmission using AC, the DC amplitude modulated signals may suffer from low noise tolerance over a long transmission distance. A critical requirement for such oscillator is that the frequency range should match that of the biological mechanoreceptors.

The pursuit of electronic implementations that resemble the functions or structures of the biological sensory system has brought about evolutions in nano/micro- electronic devices including sensors[146], oscillators[27], memristors[149], transistors[49], etc. For example, the detectable range to pressure could be <1 kPa by introducing pyramidal microstructures[146], and ultrahigh sensitivity of 110 millivolts/decibel to auditory signal was achieved by using triboelectric nanogenerator (TENG)[24]. In the meanwhile, the increasing demands for memory/processing power and artificial intelligence have also facilitated the development of memory devices derived from neuromorphic engineering. The combination of the two key modules represents the step forward realizing artificial sensory memory, while the compatibility between the two was considered as a dominant factor of the design. For instance, to realize long-term memory by SM-ASM, researchers rationally designed the threshold voltage of the memory devices to match the response (i. e. voltage) range of the sensor module.[146] To achieve that, the threshold voltage of a resistive switch could be used as the criterion for stimulus intensity—only the strong stimulus would lead to a transition of conducting state in the resistive switch device. This mimics its counterpart in psychology, in which the intensive sensory stimulus is prone to draw attention to an individual.

These achievements thereafter give birth to the novel memory-related functions which should require complex circuits or algorithms before. Sensations, including haptic, iconic, nociceptive, and motor aspects, could be detected by artificial receptors and subsequently memorized in a long-term by synaptic devices. In parallel, short-term memory to sensory stimuli has also been achieved based on some synaptic devices such as diffusive memristor[158] and electrolyte gated synaptic transistors.[49] These devices took advantages of the temporal ionic/electronic coupling that closely resembles the biological processes. A sensory stimulus that is able to evoke a current response through the memory device could increase the device conductance in a short-term manner, and the increased responses could be observed by the closely followed stimuli. Besides, short-term and long-term memory mimicking, extracting and integrating the transiently-stored information in ASM could provide important cues/features for recognition, learning, manipulation, and so on. These advances achieved by ASM could be deemed as one step forward artificial intelligence, which might greatly enrich the application scope of this emerging device on such areas as robotics and prosthetics. Furthermore, the future robotic systems would introduce new features such as mechanical conformability, biocompatibility, self-healing. In that case, the prestretched,[191] bridgeisland,[192] origami/kirigami,[193] honeycomb lantern structures,[194] and so on, would deliver the mechanical robustness in such systems that incorporate both hard and soft materials. In addition, materials like polymer,[195] hydrogel,[196] and biohybrid materials[197] would also benefit the design of ASM with both good electronic and mechanic properties.

In the future, to reproduce an artificial perceptual system, a diversity of stimuli-responsive materials/structures are needed for the detection of external information (touch, sight, sound, smell and taste), inner information (pain, hunger, and other homeostatic conditions), and action/reaction information (body position, movement, and acceleration) of an individual. The detection of subtle sensory information is still challenged by issues with regards to resolution, sensitivity, and selectivity. In addition, synaptic devices should be designed and integrated to process the sensory information with such nature evolved merits as massive parallelism, ultralow energy consumption, and high connectivity.[198, 199] In short, several challenges need to be addressed before the practical application of such emerging bio-inspired devices.

One major challenge of ASM is the architectural design of such devices to reproduce the biological sensory memory process. To resemble the three essential components of a sensory neuron—receptor, axon, and synapse, researchers integrated pressure sensor, ionic cable, and synaptic transistors respectively in the NeuTap-based ASM.[49] The ionic cable could be further improved by using other ionic conductors with better mechanical tolerance, such as tough hydrogels.[200] In addition, the length could be extended by using materials with high ionic conductivity but unaffected transmission efficiency, being consistent with the biological afferent axon. A reported ionic cable with the length of 45 cm was able to transmit standard audio signal with high ion diffusivity up to 10^7 m^2/s,[201] which is as long as that of an afferent nerve from fingertip to spinal cord. However, pursing allelism in artificial neuron should not fall into stereotypes that simply replace the exquisite architecture of the sensory neuron with electronic implementations. Besides, the increased functionality and complexity would empower ASM devices while reducing the density of an integrated system. The biological sensory system recruits information from a large number of receptors (e.g., >100 cm^{-2} in one hand[55]). Monolithic 3D integrated sensing/processing/memory systems using advanced microfabrication techniques have greatly increased the device density and provide recognition power to classify ambient gases through FET-based classification accelerator.[202] Admittedly, these systems may be compromised by the challenge of neither constructing an artificial peripheral nervous system where the density of receptors should be quite dispersed (e. g. receptors in the skin) nor endowing such system with mechanical tolerance. This approach could implicate the digitizing of ASM-based systems to be interfaced with modern digital microprocessors.

Another challenge could arise from the poor understanding of biological memory mechanisms. The biological sensory memory system is hierarchical as shown in **Figure** 2. It is widely accepted that all forms of sensory memory are very brief (e. g., up to hundreds of milliseconds for iconic memory). Most information in the sensory memory can decay and be forgotten, while some of them could draw the attention of individuals and then be transformed into short-term memory. Through repeated rehearsals, the transition from short-term memory to long-term memory could be achieved. Such mechanism thus filters the meaningless information, allowing us to focus on something of higher importance and urgency. However, such a transition has not yet been achieved in current ASM devices. To address this challenge, suitable synaptic devices and strategies should be chosen or designed, because previous reports on synaptic electronics have already experimentally demonstrated the transition from short-term memory to long-term memory.[114, 116, 203] Furthermore, the engineered neuromorphic networks based on synaptic device arrays exhibit much greater processing power than those using a single synaptic device, which could be trained for a high order of intelligent tasks like feature extraction and pattern recognition.[44, 45]

The aforementioned hierarchical memory processes thus underlie the biological system with high efficacy and ultralow energy consumption. Energy efficiency is quite important for building an artificial sensory system with ASM as a building block. For example, hundred millions of photoreceptors are found in one eye,[204] awesome energy would be required to drive an artificial system even with milliwatts power for each pixel. There is an obvious gap between the current ASMs and biological neurons in respect to power efficiency as demonstrated in **Figure 13**. Currently, the ON state power consumption for most of ASMs is around microwatts level. The OFF state power consumption could be quite low (picowatt level) for most two-terminal-memory based ASMs (including resistive switch and TS device). As the enhancement-mode transistors are normally off, they could be chosen as the three-terminal-memory component, in order to decrease the OFF state power consumption for the transistor-based ASMs. The low OFF state energy consumption of DOT-TPE is based on such a strategy.[186] At the same time, self-powered (e. g. piezoelectric and triboelectric) sensors could be used as the sensing component to further decrease the energy consumption at ON state. A similar strategy achieved a low driving voltage and high sensitivity by the combination of piezoelectric nanogenerators (NGs) and ion gel gated transistors.[205] An important issue for integrating self-powered sensors in ASM devices is to match the signal intensity from the sensors with memory modules. For the two terminal memories, the amplitude range of the signal generated from the sensors should cover the threshold voltage of the memories, in order to achieve storage operation. While for the transistor-based memories, charges generated from the sensors would be coupled to the gate dielectric/channel interface to induce a current change through the channel. Therefore, the change of currents should be high enough compared with noise signals (to achieve acceptable signal-noise-ratio). Another approach to achieve low energy consumption is to exploit synaptic device with high transconductances, such as electrochemical cells[136] and organic nanowires-based synaptic transistors[128], and the power consumption could be several orders lower.

One major advantage of the biological sensory system is the capability to integrate two or more sensory modalities for subsequent processing, interpretation, and act together as a synthetical perception.[206-208] Although tremendous efforts have been concentrated on developing ASM devices with one sensory modality, there are only several multifunctional sensing devices that integrate multiple sensors to realize more advanced sensations such as proprioception,[209] tactile perception.[72, 108, 111] Future trend in the large-number, multimodal, and multipoint sensing/memory/processing integrated systems would be focused on developing essential components for encoding and decoding the complex sensory information and the interfaces with hardware neural networks. In this case, the electrolyte-gated synaptic transistor would be a promising candidate for integrating paralleled sensory signal through EDL capacitive coupling and constructing neuromorphic computational networks based on its electrochemical non-volatile memory property. Accordingly, the incorporation of multiple sensations would be able to execute more complex recognition or decision tasks, which may finally deliver integrated artificial sensory organs. To achieve this, the endeavor should be made in the leap from memory to perception by constructing an artificial neural network with ASM devices/modules as the first layer neurons (**Figure 14**), which allows the close imitation of biological processes. Such neuromorphic perceptual systems would greatly improve current technologies in cyborg systems, humanoid robotic systems, human-machine systems, prosthetic systems, and so on. Given the recognition of the advantages, it's reasonable to replicate intelligence highly with regards to cognitive, emotional, social as well as psychological aspects in these systems. Having witnessed the rapid development, we believe the artificial sensory memory is a promising candidate for novel architectures of hardware artificial intelligence, and it would undoubtedly shed light on future advances with respect to various translational implementations.

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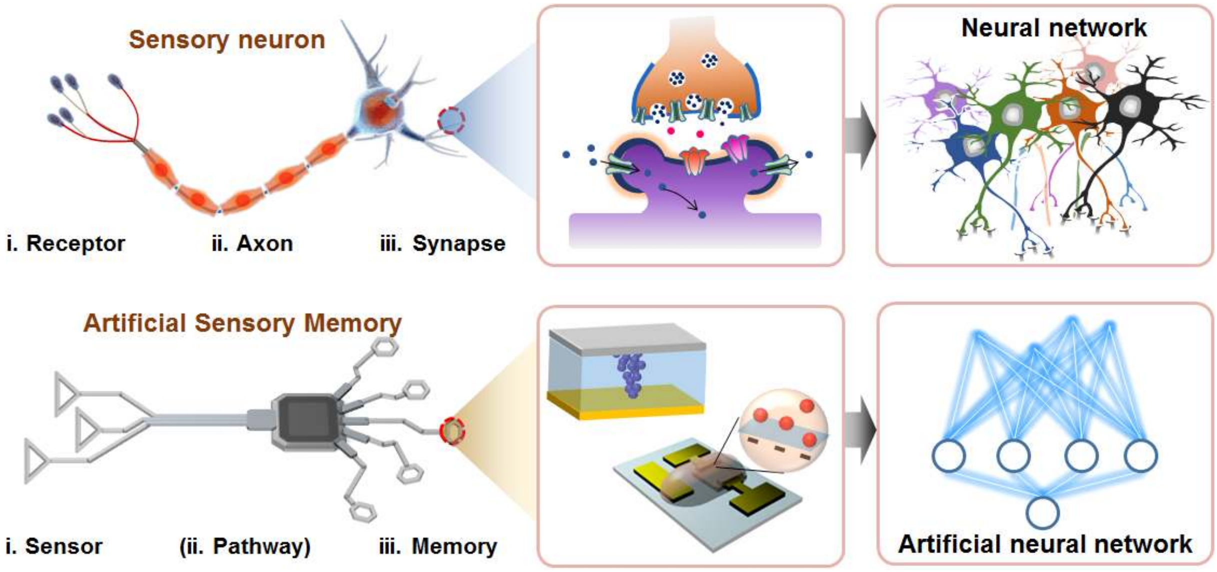

Figure 1. The comparison of artificial sensory memory and sensory neuron. The artificial sensory memory could be acted as the building block of the sensory processing artificial neural network, just as the sensory neuron in the neural network that collects, refines and preprocesses sensory information and transmit them to high order neurons for further processing. The design and fabrication of artificial sensory memory could obtain inspirations and benchmarks from the biological sensory neuron. A sensory neuron has three important components: receptor, axon, and synapse. In parallel, the artificial sensory memory generally comprises sensor, pathway, and memory. Two typical synaptic devices utilized in artificial sensory memory devices were shown, i. e. threshold switch device and ionic/electronic hybrid transistor (inset shows the electric-double-layer formed at the interface between the gate dielectric and channel).

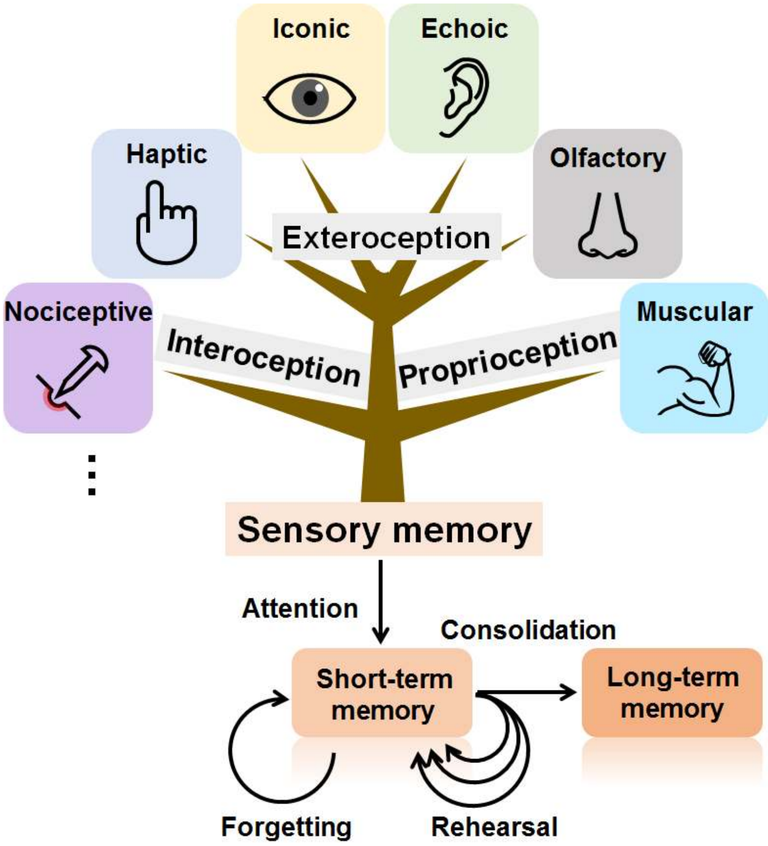

Figure 2. The sensory memory and the multi-store model of memory. Sensory memory could be divided into several categories which are involved in exteroception, interoception, and proprioception. The information flow in the multi-store model of memory could be described as: 1) the sensory information enters the sensory memory after it is detected by the sense organs; 2) it enters the short-term memory if it draws enough attention to an individual; 3) the short-term memory transfers to long-term memory by rehearsals.

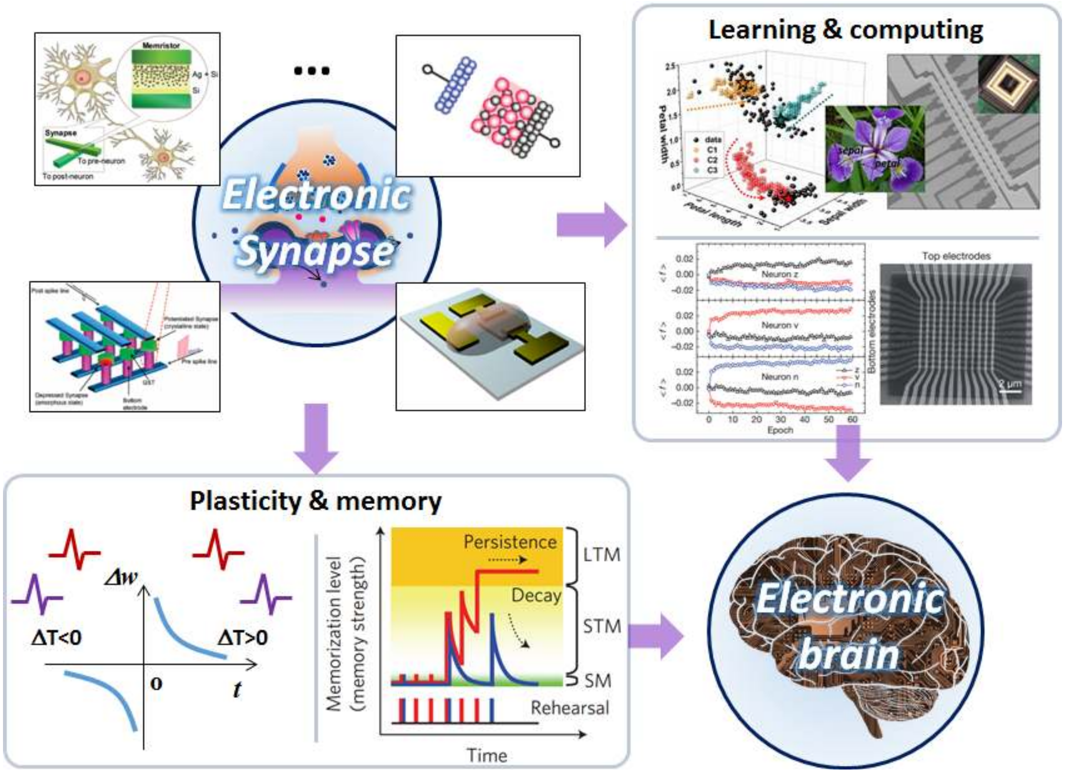

Figure 3. A brief summary of recent endeavors on neuromorphic devices. The neuromorphic devices serve as the building block of an electronic brain, which is designed and fabricated for capturing the memory or plasticity power of synapse/neuron. These memory or plasticity properties thus underlie the learning emulations by the neuromorphic devices. These achievements have no doubt facilitated the progress of achieving electronic brain ultimately. 1) Electronic synapse. Left top panel. Memristor-based synapse. Reproduce with permission.[42] Copyright 2010, American Chemical Society; Left bottom panel: Phase change memory based synapse. Reproduce with permission.[120] Copyright 2011, American Chemical Society; Right top panel: Atomic switch based synapse. Reproduce with permission.[114] Copyright 2011, Springer Nature; Right bottom panel: Electrolyte gated transistor. 2) Plasticity & memory. Left panel: Schematic diagram of spike-timing-dependent plasticity (STDP). Right panel: Simplified memorization model in the electronic synapse. Reproduce with permission.[114] Copyright 2011, Springer Nature. 3) Learning & computing. Top panel: K-means algorithm. Reproduce with permission.[46] Copyright 2018, American Chemical Society; Bottom panel: Delta rule algorithm. Reproduce with permission.[45] Copyright 2015, Springer Nature. The electronic brain. Reproduce with permission. Copyright 2018, Pixabay.

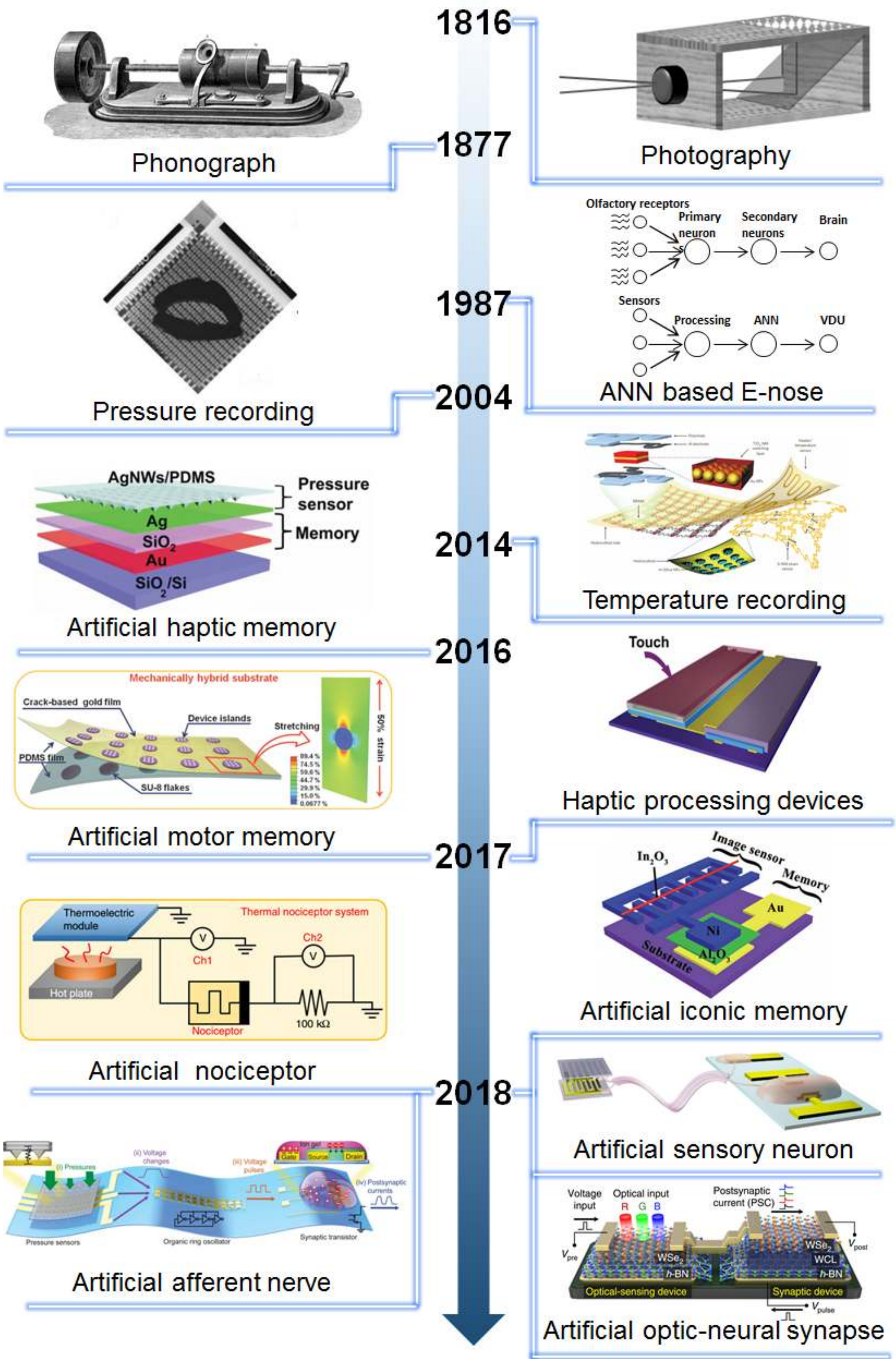

Figure 4. Timeline of milestones in pursuing the capability of sensory memory with multiple modalities. Photography. Reproduced with permission. Copyright 2000, 2001, 2002 Free Software Foundation, Inc. Phonograph. Reproduced with permission. Copyright 1965, Thinkstock. ANN-based E-nose. Reproduced with permission.[23] Copyright 1990, IOP Publishing. Pressure recording. Reproduced with permission.[21] Copyright 2004, National Academy of Sciences. Temperature recording. Reproduced with permission.[36] Copyright 2014, Springer Nature. Artificial haptic memory. Reproduced with permission.[146] Copyright 2016, Wiley-VCH. Haptic processing memory. Reproduced with permission.[186] Copyright 2017, Wiley-VCH. Artificial motor memory. Reproduced with permission.[159] Copyright 2017, Wiley-VCH. Artificial nociceptor. Reproduced with permission.[158] Copyright 2018,

Springer Nature. Artificial iconic memory. Reproduced with permission.[157] Copyright 2018, Wiley-VCH. Artificial afferent nerve. Reproduced with permission.[190] Copyright 2018, American Association for the Advancement of Science. Artificial sensory neuron. Reproduced with permission.[49] Copyright 2018, Wiley-VCH. Artificial optic-neural synapse. Reproduced with permission.[189] Copyright 2018, Springer Nature.

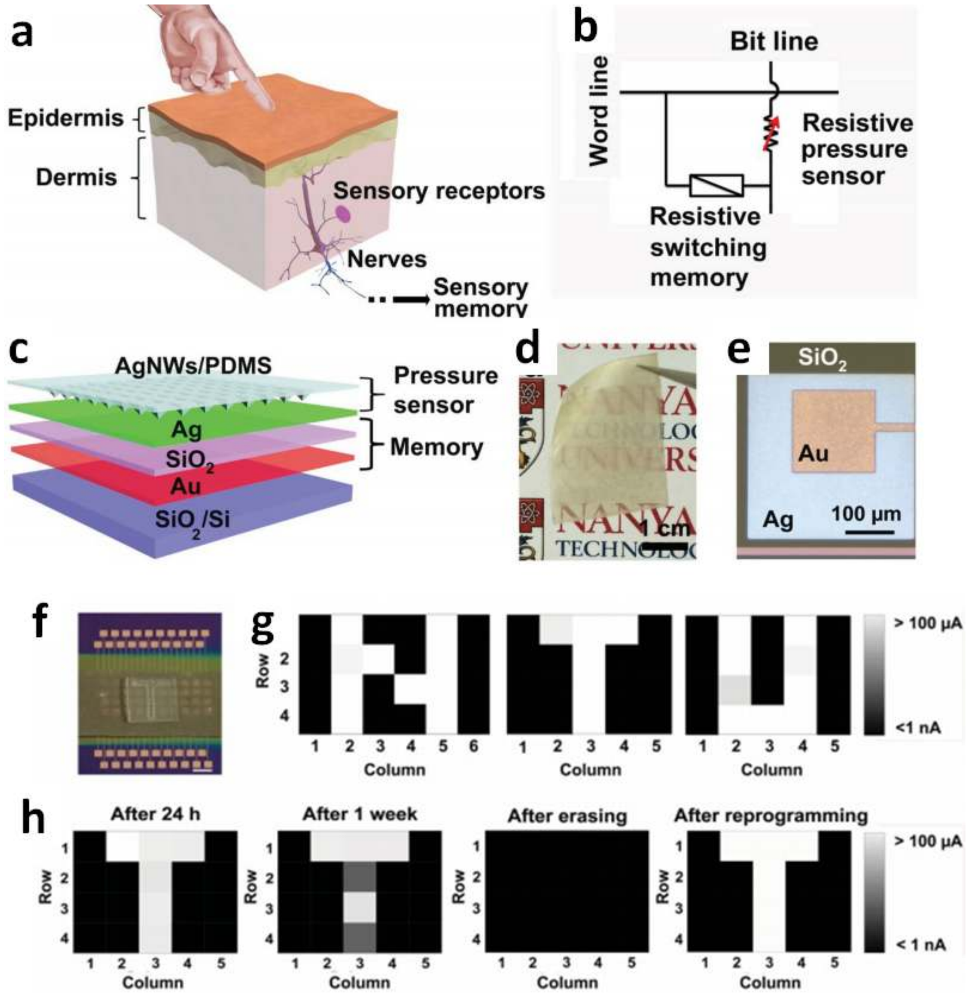

Figure 5. Artificial haptic memory. a) The conceptual diagram of haptic memory. b) The equivalent circuit model for each pixel of the haptic memory device arrays. c) Layer-by-layer structure of the haptic memory device. d) A digital photo of the sensitive layer of the pressure sensor. e) Digital image of the SiO_2 based resistive memory. f) Digital image of a 'T' pattern on the haptic memory device arrays. g) The mapping and memorizing results of the alphabetic patterns. h) Retention results for 1 week (left two figures) and the demonstration of the reprogramming capability. Reproduced with permission.[146] Copyright 2016, Wiley-VCH.

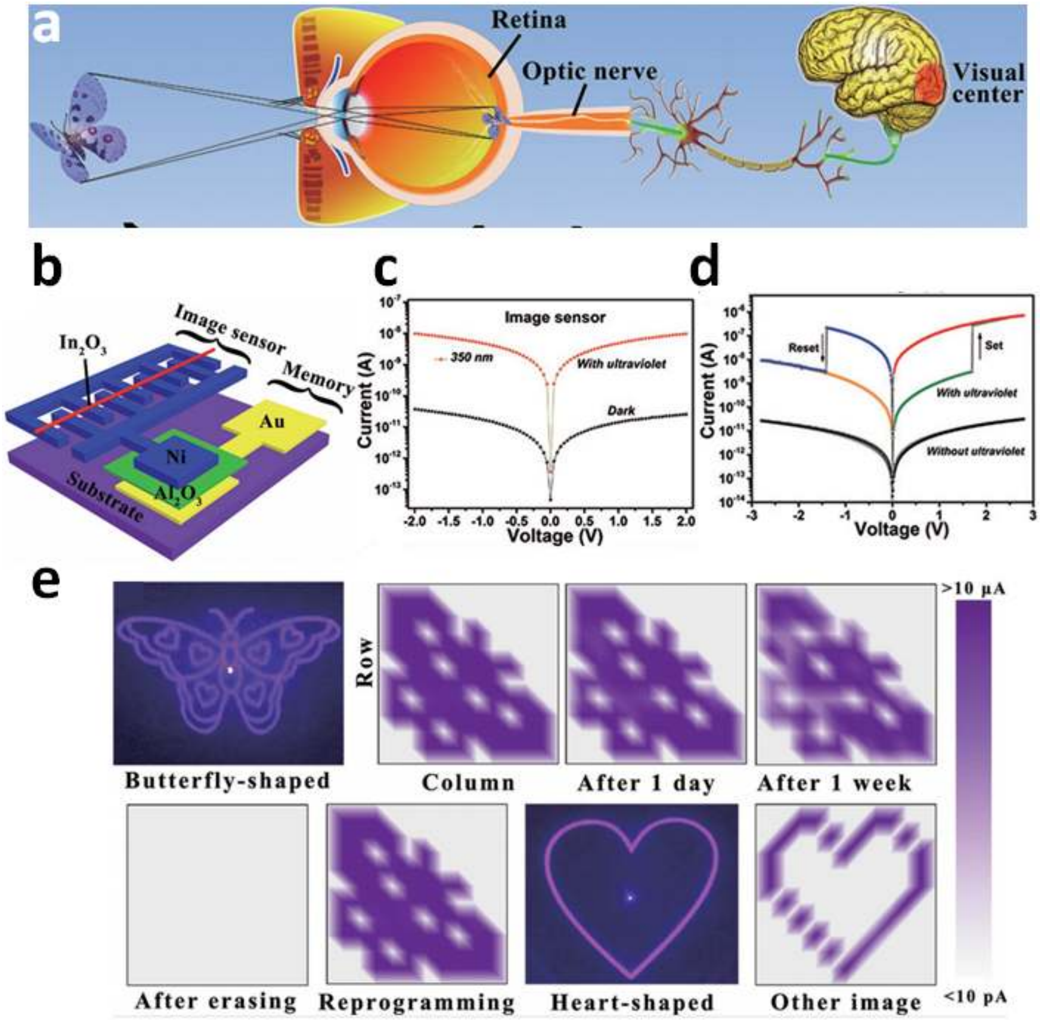

Figure 6. Artificial iconic memory. a) The conceptual diagram of iconic memory. b) Schematic diagram of each component of the iconic memory device. I-V tests for the c) single photodetector and d) integrated device. e) Retention properties and reprogrammable capability of the iconic memory device arrays. Reproduced with permission.[157] Copyright 2018, Wiley-VCH.

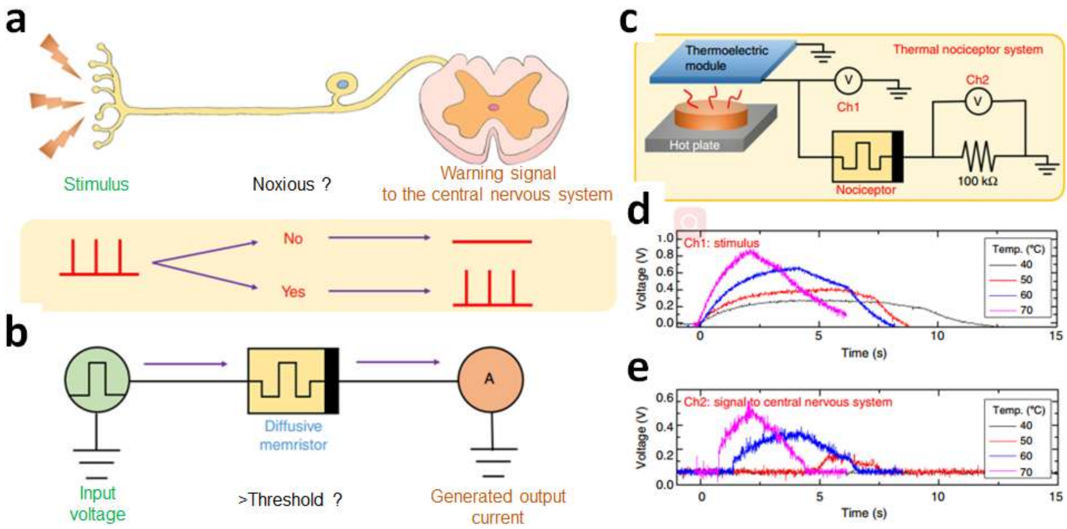

Figure 7. Artificial nociceptive memory. The conceptual diagram of a) nociceptor and b) artificial nociceptive memory. c) The equivalent circuit model of an artificial nociceptor in response to thermal stimuli. d) The voltage changes of the thermoelectric module in response to different temperatures. e) The output of the artificial nociceptor system in response to different temperature stimuli. Reproduced with permission.[158] Copyright 2018, Springer Nature.

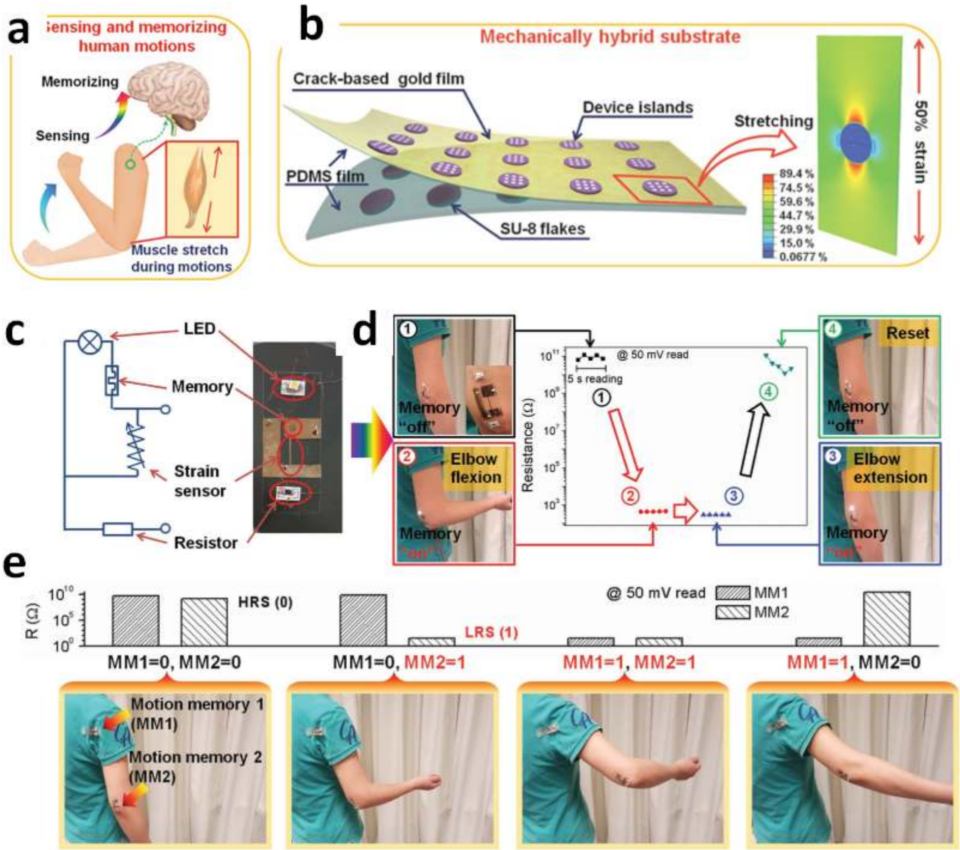

Figure 8. Artificial motor memory. a) The conceptual diagram illustrating the motor memory. b) Schematic figure of the devices and the device array. c) The equivalent circuit model for the motor memory devices. d) The allocation and response of a motor memory device on elbow flexion. e) Multi-motion recording by multiple motor memory systems. Reproduced with permission.[159] Copyright 2017, Wiley-VCH.

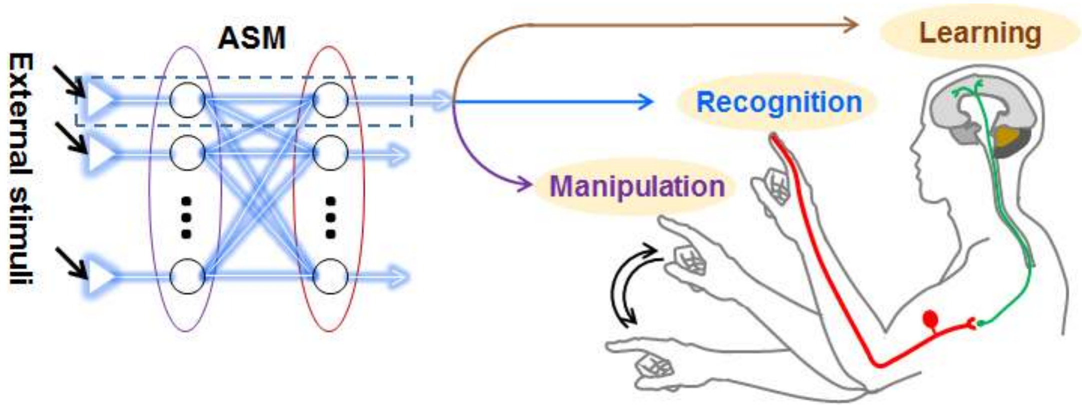

Figure 9. Artificial sensory memory could be deemed as a building block of intelligence that enables essential tasks like manipulation, recognition, and learning.

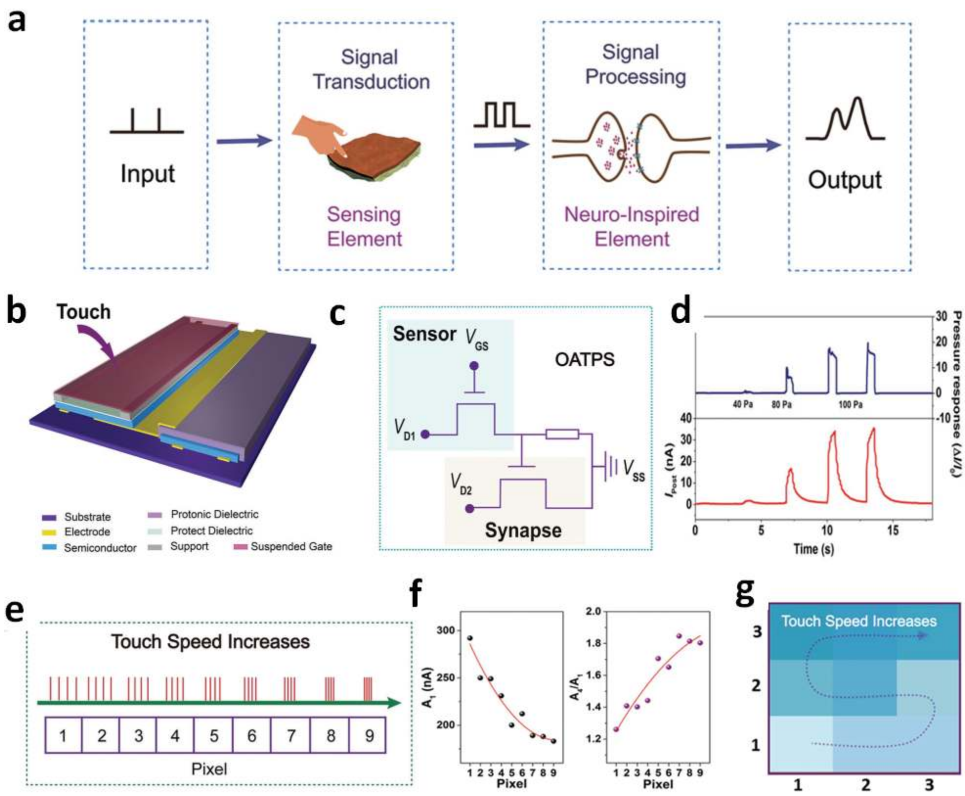

Figure 10. ASM for differentiating touch speed. a) The conceptual design of the artificial haptic memory for extracting timing information. b) Schematic diagram of the DOT-TPE device. c) The equivalent circuit model for the DOT-TPE. d) The output of the pressure sensor and the synaptic transistor in response to different pressures. e) Schematic diagram illustrating the protocol for applying touch cycles with different speeds. f) The EPSC response to the first touch (A1) and the gain (A4/A1) by touch cycles. g) Schematic diagram illustrating the touch speed recognition. Reproduced with permission.[186] Copyright 2017, Wiley-VCH.

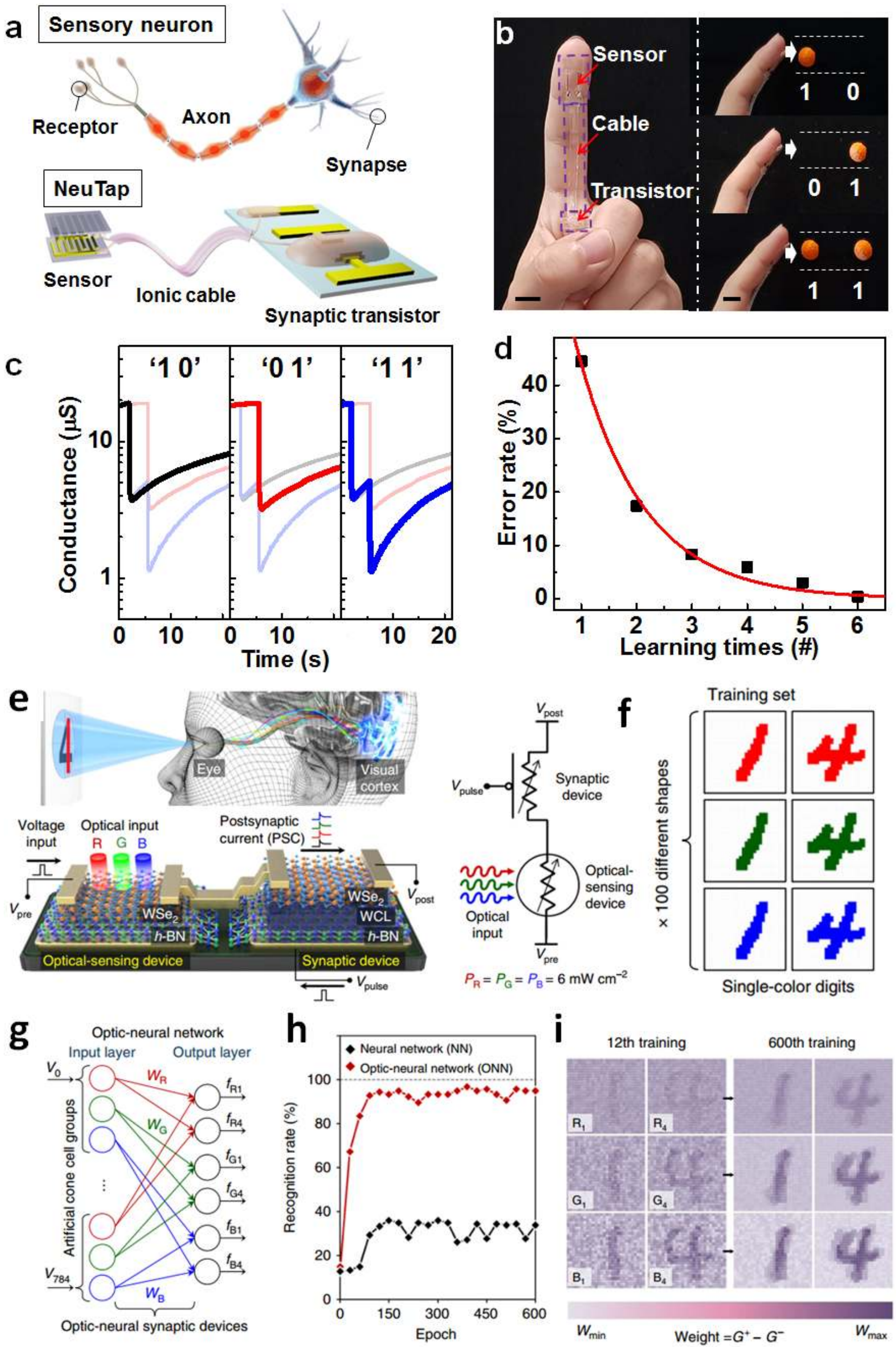

Figure 11. ASM for recognition tasks. a) The conceptual design of the NeuTap devices for tactile perceptual learning. b) Schematic figures of the devices on the finger (left), and pattern to be recognized (right), respectively. c) The typical response to the three pattern pairs. d) The recognition error rate decreases with the learning times. Artificial sensory neuron: Reproduced with permission.[49] Copyright 2018, Wiley-VCH. e) Schematic of the nerves in the human visual system versus the ONS device. The right panel shows the equivalent circuit model of the ONS device. f) Examples of the training dataset. g) The optic-neural network based on ONS devices. h) Recognition rate versus the training epochs. i) Weight mapping images after the 12th and 600th training epoch. Reproduced with permission. [189] Copyright 2018, Springer Nature.

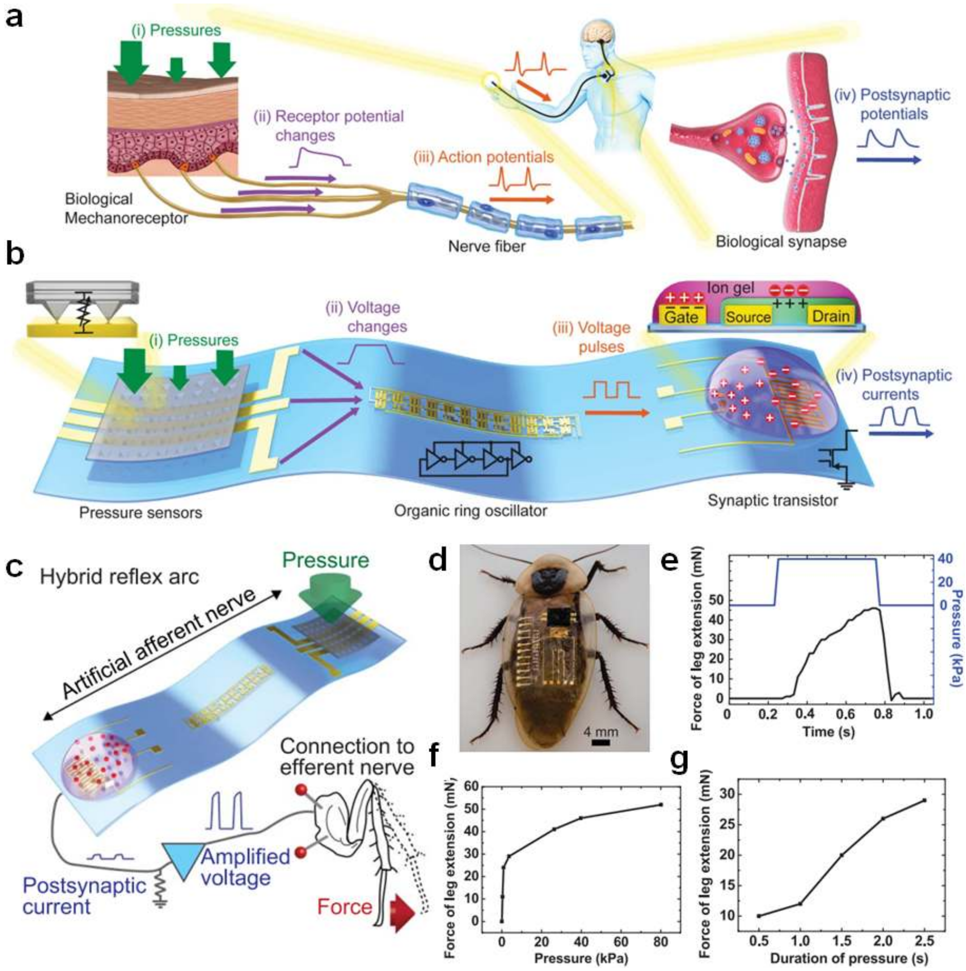

Figure 12. ASM for motion control. a) Biological and b) artificial afferent nerves that are stimulated by pressure. c) Schematic diagram illustrating the hybrid reflex. d) Digital image of an artificial afferent nerve on a discoid cockroach's back. e) Force measured from the leg with a pressure applied on the artificial afferent nerve. f) The output forces plotted as a function of the applied pressure. g) The output forces plotted as a function of the duration of the applied pressure. Reproduced with permission.[190] Copyright 2018, American Association for the Advancement of Science.

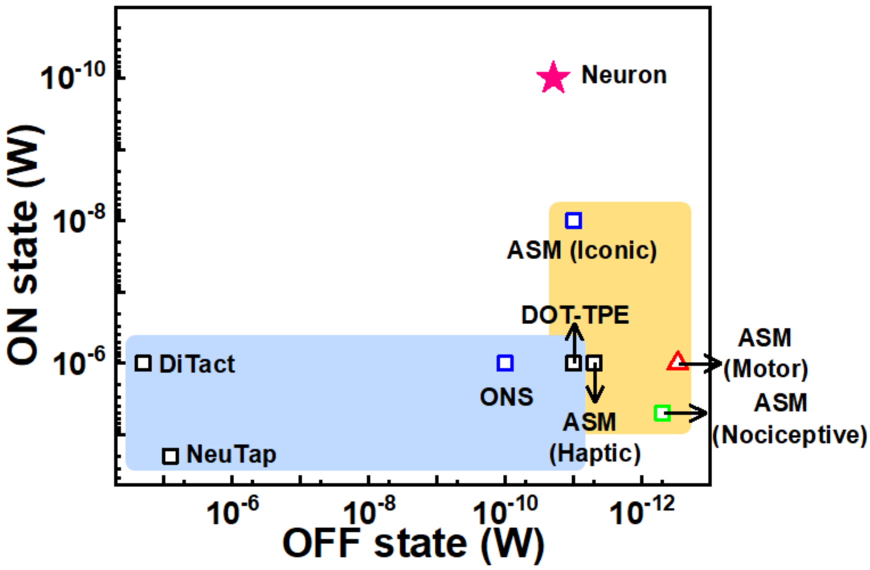

Figure 13. The power consumption for several kinds of ASM versus biological neuron. The power consumption for a biological neuron is estimated based on several references.[210, 211] To evoke an action potential, ~10^8-10^9 ATP molecules are required to be hydrolyzed. The resting potential takes nearly 5-10 folds less energy than that of the action potential. The energy from ATP hydrolysis is estimated to 57 kJ/mol (~10^{-19} J/molecules). The ON (OFF) state refers to the state with stimulation on (off). Devices in the light-blue and light-yellow domains are transistor-based ASM and memristor-based ASM, respectively. The sensory components of the devices plotted in black, blue, green, and red, respectively, are in response to pressure, light, temperature, and strain. Memory behaviors mimicked by the devices plotted by squares, circle, and triangle, respectively, belong to exteroception, interoception, and proprioception categories.

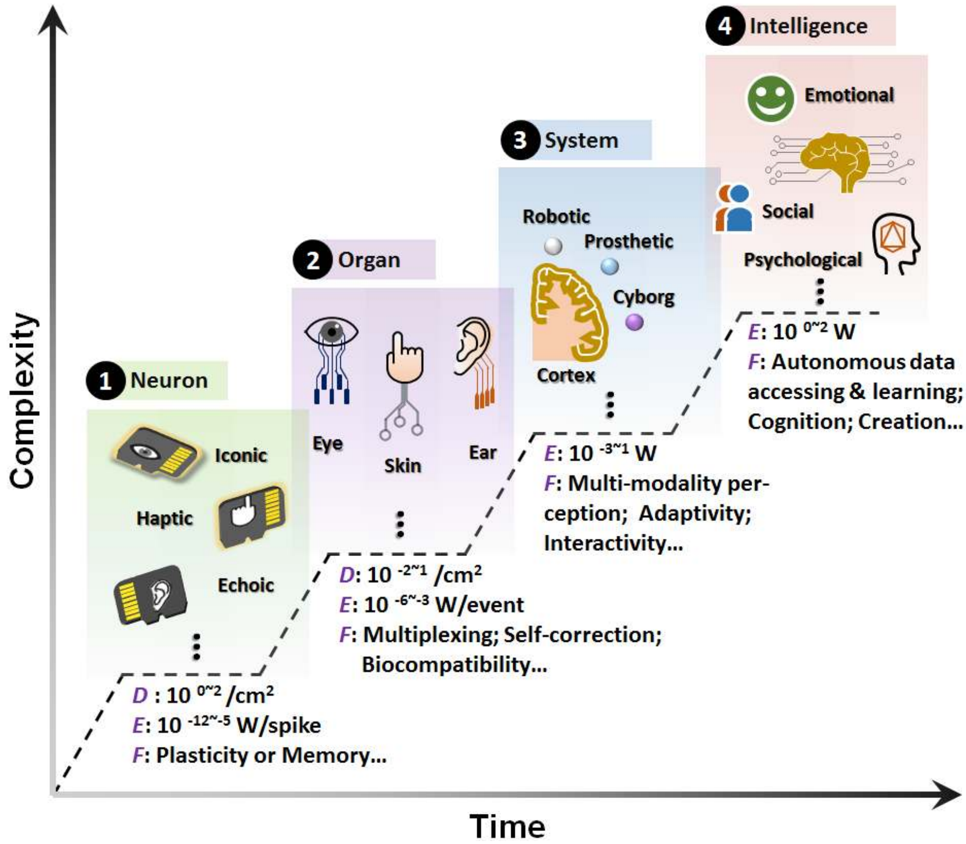

Figure 14. The technological roadmap of the artificial sensory memory to artificial perceptual intelligence. The DEF index (density, energy consumption, and functionality) for evaluation of the development of ASM.

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The table of contents entry. **Transferring** the biological concept of sensory memory into electronic implementations is promising to achieve perceptual intelligence. Recent endeavors on design, fabrication, and application of artificial sensory memory are summarized in this review. Such kind of device would undoubtedly shed light on future advances with respect to various translational implementations such as robotics, prosthetics, and so on.

Keyword artificial neuron, neuromorphic engineering, memory, bioinspired sensors

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Artificial Sensory Memory

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