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Artificial Skin Perception

*Ming Wang, Yifei Luo, Ting Wang, Changjin Wan, Liang Pan, Shaowu Pan, Ke He, Aden Neo, and Xiaodong Chen**

Skin is the largest organ, with the functionalities of protection, regulation, and sensation. The emulation of human skin via flexible and stretchable electronics gives rise to electronic skin (e-skin), which has realized artificial sensation and other functions that cannot be achieved by conventional electronics. To date, tremendous progress has been made in data acquisition and transmission for e-skin systems, while the implementation of perception within systems, that is, sensory data processing, is still in its infancy. Integrating the perception functionality into a flexible and stretchable sensing system, namely artificial skin perception, is critical to endow current e-skin systems with higher intelligence. Here, recent progress in the design and fabrication of artificial skin perception devices and systems is summarized, and challenges and prospects are discussed. The strategies for implementing artificial skin perception utilize either conventional silicon-based circuits or novel flexible computing devices such as memristive devices and synaptic transistors, which enable artificial skin to surpass human skin, with a distributed, low-latency, and energy-efficient information-processing ability. In future, artificial skin perception would be a new enabling technology to construct next-generation intelligent electronic devices and systems for advanced applications, such as robotic surgery, rehabilitation, and prosthetics.

1. Introduction

Skin, the largest organ with an entire area of ≈2 m^2 in human body, protects us from external environments, regulates homeostasis including body temperature, and mediates the sense of touch.[1–4] It houses a huge nerve network comprising a variety of sensory receptors, widely distributed within epidermis, dermis, and hypodermis layers (**Figure 1**a). These sensory receptors are responsible for detecting various internal and external disturbances, such as pressure, strain, vibration, temperature, pain, and chemical species, allowing humans to perceive and interact with the world. This inspires scientists and engineers to develop flexible and stretchable electronic devices or systems to emulate the functionality of the human skin, known as electronic skin (e-skin). Recently, tremendous efforts have been made in the development of e-skin from materials innovation to structural designs, which concentrate on the improvement of sensing capability (i.e., stretchability, sensitivity, long-term monitoring, etc.), user-friendly detection mode (i.e., noninvasive, inflammation-free, gas-permeable, implantable, etc.), system-level integration (i.e., data transmission, power supply, etc.), and the realization of new functions (i.e., self-healing).[5–7] However, as one of the essential elements to mimic human intelligence, the functionality of perception, that is, interpretation of acquired sensory data, is still lacking in most e-skin systems. Implementing the perception functionality in a flexible and stretchable sensing system, referred to as artificial skin perception is vital to realizing an authentically intelligent artificial skin, with capabilities beyond human skin (Figure 1b). Coupled with sensing, feedback, and other technologies (Figure 1c), artificial skin perception will significantly accelerate the development of next-generation soft robotics, where a low-latency and energy-efficient data processing module is required to enable fast adaptation to dynamic environments.

Currently, perception processes of most e-skin systems take place in centralized processing units, that is, computers or servers in the cloud, located far away from the sensing systems where sensory signals are generated. These sensory signals, usually time-serial, unstructured, and redundant, need to be continually sent to an external processing end. As a result, there will be a tremendous volume of data movements between the sensing end and the processing end, leading to huge energy consumption.[8,9] Moreover, the frequent and continual exchange of data causes a serious burden to data communication due to the limited bandwidth of communication channels in current sensing systems, especially when a large number of sensors are mounted on the large-area sensing system.[9–11] This leads to a notorious latency problem, known as a time delay in response for data communication.[9] The latency issue severely hinders the development of ultrafast responsive and delay-sensitive intelligent systems, such as advanced robotics and

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prosthetics. Artificial skin perception aims to overcome these critical issues.

In conventional silicon-based electronics, edge computing brings computation closer to the place where data is produced. Hence, edge computing can alleviate the issues of limited bandwidth and high energy consumption, which has been considered as an effective computing paradigm for delay-sensitive tasks, such as interactive robotics and the internet of things (IoT). When edge computing technology meets flexible and stretchable electronics, artificial skin perception becomes increasingly possible. Analogous to edge computing, artificial skin perception moves all or part of the sensory data processing from external centralized processing units to the flexible and stretchable sensing systems. The sensory data processing can be implemented by the sensors themselves or localized processing units close to the sensors. In this way, a low-latency and energy-efficient information processing can be achieved in the decentralized artificial skin perception. However, it remains a challenge to incorporate the sensory information processing into a flexible and stretchable system, as a result of current flexible integration techniques and computing technology. With recent progress in materials science, manufacturing processes, and electronic device miniaturization, the techniques of ultrathin chip and flexible hybrid electronics were successively developed, which render conventional complementary metal-oxide-semiconductor (CMOS) based processing units suitable for artificial skin perception. In the former, silicon (Si) wafers would lose their rigidity when being thinned down to ≈150 µm and become more flexible with a smaller thickness.[12–14] In the latter, rigid CMOS-based circuit components for computation and communication, and soft elements for sensing are harmonically integrated into a hybrid system, which are interconnected by flexible or stretchable wires.[15–23] Such integrated approach enables the hybrid system to possess both good mechanical properties of flexible and stretchable electronics, and superior functionalities as well as high reliability of CMOS-based electronics. Alternatively, artificial skin perception can be achieved using novel flexible and stretchable computing units such as memristive devices,[24–28] and synaptic transistors.[29–32] Extensive efforts have been made recently in novel computing devices and architectures, which have been employed to implement not only general-purpose computing such as Boolean logic and analogue matrix-vector multiplication,[33–36] but also advanced brain-inspired neuromorphic computing.[30,37–44] Unlike traditional CMOS-based electronics, the novel computing devices could be obtained using a mild, low-cost, and large-scale fabrication process that is compatible with flexible and stretchable electronics,[25–27,30] enabling a homogeneous integration with soft sensing elements. To address the key requirements and challenges of artificial skin perception arising from new manufacturing processes and emerging devices, it is urgent to review the recent progress in the interdisciplinary fields.

In this regard, here, we outline recent advances in artificial skin perception, a new enabling technology for future intelligent systems like soft robotics, from the perspectives of both emerging processes and devices. We first present the fundamentals of sensory information processing in human body, involving sensing, transmission, perception, and action, as the neurophysiologic basis of artificial skin perception. Artificial skin perception is then discussed in terms of new manufacturing processes and energy-efficient computing devices, including perception based on commercial CMOS processing units, perception based on flexible memristive devices, and perception based on flexible synaptic transistors. The existing challenges that hinder the development of artificial skin perception are also discussed. In the end, we envision the future prospects of artificial skin perception, in the hope of promoting the development of artificial skin for advanced prosthetics and soft robotics.

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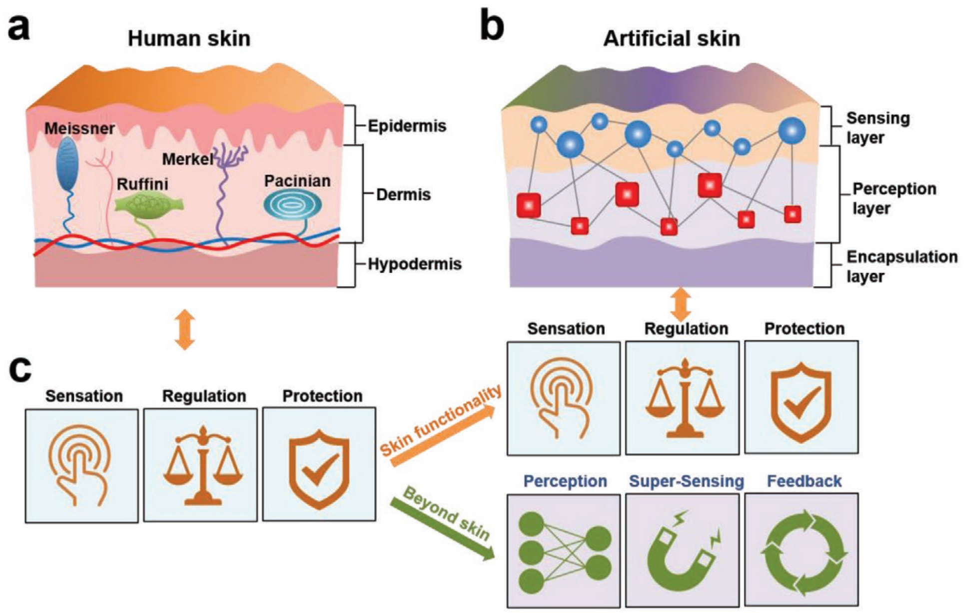

Figure 1. Schematics of human skin and artificial skin. a) Human skin consisting of the epidermis, dermis, and hypodermis layers. b) Artificial skin consisting of the sensing, perception, and encapsulation layers. c) The functionalities of human skin and artificial skin. Artificial skin not only executes the human skin functionalities such as sensation, protection, and regulation, but surpasses the human skin with the capabilities of localized perception, super-sensing, and active feedback.

2. Neurophysiologic Basis of Artificial Skin Perception

Sensory information processing in human is controlled by sensory nervous systems that detect and encode stimuli, send sensory signals to the central nervous system and thereafter, interpret the sensory information for feedback actions (**Figure 2**a). Accordingly, there are four main parts in the sensory nervous system, comprising: 1) sensory neurons consisting of various sensory receptors, 2) neural pathways for signal transmission, 3) parts of the brain involved in sensory perception, 4) muscle activation as feedbacks. The corresponding processes are simply referred to as sensing, transmission, perception, and action, which are also the basis of the robotic sensing systems (Figure 2b).

Skin is the most important organ for sensing, which comprises a variety of sensory receptors from the epidermis layer to the hypodermis layer.[45] These receptors are generally classified into four categories, namely mechanoreceptors, thermoreceptors, nociceptors, and proprioceptors. Mechanoreceptors are sensory neurons or peripheral afferents that are responsible for mechanical stimuli, such as pressure, touch, stretching, and vibration. There are totally about 45 000 mechanoreceptors within the skin,[46] which comprise Meissner's corpuscles, Merkel cells, Ruffini endings, and Pacinian corpuscles (Figure 1a). Mechanoreceptors are classified into fast adapting (FA) units and slow adapting (SA) units by adaptive response time.[45,47] FA units respond rapidly and immediately after skin deformation, while SA units show continuous response to sustained deformations. According to the receptive field, both FA and SA units are further categorized into two types: 1) small receptive fields with sharp borders, and 2) large receptors with indistinct borders. Specifications of these mechanoreceptors, such as adaptation rate, receptive field area, location, effective stimuli, and function, are summarized in **Table 1**.[45,47,48]

Thermoreceptors are a category of sensory neurons that respond to temperature change. They do not measure absolute temperatures, but temperatures relative to the temperature of human body. The sensitivity of temperature response depends on the surface area perceiving the change in temperature, and the best is about 0.3 °C. There are two kinds of thermoreceptors in the skin, namely cold receptors and warm receptors, which have different response ranges in skin temperature.[49] Nociceptors, also referred to as pain receptor, are used to detect the noxious stimuli that would or potentially give rise to tissue damages. In skin, nociceptors comprise four types of functional receptors: high threshold mechanonociceptors or specific nociceptors, thermal nociceptors, chemical nociceptors, and polymodal nociceptors. The first three types of nociceptors are specialized for detecting intense mechanical stimuli (i.e., pinching, cutting, stretching, etc.), intense thermal stimuli (extremely high or low temperatures), and intense chemical stimuli, respectively. The last type, polymodal nociceptors, can respond to various intense stimuli including mechanical, thermal, and chemical ones. Proprioceptors are sensory receptors responsible for a category of conscious sensations, including the senses of limb position and movement, the sense of balance, the sense of force, the sense of effort, and the sense of heaviness. In most cases, these senses are not generated by individual receptors, but by populations of proprioceptors that are distributed in skin, muscles, tendons, and joints.[50] The brain can further integrate the proprioceptive senses with other sensory information such as visual, audio, vestibular or olfactory senses to create an overall representation of body position and movement.

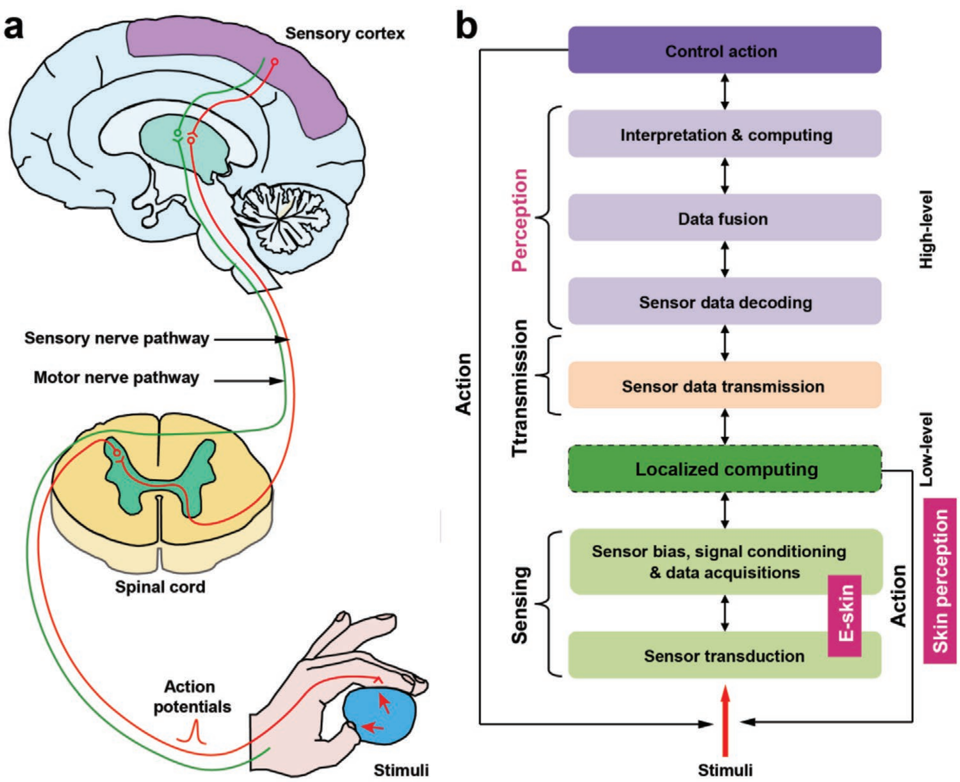

Figure 2. Sensory information processing in human and electronics. a) Neurophysiologic basis of sensory system for sensing and perception. b) Hierarchical functional block diagrams of information processing in modern electronic systems.

After receiving a stimulus, the sensory receptor converts the sensory signal from the stimulus to an electrical signal that transmits in the peripheral nervous system (PNS) and central nervous system (CNS). Specifically, the membrane potential of a sensory receptor varies with the strength and the duration of a stimulus which affects the ion channels in the membrane. Once the membrane potential reaches a threshold, the neuron will fire or generate an action potential. The action potential generated in PNS is transmitted to the spinal cord via sensory nerve pathways, and in most cases, is sent to the brain for perception.

At the end of neural signal transduction, sensory perception occurs in the brain. The brain is the processing center of perception in human. It is highly centralized and responsible for high-level and comprehensive perceptual activities such as cognition, planning, and intuition. However, several low-level perceptual activities such as reflexes and muscle activation, could be directly processed by the PNS.[51] In other words, the sensory signals of reflexes do not need to be sent into the brain, and a perceptual decision will be immediately made once the sensory signals reach the spinal cord (Figure 2a). Compared to the brain, the processing way of the low-level perceptual

Table 1. Types and characteristics of mechanoreceptors in human skin.

Receptor	Meissner's corpuscle[a]	Pacinian corpuscle[a]	Merkel cell[b]	Ruffini ending[b]
Type	FA I	FA II	SA I	SA II
Adaptation rate property	Fast	Fast	Slow	Slow
Receptive field [mm^2]	1–100	10–1000	2–100	10–500
Frequency range [Hz]	10–200	40–800	0.4–100	7
Location	Dermis of glabrous skin	Deep layers of dermis in hairy and glabrous skin	Epidermis of glabrous skin	Dermis of hairy and glabrous skin
Receptors per cm^2 in the fingertip	140	21	70	49
Effective stimuli	Temporal changes in the skin deformation	Temporal changes in the skin deformation	Spatial deformation, sustained pressure, curvature, edge, corner	Sustained downward, pressure, lateral skin stretching, skin slip
Sensory function	Low frequency vibration, motion detection, grip control, tactile flow perception	High frequency vibration	Pattern or form detection, texture perception, tactile flow perception	Finger position, stable grasp, tangential force, motion direction

[a]FA: fast adapting; [b]SA: slow adapting.

activities in the PNS is decentralized, distributed, and localized. Localized processing not only enables a rapid response to external stimuli for survival, but also can alleviate the computing burden in the brain,[52] and so it has been used in interactive robotics.[51] In addition, recent neuroscience studies have demonstrated that some sensory receptors can also perform specialized computations before sending signals downstream; this is termed on-receptor computing.[10,53] These neurophysiological evidences further highlight the importance of placing perception functionality on or near sensing modules within a flexible and stretchable system (Figure 2b), providing a bioinspired approach to develop artificial skin perception devices and systems.

In most cases, a decision-making command after the sensory signal is processed by the brain and other processing organs will be sent to muscles or glands in the form of action potentials. Decision-making information is encrypted in these action potentials and usually used for motion and status control, which can be regarded as the active feedback in response to the stimuli. This process is referred to as the process of action.

As an intelligent electronic counterpart, artificial skin first needs to emulate the fundamental functionality of human skin, such as acquiring reliable sensory signals, acting as artificial receptors. To adapt to irregularly shaped surfaces and to accommodate mechanical deformations during usage, such as bending, twisting, and stretching, artificial skin materials and devices should be flexible, stretchable, tough, and sometimes self-healing. These properties allow artificial skin devices to maintain an intimate contact with detected objects for high-quality data acquisition,[6,54] as required for skin-attached devices or robotic skins. Significant progress has been made recently in the development of various flexible and stretchable devices for data sensing from materials innovation to structural designs, which are listed in **Table 2** (classified by the type of artificial receptors).[55–121] For more details, readers may refer to the following recent review articles.[5,6,15,122,123] To achieve higher intelligence, artificial skin should have the perception functionality to go beyond human skin. However, artificial skin perception is still in its infancy.

Table 2. Recent progress in flexible and stretchable sensing devices via materials innovation and structural designs.

Type	Target	Application
Mechanical sensing	Pressure	Force touch,[55–57] acoustic vibration,[58] pulse wave,[59,60] intraocular pressure,[61] heart rate,[62] robotic skin,[63,64] tactile glove[65]
	Strain	Human motion,[67–69] pulse wave,[66] acoustic vibration,[70] swallowing motion,[71] tactile glove,[72–74] soft robotic[75–77]
	Slip and force vector	Slip detection,[78–80] acoustic vibration,[81] robotic skin[79,81]
Temperature sensing	Temperature	Skin temperature,[82–85] atmospheric temperature,[86] artificial skin,[87] soft robotic,[89] photothermal therapy[90]
Nociceptive sensing	Artificial nociceptor (Sensor + memristor)	Pressure nociceptor,[92] thermal nociceptor[93] UV damage-sensing nociceptor[94] Humanoid robots[91–93,95]
	Sensor system	Artificial muscle[96]
Proprioceptive sensing	Multimodal sensors or systems	Pneumatic artificial muscle,[97] prosthesis,[98,104,105] object motion,[99–101] human-robot interactions,[102] soft robotics[103]
Other-type sensing	Electrical signals	Electrophysiological signals, such as electromyography (EMG),[106–109] electrocardiogram (ECG),[109–112] electroencephalogram (EEG),[113,114]
	Chemical signals	Glucose monitoring,[115,116,118] sweat analysis,[19] biomarker[117]
	Magnetic	Artificial magnetoreception,[119] navigation[119,120]

3. Artificial Skin Perception

Recent advances in materials science, manufacturing processes, electronic device miniaturization, and computing architectures, enable artificial skin perception to become possible. In this section, we summarize recent significant progress in artificial skin perception based on the type of local computing units—CMOS-based computing components and novel flexible or stretchable computing elements including memristive device and synaptic transistor. Requirements and challenges for each strategy are discussed, which will shed some light on artificial skin perception for the future.

3.1. Artificial Skin Perception Based on CMOS Devices

The most straightforward strategy to realize artificial skin perception is to place commercial CMOS-based computing units into the flexible and stretchable system. Commercial computing units, such as microcontrollers, microprocessors, field programmable gate arrays (FPGAs), are commonly used to analyze the sensory signals in a mobile system, which are typically based on von Neumann architecture. To perform the von Neumann-based computing, signal conditioning modules are required for the artificial skin system, which make the sensor output suitable for arithmetic and logic operations. Signal conditioning modules include amplification circuits, filtering circuits, analog-to-digital (AD), and digital-to-analog (DA) converters. Power sources and corresponding driving modules for energy delivery are also indispensable components to construct a complete artificial skin system. Sometimes, sensory data need to be sent to exterior systems, such as servers and clouds, for further analysis and storage. Thus, wireless communication modules are required. These computing and other functional modules are usually rigid and brittle, which are challenging to be incorporated into the flexible and stretchable system.

To solve this issue, one approach is to directly decrease the thickness of Si wafer to make it flexible, named as ultrathin chip. When a system is physically built on the ultrathin (typically <50 μm) substrate, it will become flexible and bendable.[14,124] Such ultrathin chips can be obtained by wafer thinning from a bulk Si substrate (**Figure 3**a) or exfoliating from a silicon-on-insulator (SOI) substrate (Figure 3b). The manufacturing processes for ultrathin chips generally involve techniques like polishing, grinding, thinning-by-dicing, die assembly, interconnection, etching, transfer, and packaging.[12,125–129] Ultrathin chip technique can be employed to fabricate various functional components including sensing elements, computing units, driving circuits, power supply, and data transmission modules.[14,128–130] Due to the inherent flexibility, ultrathin components are easily transferred onto various curvilinear or irregular surfaces, such as textile, paper, wood, and stone.[131] After encapsulated by biocompatible materials, ultrathin chips can be used for implantable applications, such as artificial retinal system, and under skin implantation (Figure 3b).[132] Coupling with structural design strategies, that is, wave/wrinkle pattern, stretchable systems based on ultrathin chips were achieved.[126] The ultrathin chip technique paves one possible way to building up the intelligent artificial skin systems with both sensing and perception functionalities. However, there remain several

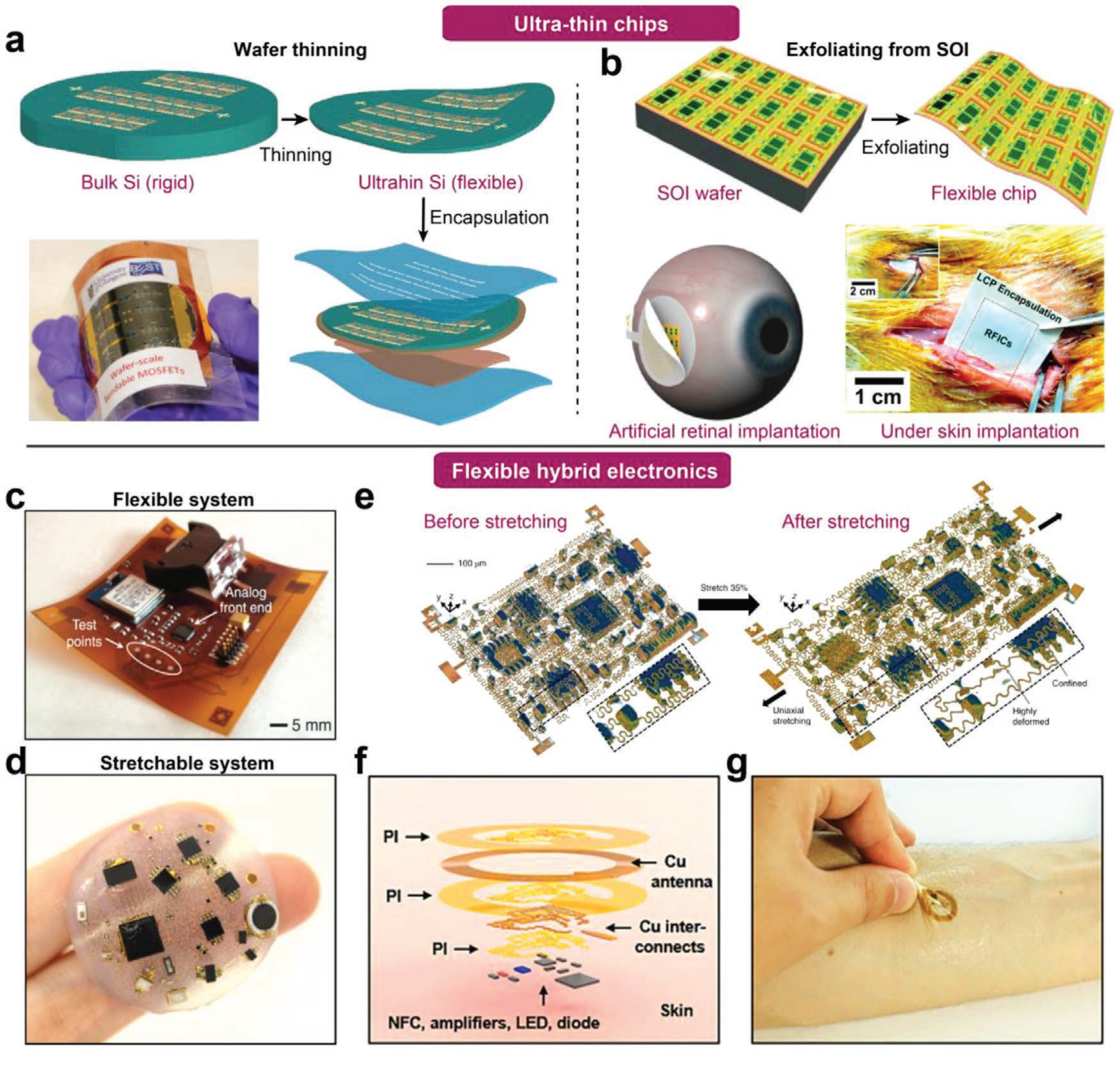

Figure 3. Artificial skin perception based on CMOS electronic devices involving ultrathin chips and flexible hybrid electronics. a,b) Ultrathin chip techniques including wafer thinning from a bulk Si substrate (a), and exfoliating from an SOI substrate (b). c,d) Flexible hybrid electronics including a flexible hybrid system (c), and a stretchable hybrid system (d). e) X-ray computed tomography images of a hybrid system before and after stretching. f) Schematic of a wireless epidermal optoelectronic system, and g) image of the device mounted on the skin. a) Reproduced with permission.[12] Copyright 2018, Wiley-VCH. b) Reproduced with permission.[132] Copyright 2013, American Chemical Society. c) Reproduced with permission.[17] Copyright 2016, Wiley-VCH. d) Reproduced under the terms of the CC-BY Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0).[133] Copyright 2017, The Authors, published by Springer Nature. e) Reproduced with permission.[134] Copyright 2018, Springer Nature. f,g) Reproduced with permission.[147] Copyright 2016, AAAS. Reprinted/adapted from ref. [147]. © The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. Distributed under a Creative Commons Attribution NonCommercial License 4.0 (CC BY-NC) http://creativecommons.org/licenses/by-nc/4.0/.

challenging issues to be solved before commercialization, such as packaging, residual stress, stress analysis model, and strain effect on electrical performance. Unlike conventional chips, ultrathin chips cannot be bonded easily by wire-bonder because a large impulsive force from the bonder tip may destroy the thin fragile wafers. Bumps coarsening and possible electrical discontinuity in/out of plane also increase the complexity of the ultrathin chip packaging, especially for 3D integrated circuits. In addition, much effort is required for the investigation of the stress-induced side effects and for further building of accurate stress–performance models to better guide the design of ultrathin chips.

Flexible hybrid integration is another effective way to implement artificial skin perception by using commercial devices. Commercial rigid functional components are directly interfaced with soft elements such as sensors and interconnection wires, to construct a flexible (Figure 3c) or stretchable (Figure 3d) hybrid electronic system.[17,133,134] When the hybrid integrated system is bent, twisted, folded, or stretched, soft parts are deformed to accommodate the strain, while rigid counterparts remain unchanged, which can be verified from the X-ray computed tomography images (Figure 3e).[134] To meet the large deformation requirements, as needed in advanced soft robotics and prosthetics, tremendous efforts have been made via various structural designs in recent years, including serpentine,[54,135–138] self-similar structure,[139,140] arc-shaped bridge,[141,142] helices,[133,143] origami,[144] and kirigami.[145,146] Based on the structural designs, a lot of stretchable electronic systems have been reported. For example, Kim et. al. demonstrated a wireless, battery-free, and stretchable epidermal optoelectronic system with a single light-emitting diode (LED) and photodetector for the tracking of heart rate and mean arterial pressure (Figure 3f,g).[147] However, most reported hybrid integration systems focus on the functions of signal detection and data transmission. In other words, sensory signals in current stretchable systems usually need to be sent to external processing units, that is, portable phones, computers, and clouds, for data analysis, which is different from the paradigm of artificial skin perception.

More recently, a hybrid integrated epidermal electronic system (**Figure 4**) with both the sensing and perception functionalities was reported by Rogers's group.[148] The hybrid system comprises four main functional layers (Figure 4a): 1) an electronic layer for monitoring and processing sensor data, 2) a microfluidic chamber for mechanically isolating the skin and interconnection wires, 3) silicone encapsulation layers, and 4) a magnetic loop antenna for wireless data transmission. The electronic layer consists of various commercial functional components, such as amplifiers, analog filters, LED drivers, power circuits, photodiodes, analog-to-digital converters, microcontroller, and system-on-a-chip, which are bonded by stretchable interconnection wires. Hence, the stretchable epidermal electronic system can perform in-sensor data analytics, that is, recognition of the peaks and valleys of data waveforms, without sending them to external processing units. The block diagram for real-time processing of the ECG waveforms detected by the system is shown in Figure 4b. The sensing and perception results of the system for ECG signals can be comparable to that of a gold standard (Figure 4c). In addition, other vital information of human body such as respiratory rate, heart rate (Figure 4d), blood pressure, and blood oxygenation can also be computed from the raw recorded ECG, photoplethysmogram (PPG), and skin temperature signals.

Despite the promise of commercial devices for artificial skin perception, there remain challenges regarding the reliability and credibility of the system, especially the stability of soft–hard interface. Commercial rigid components and soft elements often show significant differences in stretchability and Young's modulus. Specifically, rigid and hard materials typically show high Young's modulus, for example, silicon and metal materials with the Young's modulus of ≈100 MPa,[6] while soft elements have low Young's modulus, for example, polydimethylsiloxane (PDMS) of ≈1 MPa, and Ecoflex of ≈100 kPa.[15,149–151] The large mechanical mismatch will lead to stress concentration in the joint area between soft and hard components, which may lead to the failure of the whole system when bent or stretched. In practical applications, the requirements of artificial skin system in mechanical properties vary in different application scenarios. For example, to monitor physiological signals on human skin, the system must have a Young's modulus of 0.1–2 MPa and a stretchability of 30–70%, comparable to human epidermis.[15,152] Coupling with the aforementioned structural designs, proper selection of system materials according to the specific application can alleviate the soft–hard interface issue. For artificial skin perception, another issue is the increase of form factor caused by the addition of bulky commercial rigid components and immature interconnection techniques, which may limit the application in miniaturized and implantable domains.

3.2. Artificial Skin Perception Based on Flexible Memristive Devices

Memristive devices are two-terminal electrical switching devices, whose internal resistance states rely on the history of applied voltage or current.[33,153] Such devices can be employed for information storage and processing.[154] Typical memristive devices include resistive switching memory (RRAM), phase change memory (PCM), magnetic random access memory (MRAM), and ferroelectric random access memory (FRAM). Due to the simple two-terminal structure, low operating energy, high switching speed, and direct in-memory computing ability, they have been widely developed for the next-generation memory and computing components.[33,42,155–161] Moreover, the devices are easy to be fabricated using compatible processes with current flexible and stretchable electronics, such as printing and solution-based methods.[4,25,28,159,162–170] These merits make memristive devices energy-efficient computing units, which can exceed conventional CMOS-based circuit technology, and are suitable for artificial skin perception. According to computing paradigms, the applications of flexible memristive devices are classified into two main categories: 1) general-purpose computing and 2) neuromorphic computing.

3.2.1. Flexible Memristive Devices for General-Purpose Computing

According to the definition, a memristive device can be configured into different resistance states depending on external

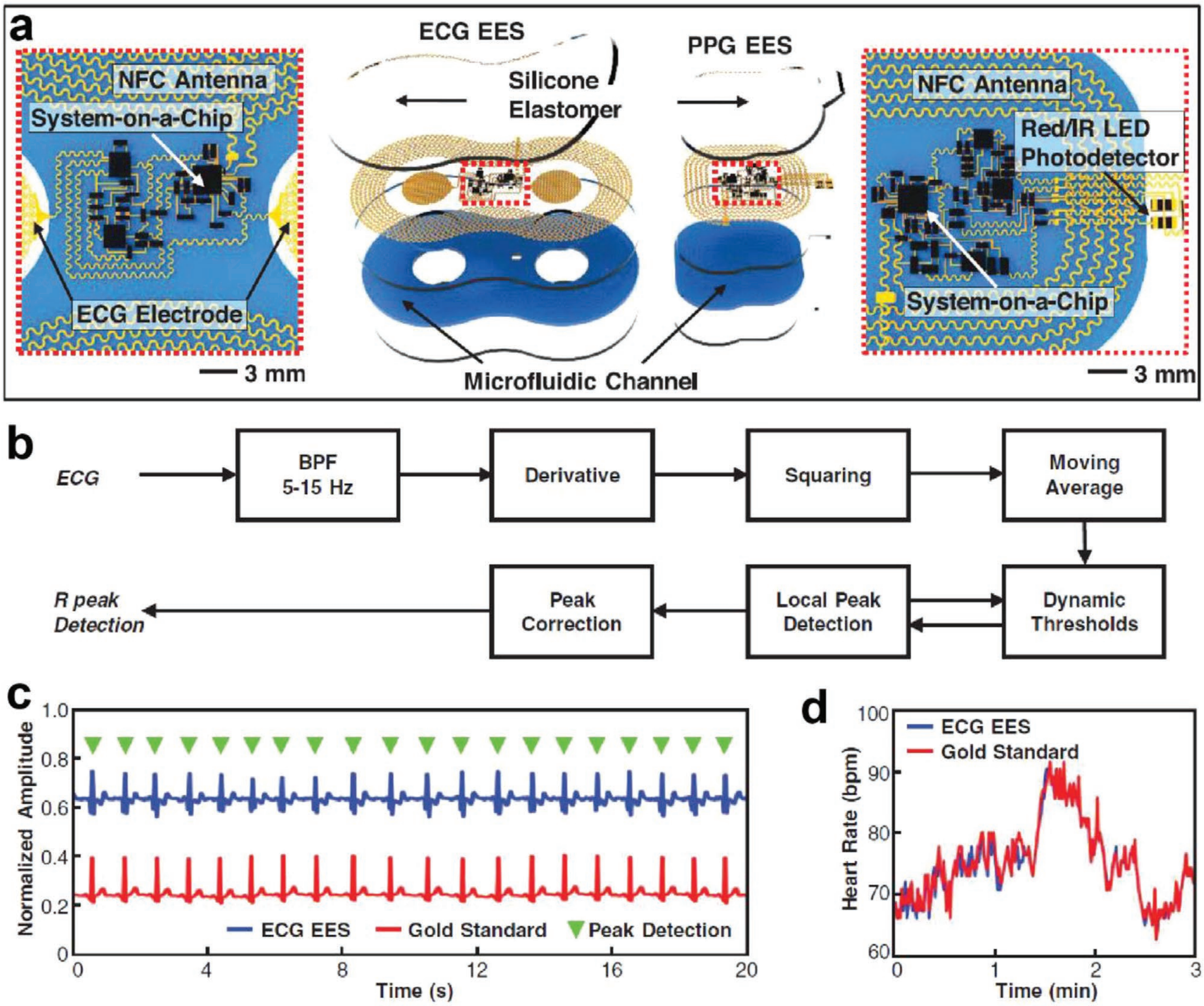

Figure 4. Hybrid integrated epidermal electronic system with sensing and perception functionalities. a) Schematic of the hybrid integrated system. b) Block diagram of in-sensor processing of ECG signals. c,d) Comparison of raw ECG signals, peak detection, and extracted heart rate from the hybrid integrated system and a gold standard. a–d) Reproduced under the terms of the CC-BY Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/).[148] Copyright 2019, AAAS.

operations and its previous internal state. Through delicately regulating the sequences of operations and/or array configuration, flexible memristive device or array can perform general-purpose computing tasks, such as threshold detection, in-memory digital computing, and in-memory analogue computing (**Figure 5**a).

In a memristive device, the resistance changes in response to electrical stimuli can be used as a criterion for threshold detection. For most of RRAM-based memristive devices, the electrical resistive switching phenomenon of the device can be well explained by the mechanism of the formation/rupture of nanoscale conductive filaments, in which the externally driven ion transport plays an important role.[155,159,171–175] When an external driving force is below a critical value, the ions cannot move. Only if the external driving force exceeds the critical value, can the ions move. The physical principle can be regarded as a natural threshold evaluation process for processing information. For instance, He et al. reported a flexible artificial reflex arc system (Figure 5b) that consisted of a pressure sensor for tactile sensing, a non-volatile resistive switching device for perception, and an electrochemical actuator that acted as the muscle in response to tactile stimuli.[52] Only when the tactile stimulus reaches a threshold, the resistive switching device can be activated and trigger the actuator to move. Here, the non-volatile resistive switching device can perform a threshold computing in the flexible system. Due to such decentralized processing way, artificial reflex arc system not only realizes a rapid response to pressure stimuli, but also liberates the centralized processing units from tremendous low-level decision-making activities. Beside the non-volatile resistive switching device, diffusive memristive device where the formed conductive filaments spontaneously break up after removing external applied voltages can better perform threshold computing, due to its natural threshold effect.[43,171,176–178] The diffusive device has

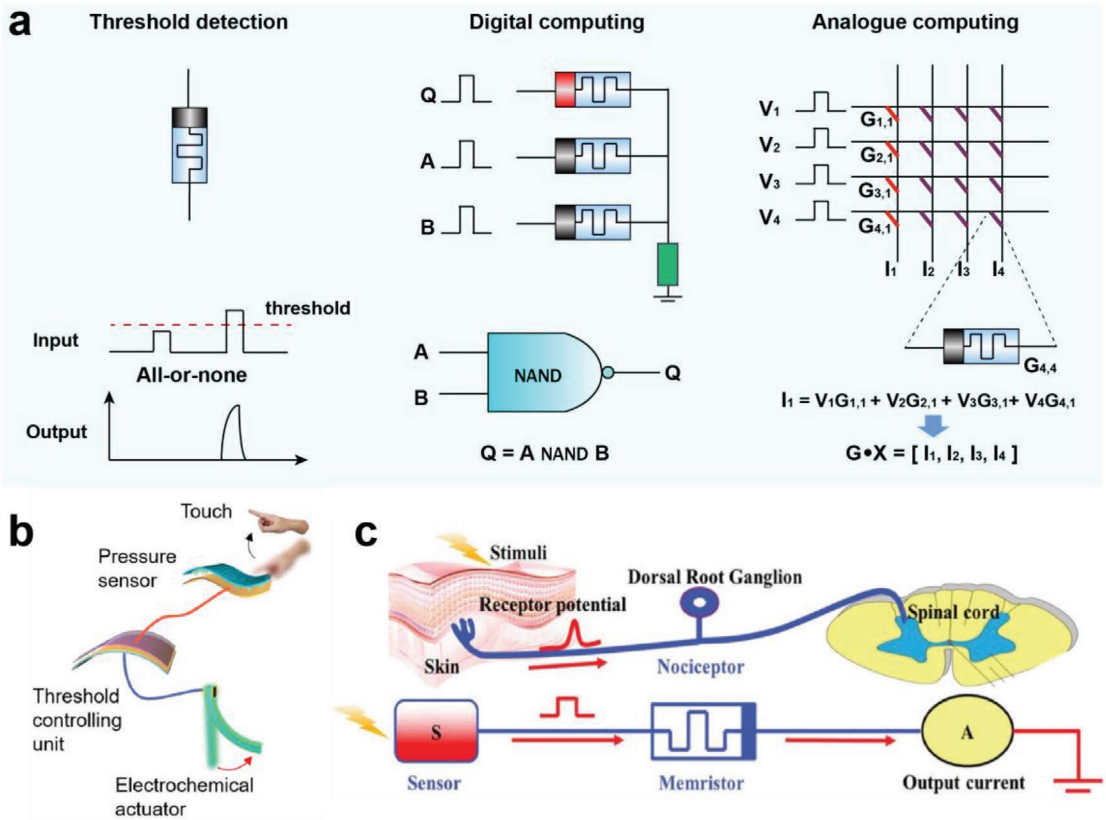

Figure 5. Flexible memristive devices for general-purpose computing. a) Schematic of the implementation of general-purpose computing using memristive device or array, including threshold detection, digital computing, and analogue computing. b) An artificial reflex arc system with artificial skin perception functionality. c) Artificial nociceptor with artificial skin perception functionality. b) Reproduced with permission.[52] Copyright 2020, Wiley-VCH. c) Reproduced with permission.[92] Copyright 2019, Royal Society of Chemistry.

been used in flexible (Figure 5c) or rigid artificial nociceptor system,[92,93] and artificial afferent nerves.[179]

On top of simple threshold detection, memristive devices and arrays can perform many complex general-purpose computing tasks via rational operations and array configurations, such as digital Boolean logical computing (Figure 5a), which is aimed to substitute the modern digital computer. Classical Boolean functions, the basis of digital computer, such as AND gates, NOT gates, NOR gates, and NAND gates, have been recently demonstrated based on rigid memristive device arrays.[154,180–184] Furthermore, a flexible one-bit full adder was experimentally verified by rationally assembling the memristive device-based Boolean logic operations.[36] Compared to significant progress in rigid arrays, in-memory digital computing based on flexible memristive devices are rarely reported,[185,186] mainly due to the unsatisfactory device reliability. Recently, Jang et. al. demonstrated Boolean logics, that is, NOT and NOR gates, using a flexible one-selector–one-memristor (1S1R) array.[186] Multiple logic operations can be simultaneously performed on different rows in the array, which realizes a parallel computing for energy-efficient flexible electronics.

In addition, in-memory analogue computing can also be performed by memristive arrays, because they are inherent to implement matrix–vector multiplications based on the Ohm's law and Kirchhoff's law.[34,37] The analogue computing operations are specialized to accelerate computationally intensive tasks such as image compression,[187] sparse coding,[188] linear equation solver,[35,189] and eigenvector solver.[35] The core multiplication operations are explained as follows. When an input vector of voltages is applied to the rows of a memristive array, the summed current along a column is collected, which can be regarded as the dot product of the input voltage vector and the memristive conductance vector of the column (Figure 5a). Obviously, multiple multiplications can be simultaneously performed through multiple columns in a single computing cycle, enabling a parallel and high-throughput computing paradigm.

In short, in-memory digital and analogue computing based on memristive devices and arrays provides a promising solution for fast and energy-efficient artificial skin perception. However, memristive devices suffer from several challenges such as poor resistance tuning ability, state instability, read-write nonlinearities, excessive cycle-to-cycle and device-to-device variations, and low device yield.[155,187] These issues will be more severe in artificial skin perception because flexible memristive devices usually exhibit worse performance than rigid counterparts. To the best of our knowledge, there has been no report on analogue computing based on flexible memristive devices or arrays. Hence, much effort is still needed to improve the device performance and fabrication process, especially in flexible devices and arrays, to realize artificial skin perception.

3.2.2. Flexible Memristive Devices for Neuromorphic Computing

Different from general-purpose computing, neuromorphic computing is a new intelligent technology, which is inspired by the neural structure and operational way of the brain. There are about 10^{12} neurons in the brain which are interconnected via synaptic connections (synapses), forming a huge neural network (**Figure 6**a). The information processing in the brain is executed through the complex neural network that is operated in a massively parallel, distributed, and event-driven way.[190] To take advantage of neuromorphic computing, artificial synapses and neurons are essential, which perform the localized computation and data storage function. Flexible or stretchable memristive devices can be used to emulate the functionality of synapses and neurons, which provides an alternative way to realize artificial skin perception.

A two-terminal memristive device is analogous to an artificial synapse connecting a pre-neuron to a post-neuron, of which the resistance state represents synaptic weights (Figure 6a). Synaptic weights can be strengthened or weakened over time in response to the synaptic activity, referred to as synaptic plasticity, which is believed to underlie the learning and memory of human beings. Recently, tremendous effort has been made in emulating artificial synapses by using various flexible (Figure 6b) or stretchable memristive device.[25–28,191–198] Typical synaptic dynamic properties (Figure 6c), such as excitatory postsynaptic current (EPSC), short-term plasticity (STP), long-term depression (LTD), long-term potentiation (LTP), paired pulse facilitation (PPF), and spike timing dependent plasticity (STDP), have been widely explored in flexible memristive systems, which demonstrates the feasibility of memristive device-based synapses for neuromorphic computing. For instance, an electrical synapse with as high as 600 continuous conductance states has been achieved recently by using a flexible organic PEDOT:PSS-based memristive device, benefiting the continuously tuned ability of artificial synapse.[191] LTP, STP, PPF, and STDP synaptic properties

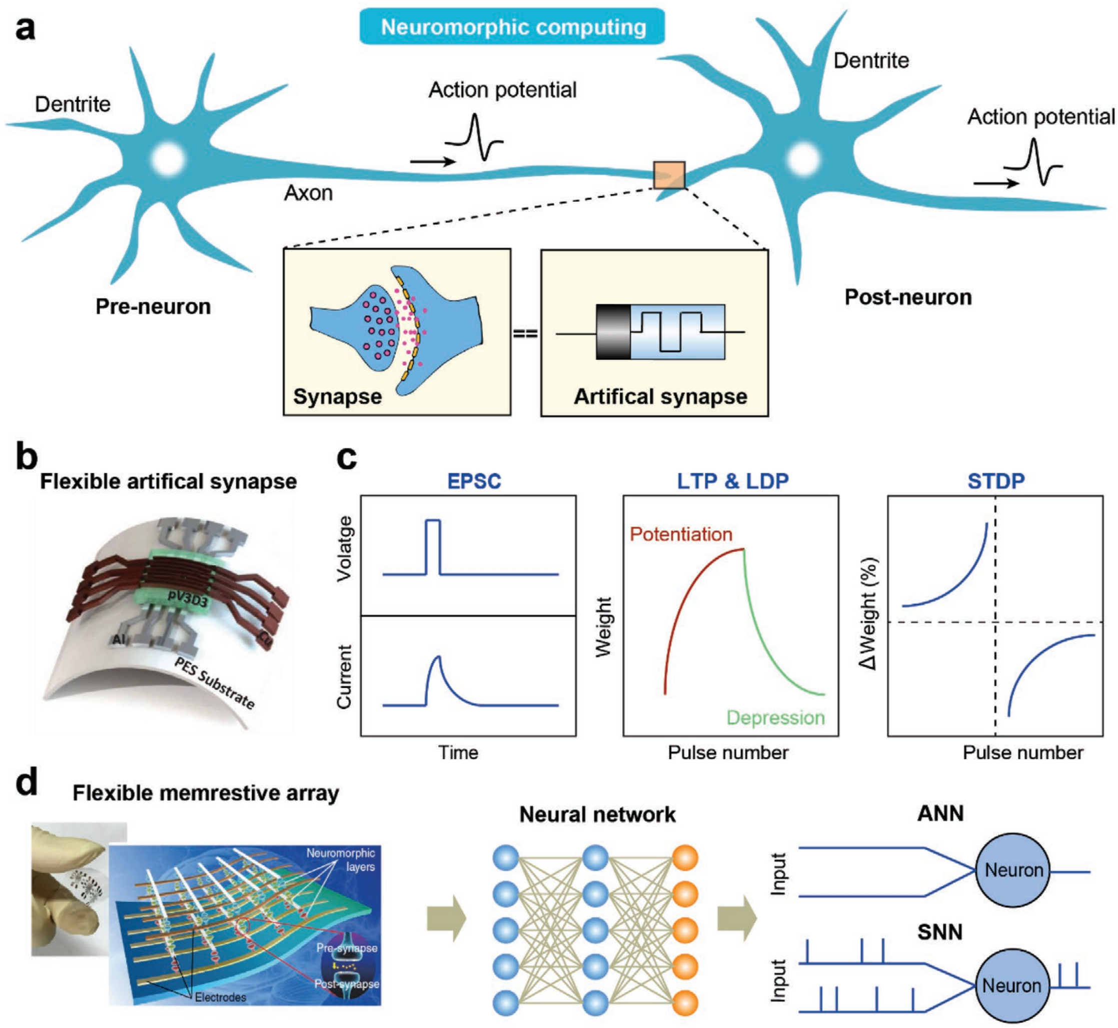

Figure 6. Flexible memristive devices for neuromorphic computing. a) Neuromorphic computing in the brain and schematic of a memristive device as an artificial synapse. b) Flexible memristive artificial synapse. c) Synaptic electrical behaviors emulated by memristive devices, including EPSC, LTP, LDP, and STDP. d) Flexible memristive array for neuromorphic computing, including conventional ANN with static input coding and SNN with relative spike timing coding. b) Reproduced with permission.[28] Copyright 2019, American Chemical Society. d) Reproduced under the terms of the CC-BY Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0).[24] Copyright 2017, The Authors, published by Springer Nature.

were mimicked in the device, which could also sustain the folded tests. To make it suitable for harsh environments such as twisting and stretching, as required in soft robotics, stretchable memristive device-based synapses are consequently developed. By rationally selecting Ag nanoparticle-doped composite materials with good stretchability and low Young's modulus, the fabricated artificial synapse can be stretched up to 60% strain while maintaining its synaptic functions.[192] In addition, the device implemented the process of "learning–forgetting–relearning", even in a stretched state of 35% strain.

As another critical element for implementing the neuromorphic computing, artificial neuron can be emulated by using memristive devices as well. Compared to synapses, the emulation of neuron is very difficult because a neuron must at least perform two complex processes of "integration" and "fire," in which a neuron can integrate information over a long time period and trigger action potentials above a critical value. Currently, most of memristive device-based artificial neurons are realized by coupling with additional commercial components, such as spike event generator.[199–201] Fortunately, Wang et. al. recently developed a hybrid neuro-transistor system that can emulate the neural functions at lower static power, which offers an alternative physical embodiment to build up a complete neural network.[202] However, to our knowledge, there is no report on flexible memristive device-based artificial neurons.

To perform complex computation tasks, flexible or stretchable memristive arrays are required. A crossbar array of memristive devices is analogous to a synaptic layer that connects the pre-neuron layer and the post-neuron layer, and multiple layers of memristive devices represent a multilayer artificial neural network (ANN) (Figure 6d). According to the encode information, ANN can be generally classified into conventional ANN with static input coding and spiking neural network (SNN) with relative spike timing coding. To date, several groups have adapted the array simulation based on flexible artificial synapses for recognition tasks, which can accelerate some intensive computation tasks. However, the performance of these devices is unsatisfactory, and it is still a big challenge for flexible memristive device-based neuromorphic computing, like in analogue computing. In addition, neuron emulation using physical embodiments needs to be extensively explored. There is a very long way to achieve a practical neuromorphic computing using flexible or stretchable memristive devices, but it opens a novel direction toward artificial skin perception.

3.3. Artificial Skin Perception Based on Flexible Synaptic Transistors

Flexible synaptic transistor is another emerging physical embodiment to execute artificial skin perception. Here, we focus on the prevalent neuromorphic computing using flexible synaptic transistors (although the synaptic transistors can also be employed to perform general-purpose computing). In the synaptic emulation of synaptic transistor, the voltage or current pulse is traditionally applied on the gate electrode as a presynaptic stimulus from a pre-neuron, and the channel conductance of the transistor is regarded as the synaptic weight (**Figure 7**a).[203] Compared with memristive devices that often exhibit the uncontrolled resistance tuning behavior due to the

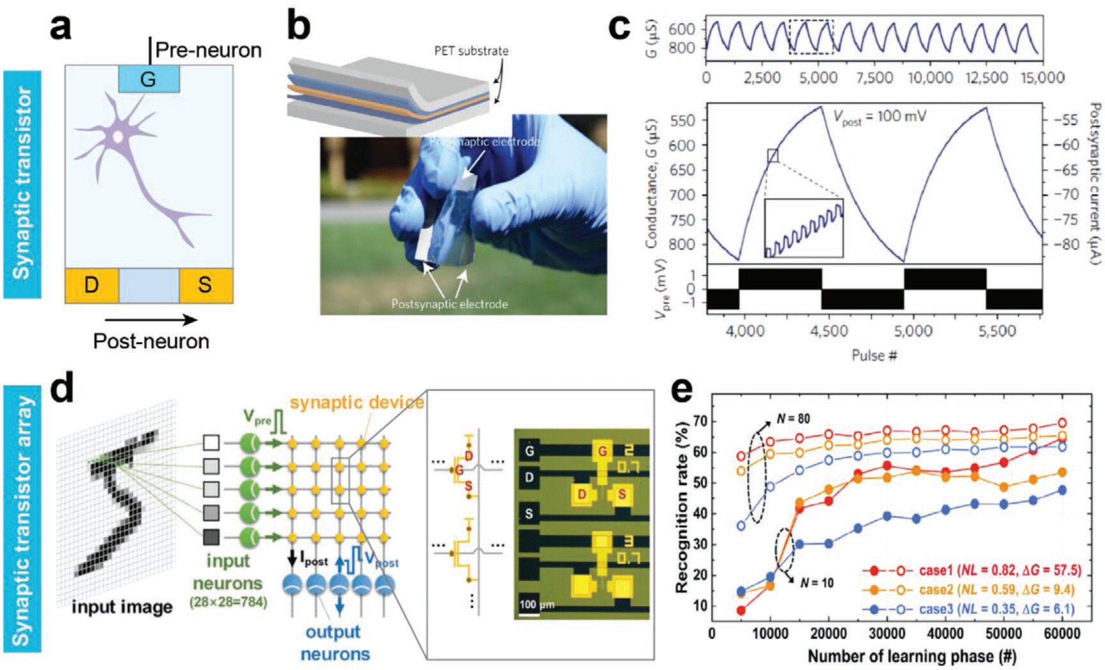

Figure 7. Flexible synaptic transistors for neuromorphic computing. a) Schematic of a transistor as an artificial synapse. b,c) Flexible organic electrochemical synaptic transistor with multiple discrete conductance states. d) Array configuration of synaptic transistors for pattern recognition. e) Handwritten digit recognition accuracy as a function of the number of learning phases based on the simulation of a flexible neuromorphic system. b,c) Reproduced with permission.[29] Copyright 2017, Springer Nature. d) Reproduced with permission.[222] Copyright 2018, Wiley-VCH. e) Reproduced with permission.[223] Copyright 2017, American Chemical Society.

stochastic formation/rupture of conductive filaments, three-terminal transistors can easily obtain continuous channel conductance states by gate control, which enables synaptic transistors to be a promising candidate for artificial synapse. A variety of synaptic transistors that exhibit various operational mechanisms such as electrochemical doping,[29,41,203–209] charge-trapping,[210–212] and light-assisted reaction,[213] has been continually developed for synaptic emulation and related computation tasks. Here, we focus on recent progress in flexible synaptic transistor-based devices and systems which have been or can potentially be executed for artificial skin perception.

3.3.1. Flexible Synaptic Transistors for Neuromorphic Computing

To effectively execute neuromorphic computing algorithms, flexible synaptic transistors should be capable of emulating synaptic functionality with high energy efficiency. Recently, tremendous efforts have been made in developing such flexible synaptic transistors, in which the fundamental synaptic properties such as EPSC, STP, LTD, LTP, PPF, and STDP learning rule, have been extensively verified.[29,204,214–219] For instance, a low-power flexible synaptic transistor has been reported based on an organic core-sheath nanowire, which can emulate the morphology and working principles of the nerve fiber.[220] In the synaptic transistor, each synaptic event consumed only around 1.23 fJ energy, which is comparable to biological synapses (≈10 fJ per synaptic event). In most of synaptic transistors, the retention time of conductance states is very short, ranging from seconds to hours, which limits their practical application in long-term invariant tasks such as pattern recognition and classification. By modifying or doping organic polymers, the retention time in synaptic transistors can be increased.[29,206] van de Burgt et al. demonstrated a flexible organic electrochemical synaptic transistor (Figure 7b), in which long-term data retention of more than one day was achieved due to the battery-like switching behavior.[29,221] The synaptic transistor also displayed a number of discrete conductance states with extremely low noise in a small voltage range (<1 V). In addition, the device is compatible with low-cost and large-scale flexible fabrication processes, which enables seamless integration of on-skin neuromorphic computing and learning in soft robotics and implantable prosthetics.

For practical applications such as classification and recognition tasks, large-scale synaptic transistor arrays are required. Taking handwritten digit recognition as an example, each image pixel of the handwritten digit after encoding is connected to a pre-neuron in the input layer, and synaptic transistors are located at the junctions between the input and output neurons.[222] As shown in Figure 7d, a presynaptic spike fired from one input neuron simultaneously acts on multiple columns, enabling a highly parallel computing way. Based on such configuration, Kim et al. demonstrated a flexible, lightweight, and disposable neuromorphic system for handwritten digit classification.[223] Simulation results demonstrated a recognition rate of about 70% based on the flexible neuromorphic system (Figure 7e). To date, the flexible synaptic transistor-based neuromorphic computing is still in its infancy and there is no experimental demonstration due to the difficulty in the fabrication of the larger-scale flexible synaptic transistor array. In addition, challenges remain in device downscaling and the improvement of switching speed for realizing a low-latency and energy-efficient artificial skin perception.

3.3.2. Synaptic Transistor-Based Artificial Skin Systems

As mentioned in Introduction, to enable artificial skin, flexible intelligent systems with integrated sensing and perception functionalities are highly desired. Owing to the capabilities of synaptic computing and compatible integration, flexible synaptic transistors are good on-skin perception candidates for the development of intelligent e-skin systems. Next, we will discuss recent progress about flexible synaptic transistors-based skin perception in integrated artificial skin systems.

The pioneer research on such integrated system is the demonstration of a dual-organic-transistor-based tactile perception system reported by Zhu and co-workers.[224] In the system, one suspended-gate OFET was used as the pressure-sensing mechanoreceptors for transducing dynamic tactile information into electrical signals, and another synaptic OFET acted as a localized perception element for processing the received electrical signals to gather cognitive tactile information (**Figure 8**a). By virtue of the short-term synaptic plasticity, pressure stimuli with varied intensity, frequency, and duration caused distinct postsynaptic currents in the synaptic OFET, due to the accumulation of holes at the chitosan/organic semiconductor interface. The postsynaptic currents read from the EPSCs represent the cognitive tactile information after computing, that is, touch speed, which is different from that obtained from the sensing device alone. More importantly, two OFET devices were seamlessly integrated through fully compatible fabrication processes that are also suitable for flexible electronics. However, as the authors mentioned, quantitative extraction of the dynamic tactile information, such as touch pressure, duration, and frequency, is very challenging in this system, due to the coupling effect of multiple tactile signals. Considerable efforts should be devoted into the signal coupling and decoupling analysis for such application scenario.

In addition, a neuromorphic tactile processing system with perceptual learning function was developed, which comprised a resistive pressure unit, an ionic conducting polyvinyl alcohol (PVA) cable for signal transmitting and a flexible indium-tungsten-oxide-based synaptic transistor (Figure 8b).[225] The pressure sensing unit and synaptic transistor are separated by the soft ionic cable, which could suppress the signal interferences between these two elements and endowed the system with flexibility. Similarly, the system utilized the short-term synaptic plasticity of the synaptic transistor to process dynamical pressure stimuli for extracting their spatiotemporal correlated feature. The extracted features could be further classified by using machine learning models to realize recognition capability, such as pattern recognition. The system possesses the ability of on-skin feature extraction, which could be integrated into robotics and prosthetics for intelligent artificial skin. However, the features extracted from the system are usually unstructured and user-dependent possibly due to the variations of device or touch process.

To further improve the mechanical flexibility of systems for soft robotic applications, synaptic transistors for processing

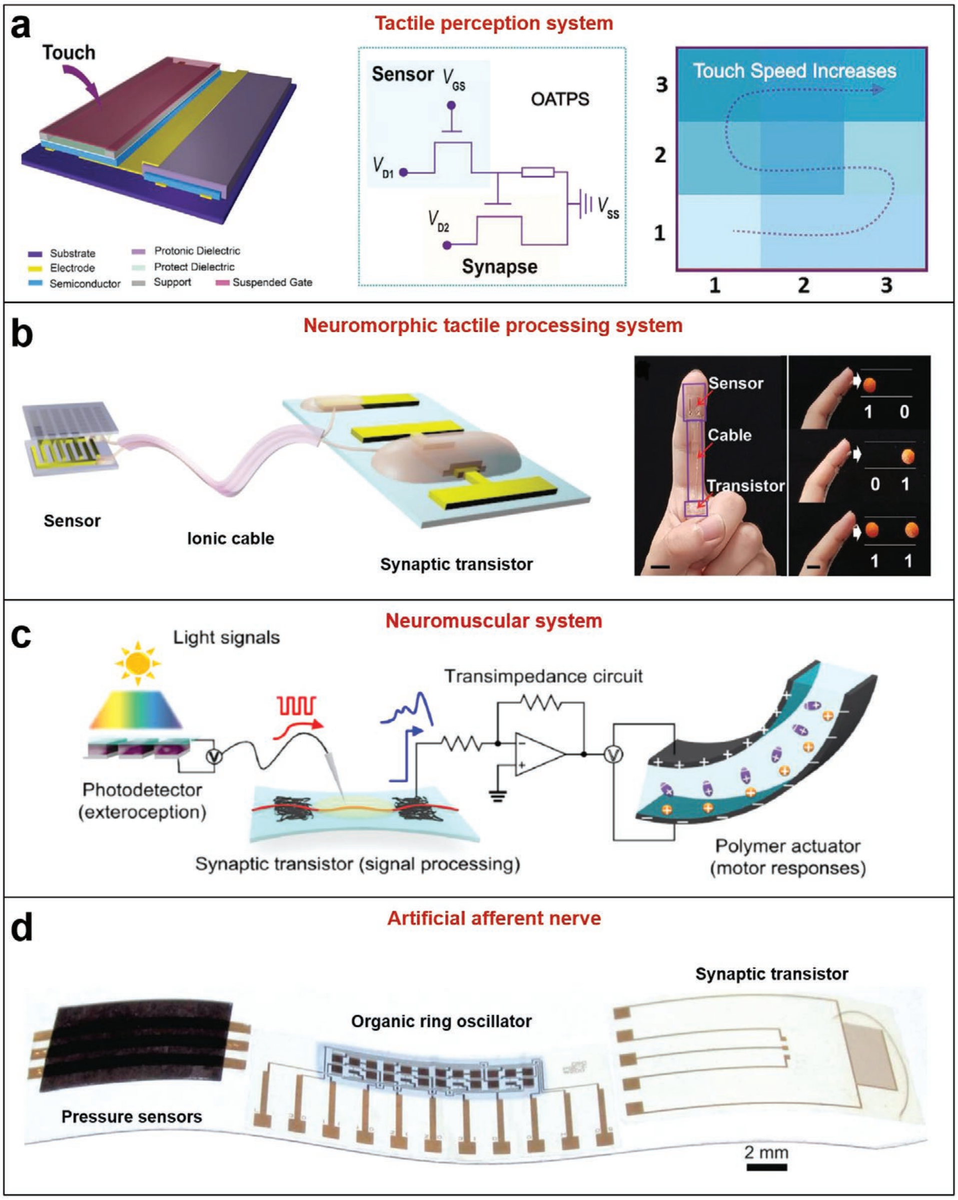

Figure 8. Flexible or stretchable artificial skin perception systems based on synaptic transistors. a) Flexible tactile perception system. b) Flexible neuromorphic tactile processing system. c) Stretchable neuromuscular system. d) Flexible artificial afferent nerve. a) Reproduced with permission.[224] Copyright 2017, Wiley-VCH. b) Reproduced with permission.[225] Copyright 2018, Wiley-VCH. c) Reproduced with permission.[226] Copyright 2018, The Authors, published by AAAS. Reprinted/adapted from ref. [226]. © The Authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. Distributed under a Creative Commons Attribution NonCommercial License 4.0 (CC BY-NC) http://creativecommons.org/licenses/by-nc/4.0/. d) Reproduced with permission.[228] Copyright 2018, The Authors, published by AAAS.

sensory signals should be stretchable. A stretchable synaptic transistor can be obtained by unconventional fabrication processes, such as spray-coating, printing, or transfer, which has been implemented in a bioinspired neuromuscular system (Figure 8c).[226] In the system, the single-wall CNT-based stretchable synaptic transistor was used to modulate the optical stimuli and generate the electrical postsynaptic signals to activate an artificial muscle actuator, which mimicked the biological sensory and motor functions. Combining with optics, electronics, and biological technology, the neuromuscular system enables an optical wireless communication method, which is promising for the development of next-generation soft robotics, neurorobotics, and prosthetics. It should not be neglected that the complete functional implementation of the system relied on a rigid silicon-based transimpedance circuit that converted postsynaptic currents to appropriate voltages.

In biological neural systems, neurons interact with each other in the spike (action potential) code, which is quite different from the coding scheme (direct coupling of current/voltage signals) in the aforementioned intelligent artificial skin systems. The spike code enables computing in human brain to be event-driven, distributed, parallel, and power efficient. To fully take advantage of the brain computing for skin perception, the first step is to covert the external stimuli information

Table 3. Comparison of three acritical technical approaches for skin perception: CMOS devices, flexible memristive devices, and flexible synaptic transistors.

Type	Advantage	Disadvantage	Application
CMOS device-based skin perception	Mature computing ability, functional reconfigurability, good mechanical compliance.	High fabrication cost, large form factor, poor system reliability.	Intelligent healthcare, interactive robotics, prosthetics, biomedical applications, industrial and environmental intelligent sensing, etc.
Flexible memristive device-based skin perception	Large-scale manufacturing, low fabrication cost, low-power consumption, small form factor.	Immature computing ability, unsatisfactory device performance, insufficient mechanical compliance.	Internet of Things (IoT), automatic drive, robotics, neuroprosthetics, etc.
Flexible synaptic transistor-based skin perception	Large-scale manufacturing, low power consumption, moderate fabrication cost, moderate form factor.	Immature computing ability, moderate device performance, insufficient mechanical compliance.	Internet of Things (IoT), automatic drive, robotics, neuroprosthetics, etc.

into spikes like those exchanged in neural systems. By virtue of organic electronics technology, flexible functional circuits such as ring oscillators are used to implement the signal conversion in artificial skin systems.[227,228] Combining with a pressure sensor and a synaptic transistor, researchers developed a flexible organic artificial afferent nerve (Figure 8d) that can collect pressure information, convert the external stimulus into spikes, and then perform synaptic computing to infer the underlying information.[228] The system realized a simple spike-based information processing way, but it inspires the feasibility of the SNN that is usually used to implement complex perception tasks such as speech recognition, emotion understanding, global decision, and consciousness. Moreover, the hybrid system can be directly used to stimulate a biological neuron, which enables flexible electronic devices to restore muscular activation or to substitute for human tissues or organs.

In the end, a comprehensive comparison of three acritical technical approaches for skin perception: CMOS device, flexible memristive device, and flexible synaptic transistor, are summarized in **Table 3**. Among them, CMOS device-based skin perception might be the sole way for industrial production at present, due to its mature computing ability and a complete product ecological chain including both hardware and software. In addition, it has other merits, such as functional reconfigurability and good mechanical compliance, compared to the flexible memristive device- and synaptic transistor-based skin perception approaches. As a result, CMOS device-based skin perception can be widely used for various intelligent and interactive applications, such as intelligent healthcare, robotics, prosthetics, and biomedical applications. However, there remains several challenges: 1) high fabrication cost and immature large-scale manufacturing ability due to the use of many unconventional fabrication techniques, such as transfer, alignment, and interconnection, 2) the large form factor especially when integrating more units and/or functions in a space-limited system, and 3) poor system reliability mainly due to the soft-hard interfaces. As for flexible memristive device- and synaptic transistor-based skin perception, the unique characteristics of these emerging computing devices, such as simple structure, high speed, low-power consumption, and compatible fabrication processes with current flexible and stretchable electronics, lead to the feasibility of low-cost and large-scale manufacturing. Compared to the stochastic memristive devices, synaptic transistors have the capability to obtain continuous channel conductance states (one of critical parameters for neuromorphic computing) but with the sacrifice of device size. The main weakness for these two approaches is the immature computing ability, which hinders their real application for industrial production at present. The immature computing ability, shown in the executions of specific computing tasks and the demonstration on low-density computing arrays, is mainly attributed to the unsatisfactory device performance and low device uniformity. In addition, the associated development environment for both the hardware and software is immature, compared to the CMOS-based approach. Currently, these two approaches can be considered as one promising solution for embedded and mobile systems, such as IoT, automatic vehicles, robotics, and neuroprosthetics.

4. Summary and Perspectives

The past few years have witnessed tremendous efforts in areas of flexible and stretchable electronics involving new manufacturing processes and innovative electronic computing devices (**Figure 9**), which enable a promising attempt to implement artificial skin perception. Unlike conventional data-centralized processing approach, artificial skin perception has the ability of processing sensory data within a flexible and stretchable sensing end, leading to a low-latency and energy-efficient system response. In this progress report, we discussed the recent progress in artificial skin perception, which involves the state-of-art computing units from commercial CMOS-based elements to novel flexible electronic devices. New manufacturing process techniques, such as ultrathin chips and flexible hybrid electronics, utilize the off-the-shelf computing components to implement the perception function in a flexible and stretchable system. Researchers have recently demonstrated such intelligent systems for advanced healthcare and gaming control.[229] Emerging flexible computing devices, such as memristive devices and synaptic transistors, can perform massively parallel, fast, and energy-efficient information processing. It is

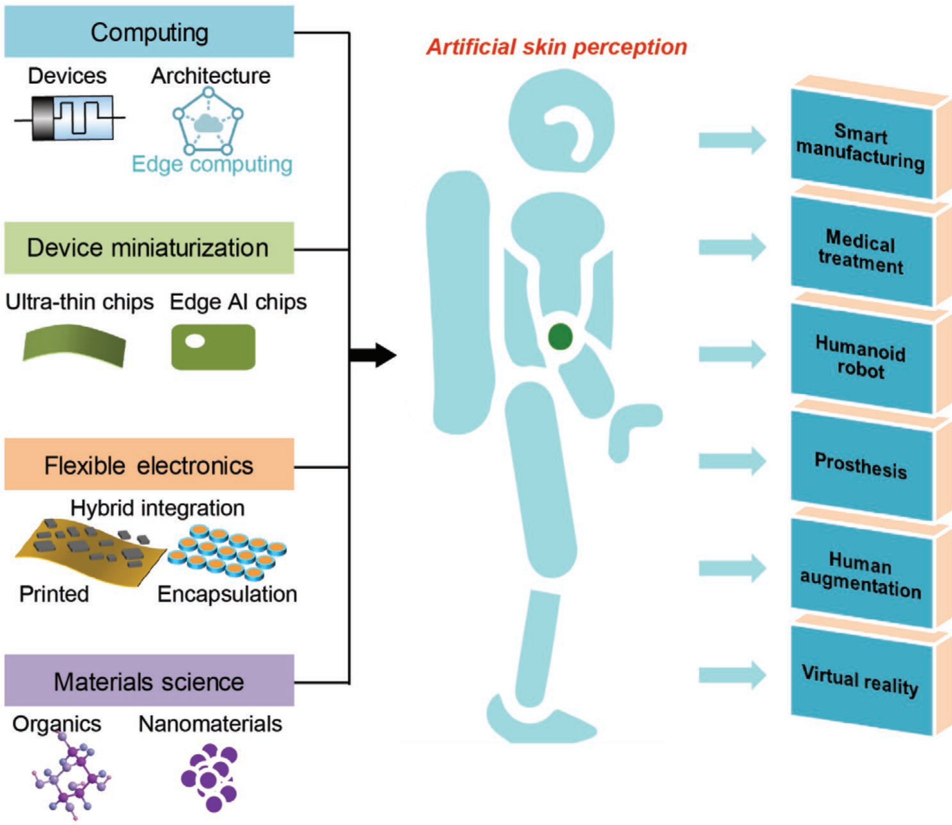

Figure 9. Perspectives of artificial skin perception. Materials science, flexible electronics, electronic device miniaturization, and emerging computing devices and architecture will enable sensory information to be processed in a low-latency and energy-efficient way, potentially promoting the development of many domains.

promising to integrate them into current flexible and stretchable systems to implement general computing or neuromorphic computing for sensory perception. Nevertheless, artificial skin perception is still in its infancy, particularly for emerging computing devices-based perception. Challenges remain in several respects such as limited computing ability, immature system-level integration, and increased form factor, which are discussed in detail below.

1. Limited computing capability. Current artificial skin systems with the perception functionality are limited to solving relatively simple computation tasks, such as threshold evaluation and peak detection, which are far away from complex and varied requirements like materials recognition, pose estimation, shape perception, and in situ analysis. For CMOS device-based artificial skin perception, integrating more functional components into flexible or elastic materials is a direct way to increase the computing capability of the system. However, advanced intelligent algorithms like deep learning are still challenging to be deployed in the flexible and stretchable systems, because there are millions of internal parameters need to be simultaneously stored and adjusted during running procedures.[230–232] Recently, edge artificial intelligence (AI) chip technology, referring to running AI processing on a standalone device, enables the miniaturization of AI-capable processors. Several prototypes of edge AI chips, such as Arm Cortex-M55, Ethos-U55, and tensor processing unit (TPU), have been successfully developed by companies like ARM, Apple, Intel, and Google. The edge AI chips offer a possibility to realize a much stronger and more powerful artificial skin perception with the help of flexible hybrid integration. For emerging computing devices-based artificial skin perception, there is still a long way to achieve real applications. This is due to the fact that most physical devices can only perform a single or several-step computation, which is far from enough for completing a practical task. Depending on the specific application, developing an artificial skin system where only simple computation steps are required might be an effective way to utilize the emerging computing devices at the current stage. Bioinspired systems can provide some valuable guides toward this direction.
2. System-level integration. Seamless integration in system level is challenging for artificial skin perception, partly because it involves multidisciplinary domains such as materials, mechanics, electrical engineering, and computing science. For the promising hybrid integrated systems, despite that many efforts have been made recently, soft–hard interface issue is still one of the biggest barriers before its commercialization. A variety of fabrication process techniques and structural design strategies have been adapted to improve the stretchability and reliability of the system. However, there is still a lack of universal standards used to define critical

process steps and layout parameters, such as interconnection structures, line widths, unit-to-unit connectors, and layer-to-layer connections, as in CMOS technology. Moreover, simulation tools for predicting the performance of an integrated system as a function of mechanical strain should be explored. For artificial skin perception systems in which the hybrid integration is not accepted, devising a compatible process that allows monolithically integrating both soft sensing elements and high-performance computing units into a flexible and stretchable substrate is very challenging. Printed electronics are capable of creating such artificial skin systems, but their computing ability is limited due to the low or moderate device performance of current organic electronics. Furthermore, to achieve a CMOS components-free stretchable artificial skin system, intrinsically stretchable materials, devices, and systems, in their early infancy, deserve more attention.[233,234]

3. Increased form factor. Compared to current e-skin systems, many functional modules such as computing units, memory, and peripheral circuits, need to be integrated into an artificial skin perception system. These components and their interconnection with other soft elements will significantly increase the volume of the whole system, leading to the increase of form factor that goes against the miniaturized and low-cost fabrication principle. In addition, it may cause discomfort to users and is not aesthetically pleasant, especially in the case of a large-area perception system where a mass of sensors and computing units are required.

Apart from these challenges, some other issues such as reliable sensing, wireless communication, and power supply, should be overcome for practical application of artificial skin perception systems. Precise and reliable sensing is the foundation of sensory perception, for which readers may refer to the recent review articles.[235,236] As for wireless communication aspect in artificial skin perception system, most sensory data will be locally processed within the system, leaving little data to be sent out of the exterior system for further analysis and storage. In this way, the volume of data that needs to be sent to external processing units will greatly decrease, which can reduce the burden of wireless data transmission. As ideal as this is, achieving so remains a challenge. Power consumption will become another major concern in the design of artificial skin perception systems. Different from e-skin systems, a large proportion of system power consumption in artificial skin perception systems will be shifted from data transmission to data computing. Hence, the design of power supply requires a careful consideration on the data storage, computing, and communication architecture. In the end, we hope artificial skin perception will provide a new computing paradigm for future flexible and stretchable systems, paving the way toward an authentically intelligent artificial skin for the applications of advanced wearable devices, adaptive prosthetics, and interactive robotics.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

artificial skin, edging and neuromorphic computing, electronic skin, skin perception, soft robotics

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