ADVANCED INTELLIGENT SYSTEMS
Open Access
www.advintellsyst.com

Recent Advances in Perceptive Intelligence for Soft Robotics

Zhuofan Lin, Ziya Wang, Wenyu Zhao, Yingtian Xu, Xiaopu Wang, Tianwei Zhang, Zhenglong Sun, Lan Lin, and Zhengchun Peng**

Over the past decade, soft robot research has expanded to diverse fields, including biomedicine, bionics, service robots, human–robot interaction, and artificial intelligence. Much work has been done in modeling the kinematics and dynamics of soft robots, but closed-loop control is still in its early stages due to limited sensory feedback. Thanks to the advancement in functional materials, structures, and manufacturing techniques for flexible electronics, flexible and stretchable sensors are developing rapidly. These sensors provide feedback for closed-loop control tasks and enable soft robots to effectively explore the unknown and safely interact with humans and the environment. Herein, recent advances in perceptive soft robots that utilize flexible/stretchable sensors and functional materials are outlined. The perceptive functions of soft robots from two different aspects, that is, proprioception and exteroception, are summarized. Furthermore, the constructions of autonomous soft robots by integrating both proprioceptive and exteroceptive capabilities for closed-loop control tasks and other challenging tasks in the real world are discussed.

1. Introduction

Biology has long been a source of inspiration for building increasingly capable machines. Distinguishing features of biological systems include flexibility and physical compliance, and they exhibit low complexity in their interactions with the environment.[1] Traditional, rigid robots are used extensively in manufacturing and can be specifically programmed to perform a single task efficiently. Nevertheless, rigid robots often with limited adaptability, interactivity, and safety because of the rigid links, motors, sensors, controllers, and joints.[2] These limitations are reflected in some tasks, such as interacting with humans in pathology and nursing, performing search and rescue tasks in unstructured obstacles, and underwater exploration tasks. Fortunately, soft robots offer an opportunity to fill these gaps.[3] Soft robots were defined as systems capable of autonomous behaviors primarily consisting of materials with moduli in the range of the moduli of soft biological materials.[4] Their main body is made of intrinsically soft or extensible materials (e.g., silicone rubbers, gels, and polymers) that can deform and absorb energy from collisions. These materials exhibit many of the same elastic and rheological properties of soft biological matter and allow the robot to remain operational even as it is stretched and squeezed. Furthermore, soft robots have a continuously deforming structure with relatively many degrees of freedom (DOFs), which has the potential to exhibit unprecedented adaptability, sensitivity, and agility. Because of the near absence of rigid materials and their similarities to natural organisms, soft robots may be considered a subdomain of the more general fields of soft matter engineering or biologically inspired engineering.[5]

In the last few years, soft robots have been rising as an emerging research topic with some remarkable achievements.[6–8] They rapidly open new possibilities for typical robotic tasks building on intrinsically soft materials or compliant mechanisms. However, the control of soft robots is much more complex than rigid robots, because they have almost infinite DOFs and can be deformed by both internal driving and external loads. Moreover, it is difficult to accurately predict the response of a soft robot because of the complex behavior of the hyperelastic materials used, such as nonlinearity, hysteresis, viscoelastic effect, large strain, or deformation. In the early years, researchers predicted the movement of soft robots based on an established precise model through open-loop control. The finite-element method (FEM) is the most general method of open-loop modeling because it can be applied to any shape or actuation mechanism.[9] However, open-loop control is limited to situations in which the

Z. Lin, Z. Wang, L. Lin, Z. Peng
Center for Stretchable Electronics and Nano Sensors
College of Physics and Optoelectronic Engineering
Shenzhen University
Shenzhen 518060, China
E-mail: wangziya@szu.edu.cn; zcpeng@szu.edu.cn

W. Zhao, Y. Xu, Z. Sun
School of Science and Engineering
The Chinese University of Hong Kong
Shenzhen 518172, China

X. Wang, T. Zhang
Shenzhen Institute of Artificial Intelligence and Robotics for Society
Shenzhen 518129, China

The ORCID identification number(s) for the author(s) of this article can be found under https://doi.org/10.1002/aisy.202200329.

DOI: 10.1002/aisy.202200329

environment and properties of the objects that the robot will interact with are already well known. In the absence of feedback, small nonidealities in taking time-varying materials properties into account can propagate and result in large errors through sequential actuation tasks.[10] Therefore, a soft robot cannot perform a task accurately with open-loop control even in a well-constructed environment.[11] The lack of precise control on soft robots significantly weakens the advantages of intrinsically soft materials and compliant mechanisms and seriously hinders future applications. Interestingly, deformable shape control is also a very active research topic in the field of robotics in recent years, where rigid robots are used to control soft objects (such as ropes, tablecloths, and sponges).[12] The difference between soft and rigid robot control is whether the robot itself is soft or not, but the goal of control is the same: both are shape control of deformable objects.

Closed-loop control on soft robots is necessary when the environment or task is varied or uncertain and sensing is essential for the soft closed-loop control system. Obtaining autonomy and going beyond open-loop control requires the integration of multimodal sensors into these soft-bodied systems to provide sensory feedback. In the human physiological perception system, according to the classification system described by Sherrington,[13] a person's bodily sense of self consists of three interrelated physiological systems: proprioception (sensory input generated by the body itself), extrasensory (sensory input generated from the surrounding environment), and interoception (awareness of sensations within the body). Sensor feedback of the actuator's deformation state and its contact state with the surrounding environment is the basis of the closed-loop control of the soft robot. However, there are many challenges in manufacturing perceptive soft robots. Although a great deal of work has been done on modeling the kinematics, statics, and dynamics of soft robots, closed-loop control is still in its early stage, owing to the limitations of sensors to feedback on a robot's shape in real-time.[14] Conventional sensors suffer from poor-quality signal transduction due to their rigidity in capturing analytes for soft targets.[15] In addition, traditional sensing techniques (e.g., embedding magnets and Hall sensors in soft robots[16]) introduce unnecessary stiffness in soft robotic systems and hinder soft robot actuation and deformation. Notably, sensing has been investigated since the birth of soft robots,[17] sustainable progress has been achieved, benefiting from advances in soft materials and structures, flexible and stretchable sensors, fabrication techniques, and flexible electronics. Flexible and stretchable sensors are prominent in emerging electronic fields, demonstrating a significant mainstay during the evolution of soft robotics sensing.[15] Especially self-sensing technology for soft robots has dramatically advanced the development of integrated systems of actuation and perception, benefiting from the development of advanced and functional materials. Nevertheless, soft robotics sensing could be more developed than actuation and stiffening in soft robotics.

In the past decade, a large number of review papers have been published, focusing on the design,[4] material,[18] fabrication,[6] and control[10] of soft robots. A few review articles have discussed the sensing aspects of soft robots, for example, Wang et al.[11] published a review article on understanding the physical perception of soft robots. However, the closed-loop control frame of soft robots based on sensory feedback has yet to be discussed in depth. Recently, Shih et al.[19] published a review focused on electronic skin and machine learning (ML) for soft robots and briefly touched on haptic feedback. This review did not cover the proprioceptive aspect of soft robots. In this review, we present a comprehensive review of the recent development of perceptive soft robots, focusing on the advanced perceptive intelligence in soft robotics, including both proprioception and exteroception. We also summarize the advancement of closed-loop control of soft robots based on perceptive intelligence. Furthermore, we identify the key obstacles and provide a perspective in this research field.

2. Sensory Feedback for Soft Robotics

Several different types of soft robots have been developed to perform closed-loop control tasks such as motion, manipulation, reaction, and exploration (**Figure 1**). Their capabilities could be significantly enhanced by enabling both proprioception and exteroception,[11] including bending, twisting, stretching, pressure, temperature, etc. For example, when a soft-jaw robot is in a closed-loop manipulation task, compressive and tensile strain distribution can be used for closed-loop control of its locomotion. Tactile contact helps the soft-jaw robot recognize the objects' physical properties and shape, and contact pressure helps the soft-jaw robot adjust its gripping force to improve stability.

Compared with rigid robots, soft robots can change their shape actively and passively due to inherent material compliance. This property enables soft robots to be safer, more adaptable, and more effective in environment–robot interaction.[11] However, the high-dimensional deformations of soft robots increase the difficulty of control. Specifically, the response of soft robots is difficult to track under certain conditions due to the complex deformation of the hyperplastic materials or compliant structures. In addition, external loads and force can also change soft robots' shape, position, and status of motion passively. To solve these problems, developing sensors and enabling technologies to provide diverse potential solutions for soft robot perception is essential.[20] Integrating sensors into soft-bodied systems to supply the ability of sensory feedback is of critical significance for the realization of the autonomy and intelligence of soft robots.[21] Sensory feedback allows the soft robots to track their shape-deformation and motion, sense the state of the surrounding environment, and enable closed-loop control of the soft robots. Generally speaking, there are two strategies to achieve sensory feedback. One is to integrate sensors into soft robot systems, which need to have qualities such as stretchability, low modulus, easy integration, and high accuracy. This strategy is the simpler and the more common one. Another is self-sensing actuators (SenActs), which refer to a system where the same piece of material is simultaneously used for actuation and sensing.[22] The "smart materials" or "smart structures" are utilized to achieve accurate synergistic sensing and closed-loop control systems with no additional cost.[23] In general, the state information of a system considered to be self-sensing is provided by reading the behavior of the input signals, using special input signals, or adding additional cues to existing hardware.[22]

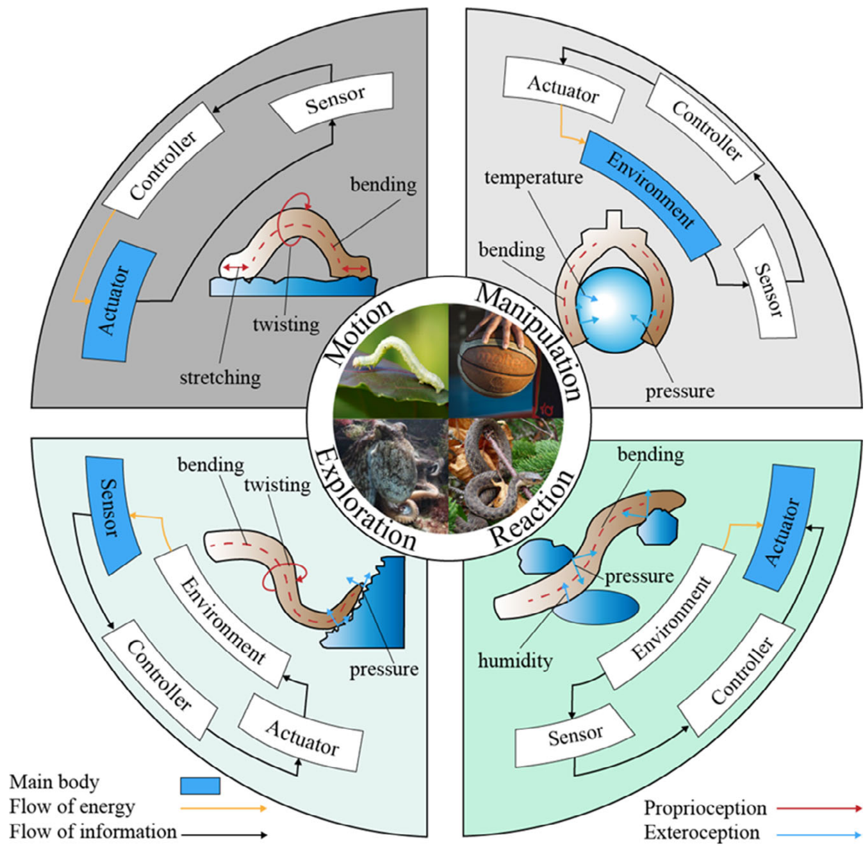

Figure 1. Demonstration of bioinspired soft robots with proprioception and exteroception for performing different closed-loop control tasks.

Robots have been developed as automated machines with some human or biological-like intelligence (e.g., perception, planning, movement, and collaboration) to simulate or replace humans in performing various tasks. In biological systems, different receptors are used to convey information about numerous parameters,[24] like temperature, sound, force, pain, etc. Therefore, for clarity and convenience in discussing soft robot perception, we focus on the subsystems of the perceptual system—sensory input generated by the body (proprioception) and sensations from the surrounding environment (exteroception). The distinction between these senses is for better understanding in this review. In reality, there may be considerable overlap between proprioceptive and exteroceptive systems to ensure a central representation of the body.

2.1. Proprioception

Proprioception is the ability to feel inputs (e.g., position, shape, force, and locomotion) generated by the body, which is a valuable trait in complex robotic systems.[25] By convention in biological systems, proprioception consists of four senses:[26] 1) the sensation of movement and limb position (kinesthesia); 2) the sensation of tension or strength; 3) the sensation of effort, and 4) the sense of balance. Kinesthesia refers to sensations of limb position and movement (e.g., bending, twisting, and stretching).[27] In the human sensory system, the two senses of limb position and movement share input from the same mechanoreceptors within the muscles, the muscle spindles.[28] The corresponding feedback is projected to the cerebral cortex to provide information about body posture and whether or not it is moving. In soft robotic systems, due to the soft, flexible, and stretchable nature of the soft actuator material and the different compliant structural designs within the soft actuator, the connection between the input power source and the soft actuator output is difficult to estimate and measure. The kinesthetic perception method of the soft robot is proposed to solve the nonlinearity and nonreciprocity between the power input and the action output of the soft robot. It allows soft robots to quantify their position and motion information and use them as feedback signal inputs to the controller to compensate for soft robots' uncertain deformations. Therefore, kinesthetic perception is crucial for soft robot proprioception and closed-loop control, which has been extensively studied. Therefore, we focus on kinesthetic perception as the main line to better elaborate the proprioception of soft robots. Based on the available literature, we discuss kinesthetic perception in three categories: bending perception, twisting perception, and stretching perception.

2.1.1. Bending Perception

Bending is the most widespread movement pattern in soft robots. To date, soft robots with bending motion as the primary movement mode have been developed and used in a large number of applications, such as soft bending actuators,[29–31] soft grippers,[32] and crawl robots.[33] Soft robots are more pliable than rigid robots because they are made of low-elastic-modulus materials and are more compatible with human tissue and soft objects. However, many of these flexible actuators need more sensing capability to monitor the movement of the actuator in real time. In addition, the lack of effective feedback loops may even cause difficulties in improving adaptability and interactivity. One strategy to achieve bending sensing of the soft robots by sensory feedback is to integrate several stretchable sensors into soft bending actuators to measure the curvature, such as fiber optic sensors,[34] microfluidic sensors, and[35] conductive elastomer sensors.[36,37] In addition, several research groups have embedded different flexible bending sensors on soft robots to improve their ability, such as sensing bending deformation with high accuracy,[38] bending deformation in multiple directions,[39] and curvature estimation with fast response and high robustness.[36] So far, bending sensing methods used for soft robots can be roughly categorized into three groups: optical, microfluidic, and electrical.

Optical methods have been proposed that integrate optoelectronic sensors (e.g., optical waveguide sensors,[38] and fiber optic sensors[34]) into soft robots for bending sensing. The optical sensors appear as a class of soft sensors that detect motion through changes in the emission and reception of light. Due to the high quality, low price of fibers and optoelectronic components, and compatibility with these large strains caused by soft actuators, optical sensors have broad applications in sensing curvature.[40] For example, Zhao et al.[38] reported using stretchable optical waveguides for bending sensing in a fiber-reinforced prosthetic hand. They measured the light power loss of the waveguide using a photodetector to indicate the deformation of the prosthetic hand. The 3D integration of the sensors and actuators means that the waveguides are parts of the body and they will deform when the actuator does, serving as proprioceptive sensors to feel the bending of the fingers like the natural hand (**Figure 2**a).

Microfluidic sensors, as a liquid-based approach, possess a high degree of deformability.[35] Several materials can be chosen to make microfluidic sensors, including carbon greases,[41] ionic liquids,[35,42,43] liquid metals (LMs),[44,45] etc. For example, Xie et al.[42] designed a liquid metal (EGaIn) microfluidic stretch sensor as a transverse elongation (EL) sensor and an expansion (EP) sensor and crossed them to form a combined sensor that can acquire 2D accurate sensing feedback (Figure 2b). This combined sensor was integrated into a flexible pneumatic jaw to simultaneously obtain sensory feedback on EL and EP caused

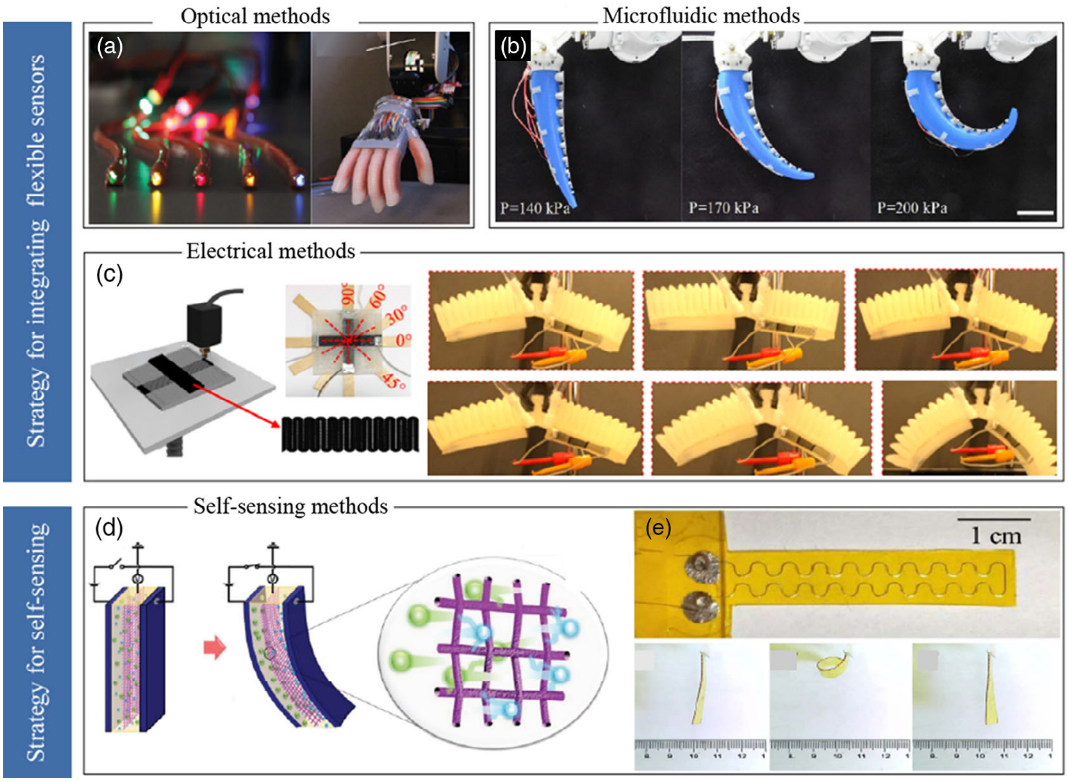

Figure 2. Demonstration of soft robot with bending perception. a) Optical waveguide strain sensors are integrated into fiber-reinforced soft robotic hands for bending sensing. Reproduced with permission.[38] Copyright 2016, American Association for the Advancement of Science (AAAS). b) Liquid metal (EGaIn) microfluidic combined stretch sensors integrated into a pneumatic soft-touch hand can obtain 2D bend-sensing feedback. Reproduced with permission.[42] Copyright 2020, Institute of Electrical and Electronics Engineers (IEEE). c) Active material strain sensors are integrated into pneumatic soft grippers for multidirectional bending sensing. Reproduced with permission.[54] Copyright 2020, American Chemical Society. d) Bending self-sensing ion soft actuator. Reproduced with permission.[55] Copyright 2019, Wiley-VCH. e) Bending self-induction electrothermal actuator. Reproduced with permission.[59] Copyright 2021, Institute of Electrical and Electronics Engineers (IEEE).

by pneumatic EP. They experimentally verified the sensory response, as well as the accuracy of the bending sensing system and model under air-pressure bending, external pressure bending, and gripping conditions. However, fluids with high viscosity and resistivity may be difficult to be injected into microchannels during the manufacturing process and may affect the response time of the sensor, leading to complicated measurements.[44]

The electrical methods integrate sensors made of sensitive materials with good electrical conductivity and the ability to withstand a wide range of deformation (e.g., conductive polymer sensor[37,46]) into the soft robots for bending sensing. In recent years, several types of skin-mountable and wearable sensors have been proposed using nanomaterials coupled with flexible and stretchable polymers.[47] Flexible strain sensors based on the elastic substrate of the conducting nanomaterial, including carbon nanotubes (CNTs),[48] reduced graphene oxide (rGO),[49,50] Ag nanowires(AgNWs),[39] and metal nanoparticles,[51] have been widely reported. These sensors maintain good performance under large deformation and adapt to the bending motion of flexible robots. For example, Yeo et al.[36] integrated a conductive elastomer strain sensor, which has an extremely high sensitivity to strain displacement, into a soft pneumatic actuator, to measure the bending motion of the actuator. The strain sensor comprises a thin layer of screen-printed silver nanoparticles (AgNPs) on an elastomeric substrate, which provides the sensor with excellent electrical conductivity and robust electrical properties even under high strain conditions. Furthermore, these sensors have a similar modulus as the soft robots with no impact on their actuation.[52] Banerjee et al.[37] proposed an ultraelastic, ultrasoft natural rubber composite containing multiwalled CNTs to produce a conductive elastomer sensor with striking properties such as low electroosmotic flow, ultrasoftness, elastic modulus in the kPa range of 100% EL, ultrastretchability, and high tensile strength. In addition, the ease of fabrication and customization makes these sensors valuable for bending sensing in soft robots. Compared with traditional manufacturing, 3D printing technology benefits from the diversity of raw materials, precise structural design, and simplified preparation process, providing a promising method for manufacturing flexible strain sensors.[53] For instance, Mousavi et al.[54] used 3D printing to integrate a multidirectional, anisotropic, and shrinkage-resistive strain sensor directly into the interior of a soft pneumatic robot (Figure 2c). The sensing elements and conductive interconnections of the sensor system were 3D printed using carbon nanotube-reinforced polylactic acid (PLACNT). The ability to fabricate sensors with customized footprints and directional selectivity during 3D printing of soft robotic systems paves the way for highly customizable, highly integrated, and versatile soft robots that are better able to bend sensing and proprioceptive perception.

Another strategy for bending sensing in soft robots is the application of a self-sensing system. The SenAct is the most central part of this system, in which sensing and actuation are integrated within a single component for real-time monitoring of the actuator movement.[55] The self-sensing capabilities of soft robots likewise include proprioception and exteroception, which are classified according to the properties of the functional materials. Functional materials that are sensitive to deformation (sensing) and responsive to specific stimuli (actuation) are often used to manufacture proprioceptive self-sensing soft robots. Moreover, the actuation and sensing of a self-sensing soft robot are realized by the same component, so the function of sensing is usually related to the actuation method, for example, a self-sensing robot with mainly twisting motion senses deflection. However, the functional materials that make up exteroception self-sensing soft robots are usually sensitive to environmental information (sensing) while corresponding to the stimulus (actuation), and the environmental information and stimulus cannot be the same to avoid coupling of actuation and sensing, for example, an electrically actuated humidity self-sensing soft robot.

The most commonly used bending self-sensing methods are resistive self-sensing, and the selection of the sensing strategies largely depends on the correlation between the measurands and the features of the actuator. Resistive self-sensing mechanisms require the indirect measurement of bending by simultaneously measuring resistance along the actuator electrodes during actuation.[55] One approach is to measure the voltage drop across the electrodes of the movable portion of the actuators and compare it to the voltage drop of the fixed portion to quantify the resistance change and thus estimate the curvature of the actuator. For example, Punning et al.[56] described a novel bending self-sensing ion-conductive polymer metal composite (IPMC) actuator. The curvature of the actuator was estimated by measuring the voltage drops along the electrodes in the movable section and comparing it with the fixed section to quantify the resistance change. However, the accuracy of the indirect curvature measurement is compromised by the inevitable differences in the physical and geometric properties of the fixed and moving portions.[57] This approach by measuring the voltage drop between electrodes is also used for ion self-sensing soft robots, where the curvature is estimated from a sensing signal consisting of the electrodes-induced potential and the ions-induced potential. Tabassian et al.[55] developed a self-sensing ion soft actuator that uses 3D graphene mesh electrodes to precisely sense the bending motion during actuation (Figure 2d). The graphene mesh electrode is permeable to moving ions within the ion-exchangeable polymer, shows low resistance, and maintains high conductivity over large bending deformations. At a very low drive voltage of 0.1 V, the deformation can be estimated accurately using a SenAct system even if the resulting displacements are very small. However, inferring the resistance value by measuring the voltage drop along the active element is still a complex task. An alternative approach is to use patterned electrodes to measure the resistance change during actuation. In this approach, the electrodes are split into separate sensing and actuating parts, and the resistive sensing signal is obtained from the electrode part that is not connected to the active element. Kruusamäe et al.[58] proposed a self-sensing ionomer–metal composite actuator by special patterning of the relative metal electrodes of IPMC strips. An actuator and a sensor are formed on a piece of material, and bending self-sensing is achieved by measuring the changing resistance of the sensor part of the structure. The electrodes are split into separate sensing and actuating sections by patterning techniques, which reduce the crosstalk effect between adjacent segments to some extent. However, the split electrodes require the connection of additional wires to collect sensing signals, resulting in an increase in actuator size and undermining its ability to be used in tiny systems. Depending on the properties of different functional materials, the relationship between curvature and resistance for a particular self-sensing soft robot can also be obtained by other approaches, such as indirectly measuring the resistance by measuring the temperature of the actuator[59] and estimating the actuator resistance by vision signals.[60,61] For example, Cao et al.[59] proposed a resistive self-sensing method based on electrothermal actuators, which achieves bending self-sensing of the actuator by measuring the temperature to estimate the change in resistance of the embedded microfilament heater (Figure 2e). Zhao et al.[60] proposed a resistive bending SenAct with electrical and visual dual-channel signal feedback functions. Cellulose paper and polyimide tape are assembled as a bimorphic actuator layer, on which an MXene/graphene bilayer is coated for electrothermal actuation function and electrical signal feedback, and a thermochromic sandwich layer is used for real-time visual sensing signal estimation of the curvature of the actuator. These two approaches provide ideas for specific bending self-sensing soft robots that eliminate the crosstalk effect of electrodes between actuation and sensing. Nevertheless, the challenge of low accuracy of curvature sensing limits the performance of sensing soft robots and further quantification of the relationship between bending-induced changes (temperature or vision) and curvature is the key to developing intelligent bending self-sensing soft robots.

2.1.2. Twisting Perception

Soft robots with twisting movements as the main mode of action have been used in many different fields, especially in the bionic field (e.g., bionic torsional artificial muscles,[62–64] and bionic vine soft robots[65]). Furthermore, because of the infinite DOF, twisting movements also occur in the bodies of most soft robots. In the biological system, natural muscles achieve torsional rotation by combining with the skeleton, and they are integrated with sensory and signaling functions to form a feedback loop.[66] However, currently developed torsional soft robots or artificial muscles and sensing devices always work under external stimuli and require a separate control and signaling system, increasing the complexity of muscle design. These are two strategies to achieve twisting sensing and proprioception for soft robots, which aim to improve their ability to move and bionic degrees. The first strategy is to integrate flexible sensors into the body of the soft robot, which usually have a strong correlation with the response to twisting and are well suited to the twisting motion of the soft robot. They can provide sensory feedback without using external infrastructures.[67] The introduction of sensors into soft robot systems for twisting sensing can improve various aspects of soft robot capabilities, such as estimation of torsion angles for precise positioning of continuous soft robots; acquisition of key information such as external disturbances and target object parameters; reconstruction and closed-loop control of complex shapes of soft robots; etc. Notably, a major limitation for most existing sensors is that they can only measure a single curvature for a circular shape of soft robots due to their working principle.[68] In reality, however, soft robots can have arbitrarily 3D shapes and therefore usually require a sensor network for the perception of twisting motion. Several common approaches are summarized for twisting sensing of soft robots, including optical, microfluidic, and electric methods.

Optical methods integrate the optical sensors (e.g., fiber optic sensors[62,65,69,70]) into the soft robots for twisting sensing, and these methods have been demonstrated. For soft robots with predominantly twisting motion, in general, there are two methods for deflection estimation here: the twist sensor method and the sensor network method. The simplest method is to embed twisting sensors inside the soft robot body for direct measurement of deflection. For example, Yang et al.[71] designed a soft robot spiral gripper inspired by twisted plants that require only a single pneumatic control to execute the twisting motion and firmly grasp the target object. This soft-body robotic spiral gripper has an embedded high-birefringence (HiBi) fiber in a Sagnac loop configuration to effectively sense the twisting angle (**Figure 3**a). The second one is sensor network methods, which are to design a series of flexible sensors as a sensor network and derive a complex analytical model or apply ML techniques for direct deflection estimation. Van Meerbeek et al.[69] described an internally illuminated elastic foam trained to detect its twisting by ML techniques (Figure 3b). Optical fibers beam light into the foam while receiving diffusely reflected waves from internal reflections. The diffuse reflected light is interpreted by ML techniques to predict whether the foam is distorted or not, and ML techniques are also used to predict the size of the distortion. At the new data point, the model predicted the type of distortion with 100% accuracy, with an average absolute error of 0.06° in the magnitude of the distortion. This capability could give the soft robot more complete proprioception.

Microfluidic methods realize the twisting sensing for soft robots by embedding the microfluidic sensor network, which is applied to decouple twisting from other motion states (disturbances). For example, Lin et al.[72] developed an embedded fiber-based microfluidic displacement sensor network based on a similar high-density sensor design for measuring the torsional state of the robot (Figure 3c). Flexible but nonstretchable/noncompressible nylon fibers are placed in air-filled microchannels with flexible elastic fingers. These passive sensors transmit information from the soft robot to a nearby display assembly where a digital camera records displacement and pressure data. This physical approach is accompanied by hysteresis loops (drive paths do not overlap with release paths), which are due to the internal characteristics of the sensors.

Electrical methods embed conductive materials sensors (e.g., conductive elastomer sensors,[73] and conductive hydrogel sensors[74,75]) into soft robots to achieve twisting sensing. An ideal soft sensor should provide state information along the body of a soft system with minimal effect on the dynamics of the system.[76] Wang et al.[74] designed a highly stretchable hydrogel resistive sensor for multimodal sensing of soft fingers, which is simple and low cost to fabricate. The hydrogel has a maximum tensile strain of up to 1200%, which ensures that it can withstand large deformations of pneumatic actuators. The sensor can sense twisting in actuator state estimation with high sensitivity, low hysteresis, and high reliability (Figure 3d). However, there are no adequate studies on how the hydrogel sensor simultaneously estimates the robot's kinematic configuration and the external forces applied to it. Moreover, due to the twist and other motions of the elastomer sensor being coupled, the sensor cannot make an accurate calculation of the deflection, only a rough estimate of the twisted state in the electrical approach.

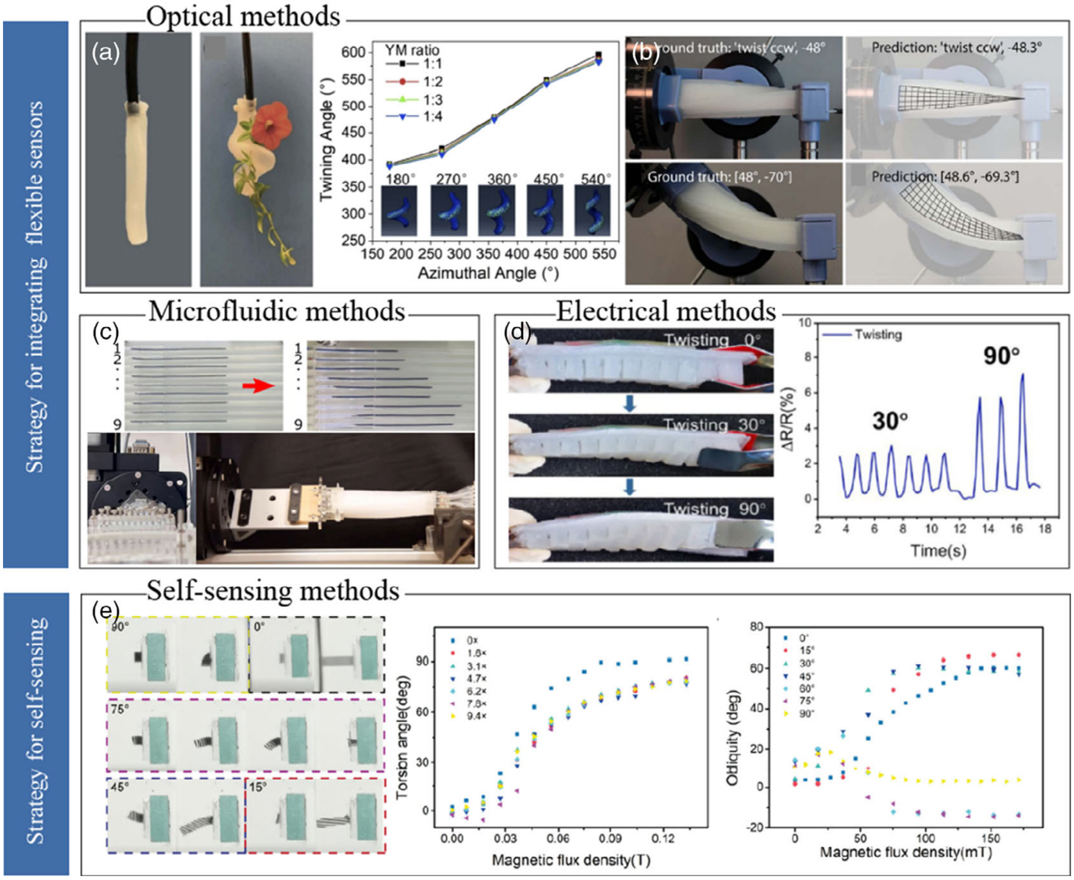

Figure 3. Demonstration of soft robot with twisting perception. a) Fiber optic sensors are embedded in the foam to detect twist deformation. Reproduced with permission.[69] Copyright 2018, American Association for the Advancement of Science (AAAS). b) Fiber optic sensor embedded in the spiral gripper of a soft robot senses the angle of twisting. Reproduced with permission.[65] Copyright 2020, Optica Publishing Group. c) Microfluidic displacement sensors to measure the twisting state of the robot. Reproduced with permission.[72] Copyright 2021, MDPI. d) Hydrogel resistive sensor in pneumatic actuator sensing twisting. Reproduced with permission.[74] Copyright 2021, Elsevier. e) Self-sensing magnetically anisotropic films. Reproduced with permission.[78] Copyright 2021, American Chemical Society (ACS).

Twisted self-sensing is usually based on twisted and coiled actuators or artificial muscles using Joule heating for actuation and sensing. The actuation principle is represented by twisted and coiled polymer muscles (TCPMs)[77,78] and twisted string actuators (TSAs).[79] They are known for their low weight, low cost, high-energy efficiency, and large linear strain and stress outputs. The operating principle of such actuators is based on the torsional effect of twisting fibers with substructures (e.g., polymer chains or CNTs) that are highly aligned in the direction of the fibers, which can produce spirally aligned substructures. The radial EP of said twisted fibers and the entropic contraction of the helical substructure produce a torque opposite to that of said twisting.[80] The principle of twisted self-sensing is precisely to create twist actuators using conductive functional materials and to indirectly measure twists by detecting the relationship between the electrical parameters of the twist actuator construction and the deflection. For example, Ding et al.[78] reported a facile preparation method for self-sensing magnetically anisotropic films, in which magnetic and conductive materials can be predesigned. In this method, magnetically active films of various shapes with complex chain-like oriented structures, are used to achieve advanced driving functions. It is experimentally verified that the samples coated with sensing layers can achieve torsional self-sensing (Figure 3e), which will facilitate further exploration and development of directionally responsive intelligent actuation systems and soft robotics applications. However, there are a limited number of twist sensors that improve the efficiency of sensing by forming twisted and coiled shapes to obtain a certain twist amplitude and direction, which are not considered to be self-sensing because they are passive sensing with a lack of actuation. This category of sensors can be well integrated into the cylindrical continuum soft robots to provide proprioception due to their helical shape. For example, Xu et al.[62] integrated helically wrapped fiber Bragg grating sensors into a needle-shaped continuum robot for torsion estimation, and the results showed that accurate and sensitive torsion could be obtained from this sensor and a corresponding model.

2.1.3. Stretching Perception

Biological muscles are organic soft tissues that are lightweight, compact, and capable of producing linear forces and displacements in response to electrical stimuli. Muscles are composed of millions of contractile microdots (muscle segments) that are connected in series and parallel to provide human-scale contractile forces. The neural control scheme uses embedded organic sensors to detect the current state of the muscle. These sensors, called mechanoreceptors, detect the stretch of the muscle fibers without increasing the overall shape factor of the muscle. The primary muscle sensory receptors are the muscle spindle (which detects muscle stretching) and the Golgi tendon organ (which detects the pressure generated by the muscle).[81] These sensors work in concert to provide the body with a continuous stream of sensory data that is used to provide effective motor control of the muscular system.

For soft robot systems, stretching sensing is shown as an estimate of the displacement generated by the actuator, which is critical for accurate closed-loop motion control. Stretching sensing is easy to implement for conventional rigid robots, but very difficult for soft robots due to the compliance of the materials that make up the soft robot and the nonlinear response of the actuators due to the inputs (pressure, electricity, and light). Integrating rigid sensors into soft robots is a viable approach,[82] including linear displacement gauges and encoders and adding bulk and unnecessary stiffness to the overall system. But for soft robots, these rigid devices can interfere with their work and even destroy their internal structure. The first strategy is to integrate stretchable sensors into the interior of the soft robot to sense its uniform amount of stretch. There are several common approaches to configuring stretch sensors into soft robots for stretching sensings, such as optical methods, microfluidic methods, and electrical methods.

Optical methods to sense stretch by integrating soft optical sensors (e.g., optical waveguides[83]) into the parts stretched by soft robots are realized. Soft optical waveguides cause an optical power loss in transmission when stretched.[84] In particular, fiber optic intensity modulation (FOIM) is a common method that refers to changes in the light emitted and received in a photoconductor. In this technique, light escapes from the light guide, and the change in intensity is then measured in response to a stretching stimulus.[70] For example, Kim et al.[83] reported an optoelectronic approach to individually detect single-mode deformation (stretch) and a versatile soft sensor that combines a heterogeneous sensing mechanism to decouple different deformation modes. This approach was applied to a four-chamber soft pneumatic robot for high-sensitivity stretching sensing (**Figure 4**a).

Microfluidic methods take advantage of the fact that the channel diameter of the microfluidic sensor is sensitive to stretching motion. They have been demonstrated in several works to be feasible as a stretching sensor to embed in soft robots for stretching sensing.[82,85,86] For example, Wirekoh et al.[86] designed a perceptual, flat, pneumatic artificial muscle (sFPAM) with stretching feedback control to better mimic organic muscles by embedding microfluidic sensors into the pneumatic artificial muscle (Figure 4b). To achieve precise control of the stretch, they developed a plasticity model and validated it against the mechanics of the experimentally characterized sFPAM. The sliding mode controller is used to verify the feasibility of the embedded sensor to provide feedback during operation. The result shows that they have designed a lightweight and compact actuation system with precise stretching feedback and control.

There are electrical methods to monitor stretching motion by integrating flexible tensile sensors made of stretch-sensitive functional materials (e.g., conductive hydrogels,[87] and Ecoflex/CNTs[88]) into soft robots. Several prior works[89,90] show high stretchability and high gauge factors of strain sensors, and some of them have demonstrated complete integration of a soft strain sensor package with a soft robot. For example, Goldoni et al.[88] reported a comprehensive study of materials, mechanics, and electronics to develop highly stretchable strain sensors integrating with a soft robotic earthworm. With the sensor package, this robot can have the capabilities of stretching proprioception, which enables the control of its deformation (Figure 4c). The overall system was mechanically compliant, which facilitates integration with the soft robot.

For stretch-based soft robots (such as artificial muscles and origami robots), it is desirable to develop multifunctional soft backbones to achieve tight integration of desired robotic functions (such as stretch sensing). But this contradicts the ultimate goal of creating versatile, light, compliant, energy-efficient, and ultimately untethered robots.[91,92] Stretching self-sensing methods offer an opportunity to achieve these goals based on the principle that changes in electrical parameters (e.g., resistance, inductance, and capacitance) caused by the EP and contraction of the material used to manufacture the actuator are highly correlated with the length of the actuator.[66,79,93,94] For example, Yang et al.[95] developed a graphene oxide (GO)-enabled templating synthesis to produce reconfigurable, compliant, multifunctional metallic backbones for fabricating origami robots with built-in strain sensing (Figure 4d). Compared with traditional paper and plastic materials, the reconfigurable Pt backbones were more deformable and the conductive Pt-elastomer backbones (Pt robots) demonstrated distinct capabilities—such as stretching sensing—without the need for external electronics. Developing multifunctional soft robots that couple actuation and sensing enriches the material library for soft robotics fabrication soft robotics toward high functional integration.[96] For example, Wang et al.[66] developed artificial muscles with tensile and torsional effects using twisted natural rubber fibers coated with buckled carbon nanomaterials and sensed stretching by a single electrical signal (Figure 4e). During actuation, the contact area of the CNT sheet increases, causing a decrease in resistance through a thermal piezoresistive effect. A feedback circuit was designed to connect or disconnect the current by measuring the change of resistance related to the length of the artificial muscle.

2.2. Exteroception

The special senses of the human body are divided into three main categories: tactile, telepresence (visual and auditory), and chemosensory (olfactory and gustatory). These senses are considered exteroception because they give value to sensations from outside the body, such as the value of an odor or the intensity of an auditory stimulus. Their role in the construction of bodily representations is to define the boundaries of the organism concerning the external environment.[26]

Sensory receptors in human skin transmit a large number of signals from the external environment to the brain. This external

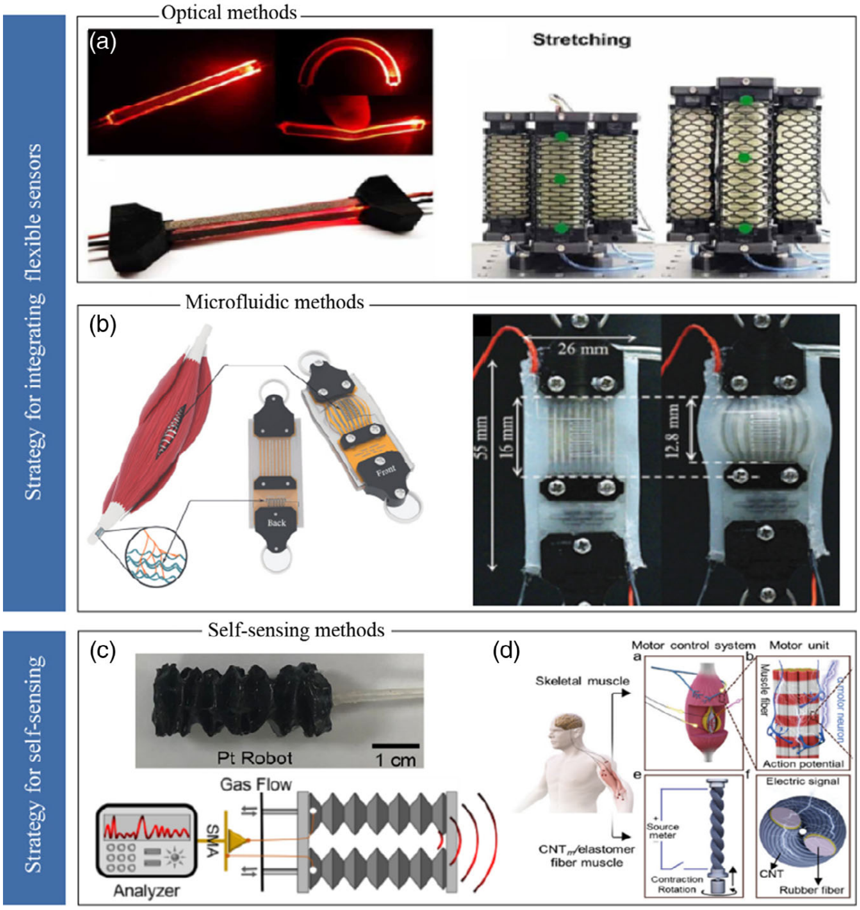

Figure 4. Demonstration of soft robot with stretching sensing. a) Photoelectric sensors are applied to a four-chamber soft pneumatic robot for tensile sensing. Reproduced with permission.[83] Copyright 2020, American Association for the Advancement of Science (AAAS). b) Liquid metal (EGaIn) microfluidic combined stretch sensors integrated into a pneumatic soft-touch hand can obtain 2D bend-sensing feedback. Reproduced with permission.[86] Copyright 2019, Mary Ann Liebert, Inc. c) Soft robotic earthworm with highly stretchable strain sensors integrated. Reproduced with permission.[88] Copyright 2020, American Chemical Society (ACS). d) Origami robot with stretch self-sensing. Reproduced with permission.[95] Copyright 2019, American Association for the Advancement of Science (AAAS). e) Artificial muscle with stretch self-sensing. Reproduced with permission.[66] Copyright 2020, American Chemical Society (ACS).

information acquired through sensation helps humans to better adapt and explore their environment. The subcutaneous layer of the human skin is littered with tactile receptors called mechanoreceptors, which provide a sense of touch to humans. There are four types of mechanoreceptors buried under human skin that respond to different types of tactile stimuli and cause the skin to respond: fast-adaptive receptors FA I and FA II and slow-adaptive receptors SA I and SA II.[97] When people touch an object, the mechanoreceptors give them continuous tactile feedback, enabling them to touch, caress, grasp, squeeze, or execute other actions. Discriminative touch signals from the hand are transmitted to the cerebral cortex along ascending pathways that include synapses in the brainstem and thalamus. Ultimately, touch signals project to the primary somatosensory cortex, where behavioral features associated with the object (its shape, size, texture, and movement) are encoded in the responses of individual neurons.[98] In soft robotic systems, several flexible sensors and electronic skins have been developed to mimic the human sense of skin. Although soft robots are not yet able to achieve human-like precision recognition and dexterous manipulation because of hardware limitations,[99] these sensory feedbacks have significantly enhanced the capabilities and applications of soft robots.

2.2.1. Pressure Perception

Pressure perception is spread throughout the skin of the organism because of the presence of mechanoreceptors, which generate feedback pressure signals that are transmitted to the brain to help the organism obtain information about the external world and respond to external environmental stimuli. The use of exploratory and informative actions, such as stroking and sliding, to refine the acquired sensory information is known as tactile perception.[26] For example, humans often use pressure perception to recognize the collision of body and environmental objects and to identify the material properties, texture, and weight of the grasped object. Similar to humans, soft robots need pressure perception for external information to improve their capabilities and intelligence.

The strategy for external sensors is to integrate flexible pressure sensors (e.g., tactile sensors,[100] and electronic skins[101]) into soft robots for pressure sensing. On the one hand, tactile sensors have unique advantages over traditional rigid sensors of target information acquisition for specific manipulation tasks (e.g., grasping, in-hand manipulation), which are compliant for adapting to different shapes of objects. However, obtaining enough information about the target object is a major challenge for the resolution of the pressure sensors. On the other hand, some works based on electronic skin have been done to improve the resolution to obtain the desired target information (magnitude and position of the pressure) by arraying pressure sensors. For example, an active matrix containing soft pressure sensors and transistors is used,[102] and object geometry and texture are obtained through an array of pressure sensors covering the entire interior of the hand to improve resolution.[103] Based on flexible pressure sensors, several methods are summarized to demonstrate pressure sensing for soft robots: microfluid methods and electrical methods.

Microfluidic methods apply microfluidic sensors to soft robots and exploit the principle that microchannels deform when subjected to pressure.[101,104] For example, Truby et al.[104] reported a method for creating soft-body somatosensory actuators (SSAs) via embedded 3D printing, which enables the seamless integration of multiple ionic-conductive microfluid sensors into an elastic matrix to produce SSAs with desired proprioceptive and pressure sensing (**Figure 5**a). A three-finger soft gripper constructed from SSAs was used to estimate the mass of different objects under the same shape utilizing a microfluidic pressure sensor at the fingertips.

The electrical approach is based on the integration of stretchable electronic-based sensors into the soft robots, which takes advantage of the correlated changes in electrical parameters (resistance and capacitance) when the sensitive layers of these sensors are subjected to pressure.[105] On the one hand, the dense array of sensors provides ideas for pressure sensing in soft robots, but the number of sensors in the array decreases, placing high demands on the accuracy of individual sensors.[19,106–108] For example, Roh et al.[109] reported a millimeter-scale soft grip based on shape-memory polymers (SMPs) and a high-performance cracked soft sensor is integrated into the soft gripper for sensing the pressure (Figure 5b). In particular, the ability to firmly grasp soft cells and organs without mechanical damage is essential for identifying the target condition and monitoring meaningful biosignatures (e.g., the pressure produced by heartbeat and breath). On the other hand, data processing methods, with the help of sensor arrays covering the working area, can reduce the dependence on the performance of a single sensor to get satisfactory results. For example, Shen et al.[108] integrated a robust soft touch skin that combines ionic hydrogels within a soft bionic hand. The touch skin provided an amputee with robust tactile feedback when handling delicate objects, illustrating its potential applications in next-generation human-in-the-loop robotic systems with tactile sensing (Figure 5c). Furthermore, the amount of information and data that can be acquired is enormous for ML, which enables more complex sensory functions and further increases the intelligence of soft robots. For instance, Sun et al.[110] integrated the developed array sensing system with patterned electrodes tactile triboelectric nanogenerator (T-TENG) and length triboelectric nanogenerator (L-TENG) into a 3D-printed triple soft gripper to achieve object recognition. A total of 15 tactile sensors on three fingers covering the gripping area and the gripper were successfully demonstrated to achieve object recognition using ML technology for data analysis of pressure.

Pressure self-sensing methods utilize the capabilities of soft matters (e.g., conductive elastomers and hydrogels) with both actuation and pressure sensing.[30,111–113] These soft matters are often used to achieve intelligence in autonomous soft robots at the material level without computer-based intelligence and rigid electrical control units. For example, Ji et al.[30] designed and fabricated a 2D metal molybdenum disulfide (MoS_2) soft actuator with the functions of dual response and pressure self-sensing (Figure 5d). The actuator and a flexible contact sensor achieve real-time pressure self-sensing by exploiting the piezoresistive properties of the MoS_2–CNT composite film. Intellectual ability is often possessed by living things, such as most animals and a few plants (e.g., Mimosas, and flycatchers). Biosensory phenomena are good inspiration for researchers to build intelligent executive systems. For instance, Ma et al.[112] reported a fully soft actuator with embedded sensing, actuation, and control at the cellular level by synergistically exploiting the mechanosensing and electrothermal properties of LM to drive thermally responsive liquid crystal elastomers (LCEs). Using an easy-to-use method based on magnetoprinting, they have created versatile LM circuits on the surface of the LCE, enabling bionic autonomous actuation in response to mechanical stimuli such as pressure (Figure 5e). Inspired by the fact that Mimosa simplifies information processing by not using a central processor when processing external mechanical stimulus signals, Zhou et al.[113] reported a novel pressure SenAct composed of a CNT filament composite and a biaxially oriented polypropylene (BOPP) film that integrates sensing, actuation, and decision-making functions at the material level without complex combinations. This research uses the tactile pressure sensing unit as a control unit providing a new avenue for developing intelligent soft robots and next-generation logic devices.

2.2.2. Temperature Perception

In the biosensory system, there are lots of temperature receptors in the skin or spine and many central thermosensitive neurons receive synaptic inputs from the skin and spinal thermoreceptors pathways. This indicates that such neurons are capable of thermal integration, increasing the likelihood that these neurons function in thermoregulation.[114] However, traditional widely used thermometers often suffer from slow response times, lack of sensitivity, low accuracy, and most importantly, the inherent stiffness of the material making it very difficult to integrate them into soft robots.[115]

Flexible temperature sensors with advantages of high sensitivity, good accuracy, fast response, and friendly interface have attracted a lot of attention, such as resistance temperature detectors (RTDs),[116] thermocouples,[117] thermistors,[118] and thermochromic.[119,120] Electrical methods are the main

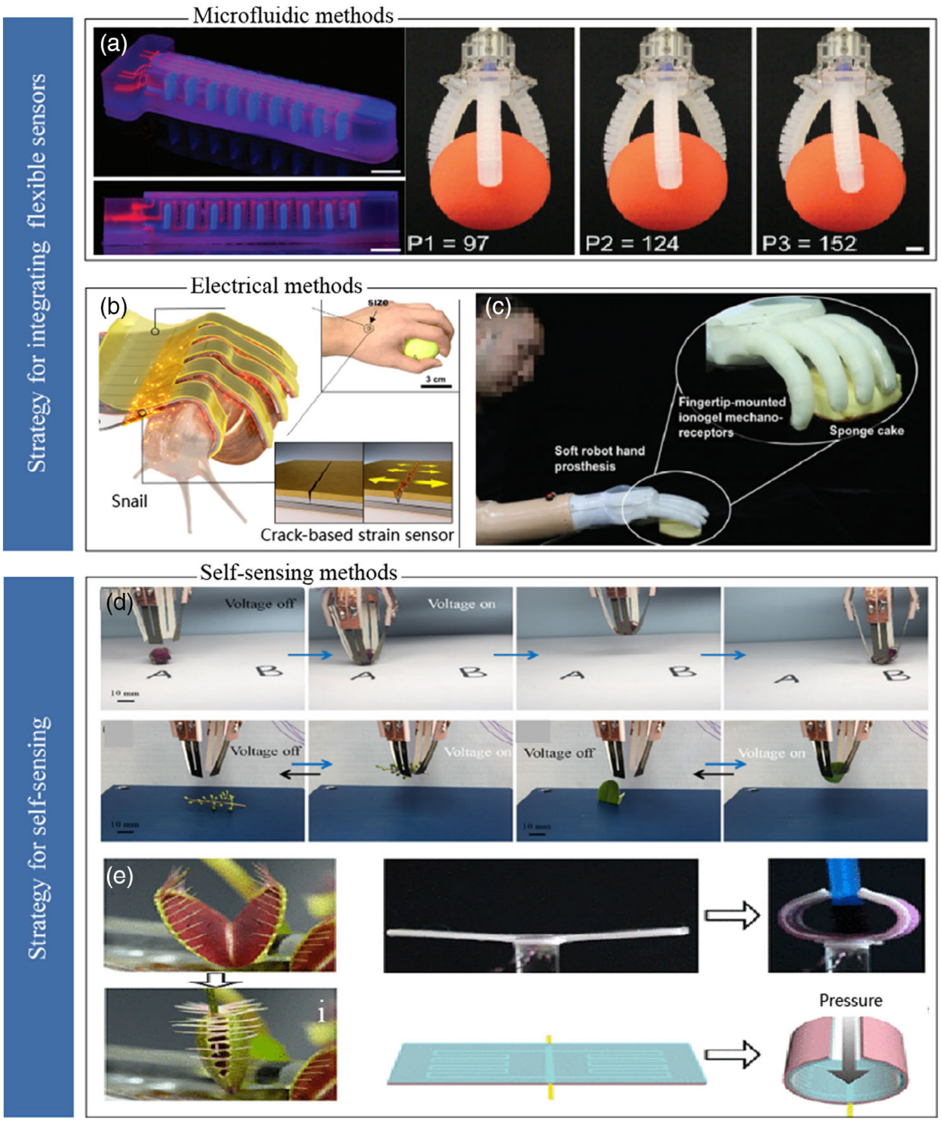

Figure 5. Demonstration of soft robot with pressure perception. a) Ion-conductive microfluidic sensor is embedded into the SSA for pressure sensing. Multiple SSAs are combined to form a soft robot gripper. Reproduced with permission.[104] Copyright 2018, Wiley-VCH. b) High-performance crack soft sensor is integrated into the soft gripper for contact perception. Reproduced with permission.[109] Copyright 2021, American Association for the Advancement of Science (AAAS). c) High-performance capacitive pressure sensor integrated into a soft robotic hand prosthesis provides powerful haptics. Reproduced with permission.[108] Copyright 2021, Wiley-VCH. d) Thermally responsive liquid crystal elastomer actuator with contact self-sensing. Reproduced with permission.[112] Copyright 2021, Wiley-VCH. e) Carbon nanotube thin film actuator with contact self-sensing. Reproduced with permission.[113] Copyright 2022, Wiley-VCH.

approaches to integrating these flexible temperature sensors into soft robots. Electrical methods integrate stretchable elastomer or hydrogel sensors into soft robots, taking advantage of the fact that the sensitive materials of these sensors produce associated changes in electrical parameters (usually resistance and capacitance) in response to changes in temperature gradients.[121–123] For example, Liu et al.[124] designed and synthesized an antifreeze hydrogel artificial skin based on a zwitterionic poly (ionic liquid) to soft gripper for temperature sensing (**Figure 6**a). This artificial skin responds well to temperature, and the sensitivity is 11.3% $°C^{-1}$ at relatively low temperatures (−20 to 25 °C) and 2.1% $°C^{-1}$ at 25–60 °C. The temperature sensor enables the soft robot to obtain one more dimensional information, especially in obtaining the properties of the target object (e.g., the surface temperature of the object, object material recognition, surface texture differentiation, etc.). For instance, Yang et al.[122] designed a multifunctional soft robotic finger with a built-in nanoscale temperature–pressure haptic sensor for material identification. The flexible multifunctional tactile sensor integrates a nanowire temperature sensor and a conductive sponge pressure sensor to simultaneously measure the temperature change and contact pressure rate to perform accurate material recognition

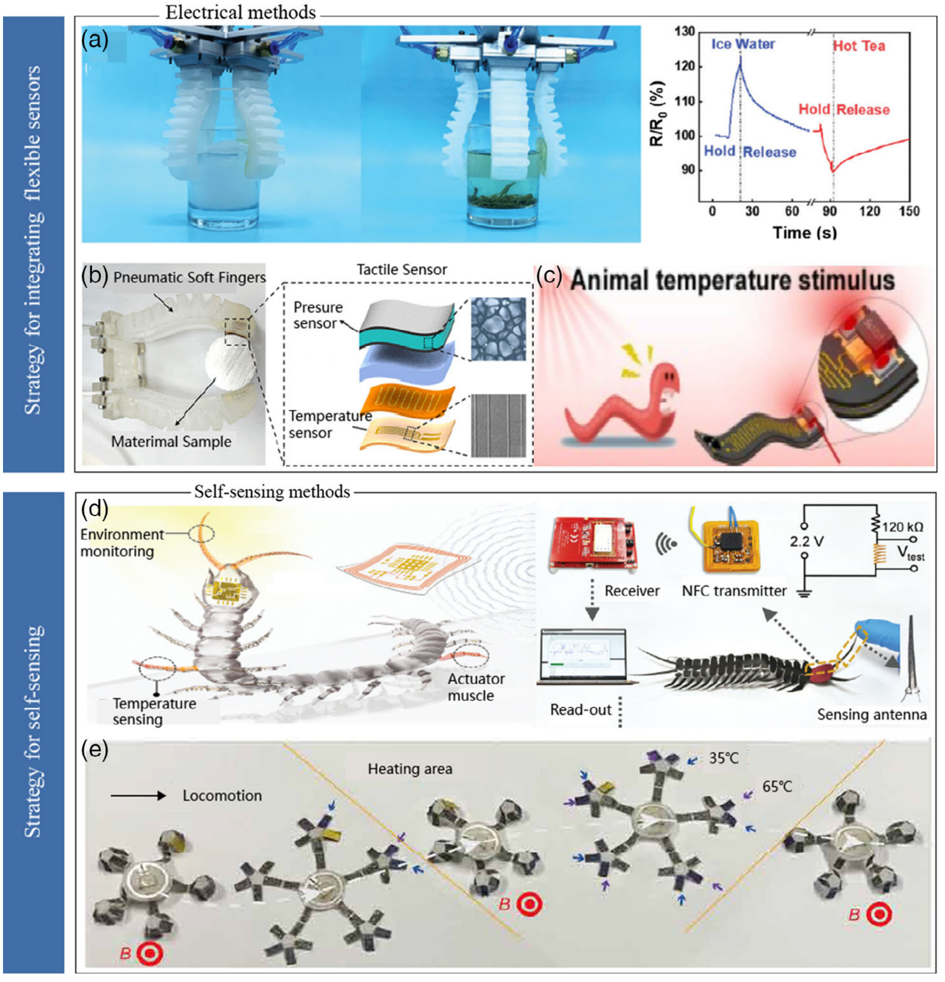

Figure 6. Demonstration of soft robot with temperature sensing. a) Temperature sensor made of ionic hydrogel that responds well to temperature is integrated into a soft robot hand for temperature sensing. Reproduced with permission.[121] Copyright 2020, American Chemical Society (ACS). b) Nanoscale temperature–pressure haptic sensor fabricated via flexible printed circuitry is integrated into a multifunctional soft robot finger for measuring temperature change rates and material identification. Reproduced with permission.[122] Copyright 2021, Wiley-VCH. c) Magnetic soft robot integrated with a variety of flexible circuitry frictional electric nanogenerators with onboard temperature sensing and self-powered charging. Reproduced with permission.[123] Copyright 2022, Elsevier. d) Miniature soft robot with integrated thin-film structural temperature self-sensing. Reproduced with permission.[125] Copyright 2020, Wiley-VCH. e) Magnetically driven soft robot equipped with a temperature-sensing module that visualizes colorimetric sensing based on temperature changes. Reproduced with permission.[128] Copyright 2022, Springer Nature.

(Figure 6b). Temperature sensing can improve the efficiency and capability of soft robots, in addition to the bionic capability of bionic robots. Because living organisms can sense and respond to their environment through reflex-driven pathways, the great challenge of mimicking this natural intelligence in bionic robots lies in achieving highly integrated body functions, drive, and sensing mechanisms.[125] Inspired by the gray field slug, Peng et al.[123] developed a slug magnetic soft robot fully integrated with a TENG for onboard sensing and self-powered charging. The soft robot integrates a variety of flexible circuits allowing for a response to high-temperature stimuli as most animals do (Figure 6c).

Temperature self-sensing provides the opportunity to realize an integrated soft robot with temperature sensing and actuation. In biological systems, insect thermosensors are generally distributed throughout the body, with the densest pack in the tarsal segments and antennae, so they are often aware of small changes in environmental temperature.[126] In soft robotics systems, some functional materials [e.g., photothermal polydopamine rGO (PDG)/poly(vinylidene difluoride) (PVDF)/graphite-CNT composites (graphite-CNT),[125] and graphite-filled polyethylene oxide/PVDF/graphite[127]] that respond to temperature gradients are used in the design and fabrication of self-sensing soft robotic systems to mimic the biological systems. The principle of these functional materials to realize the self-sensing function of temperature can be divided into two kinds. One is to use the pyroelectric effect of temperature-sensitive materials (e.g., PVDF and PDG). The temperature change generates voltage or current at both ends of the material. The other is to detect the temperature by the piezoresistive properties of the functional materials (e.g., graphite–CNTs and graphite). The dual-parameter sensing promotes real-time sensing and decoupling of the readout signal. Based on the above principles, these functional materials are compactly integrated into the actuation and sensing system for temperature self-sensing. For example, Wang et al.[125] used integrated thin-film structures that include ferroelectric PVDF, PDG, and graphite–CNT to demonstrate a customizable, miniature soft robot with temperature self-sensing feet (Figure 6d). These temperature self-sensing feet enable real-time feedback of walking gaits and assessment of terrain textures. Furthermore, these thin-film structures can be easily converted into 3D robots by kirigami technology and integrate arbitrary patterns of sensors and actuators at the material level.

Notably, temperature-sensitive color-changing materials can be used in temperature visualization self-sensing. For instance, Dong et al.[128] embedded a temperature-sensing module into a soft crawl robot with programmable magnetization profiles and geometries. The temperature self-sensing module provides the soft robot with bio-like environmental-sensing and detection capabilities (Figure 6e).

2.2.3. Humidity Perception

The ability to detect variations in humidity is critical for many animals. Birds, reptiles, and insects all show preferences for specific humidity that influence their mating, reproduction, and geographic distribution.[129] Humidity measurement in the hygrometer type of sensors is accomplished by measurement of either the electrical impedance (conductance) or capacitance of the sensing matters, which are widely used in industrial production and rigid robots.[130]

Flexible humidity sensors based on active materials, such as CNTs-coated polyelectrolytes,[131] graphene and palladium nanoparticles,[132] poly(3,4-ethylene dioxythiophene) (PEDOT),[133] and poly(3,4-ethylene dioxythiophene-poly(styrene-sulfonate) (PEDOT:PSS),[134] have been developed for humidity-sensing applications. These sensors utilize changes in the physical and electrical properties of the sensitive elements when exposed to the different atmospheric humidity conditions of the surrounding environment and provide a measure of the humidity due to some amount of adsorption and desorption of water vapor molecules. For example, Wang et al.[135] integrated a flexible active material-based relative humidity sensor into a light-driven mimetic ruler looper soft robot based on a hydrophilic GO film and communicated through a wireless module (**Figure 7**a). This soft robot integrates actuation, sensing, and communication into one, providing an innovative strategy for integrating multifunctional robots and showing great potential. Ma et al.[136] reported a flytrap-inspired intelligent insect-trapping robot based on MXene and GO and the sensor is connected to a control circuit, serving as a humidifier switch. A tiny signal caused by any insects would turn on the humidifier. Then the rapidly increased localized humidity would trigger the nine smart "fingers" to bend, trapping the target insect immediately (Figure 7b).

The second strategy is the humidity self-sensing method, which utilizes humidity-sensing mechanisms (e.g., TENG sensing[137]) and humidity-sensitive functional materials (e.g., PEDOT:PSS[138] and MXene/GO[136]) that allow soft robots to sense environmental humidity changes during motion without the need for additional sensors. On the one hand, designing actuators with sensor-like structures and humidity-sensing mechanisms is critical to building humidity-sensing soft robots. For example, Tian et al.[137] designed and fabricated a soft multilegged millirobot with a polydimethylsiloxane (PDMS) layer modified by acetylene black particles and iron powders, which can be excited by near-infrared irradiation (NIR) light and magnetic fields. The robot itself can act as a millirobot TENG (millirobot-TENG) and the voltage intensity is highly fitted to the relative humidity variation, which can be used to achieve humidity self-sensing (Figure 7c). On the other hand, introducing humidity-sensitive functional materials in the actuators can add humidity-sensing functions while safeguarding the soft robot motion functions. For instance, Shrestha et al.[138] designed a humidity sensor incorporating a dielectric elastomer actuator (DEA) capable of operating in high-humidity environments. This new humidity sensor consists of a "relatively water-free" acrylic dielectric elastomer layer and a DEA using plasticized PEDOT:PSS electrodes. The shape change of this hygroscopic bilayer with humidity is easily visualized like the scales of a pine cone (Figure 7d).

Despite advances in our understanding of sensory systems such as mechanical and thermal sensing, it remains challenging to replicate these unique sensory features in the sensing functions of soft robots. Recent efforts to develop exteroception of the soft robot using flexible pressure, temperature, and humidity sensors offer promising routes for sensor-based bionic systems with limited integration, detection range, and spatiotemporal resolution. What is of concern is that a variety of flexible exteroceptive sensors (such as gas, chemical, light, and magnetic sensors) have been developed, which gives the potential for perceptive soft robots to acquire sensing capabilities beyond those of living beings and promises to replace humans in dangerous tasks. For example, Oh et al.[107] developed a soft robotic hand that mimics a human finger and surpasses the sensing capabilities of a human finger by integrating gas sensors. The soft robotic finger is powered by a thermally responsive elastic composite material (including capsules of ethanol and LM) through an electrothermal phase transition. A hydrogen sensor is integrated into the soft robotic hand for real-time hydrogen concentration detection. The high level of integration of gas sensing and actuation capabilities of this soft robotic hand is a promising strategy for next-generation robots monitoring explosive gases in disaster areas and moving in contaminated environments.

Organisms often possess multiple sensory abilities simultaneously to maximize information about their shape and environment. For example, humans possess manual dexterity, motor skills, and other physical abilities that rely on feedback from both proprioceptive and exteroceptive perceptual systems. Currently, bionic intelligent soft robots with the ability to fully perceive their deformation and acquire information about their environment like humans have not been proposed. However, soft robots with partial proprioception and exteroception have been reported. Truby et al.[104] reported a method to fabricate an SSA by embedded 3D printing technology, which enables both proprioception (bending perception) and exteroception (pressure perception and temperature perception) through the integration of multiple conductive materials. This new fabrication method enables the

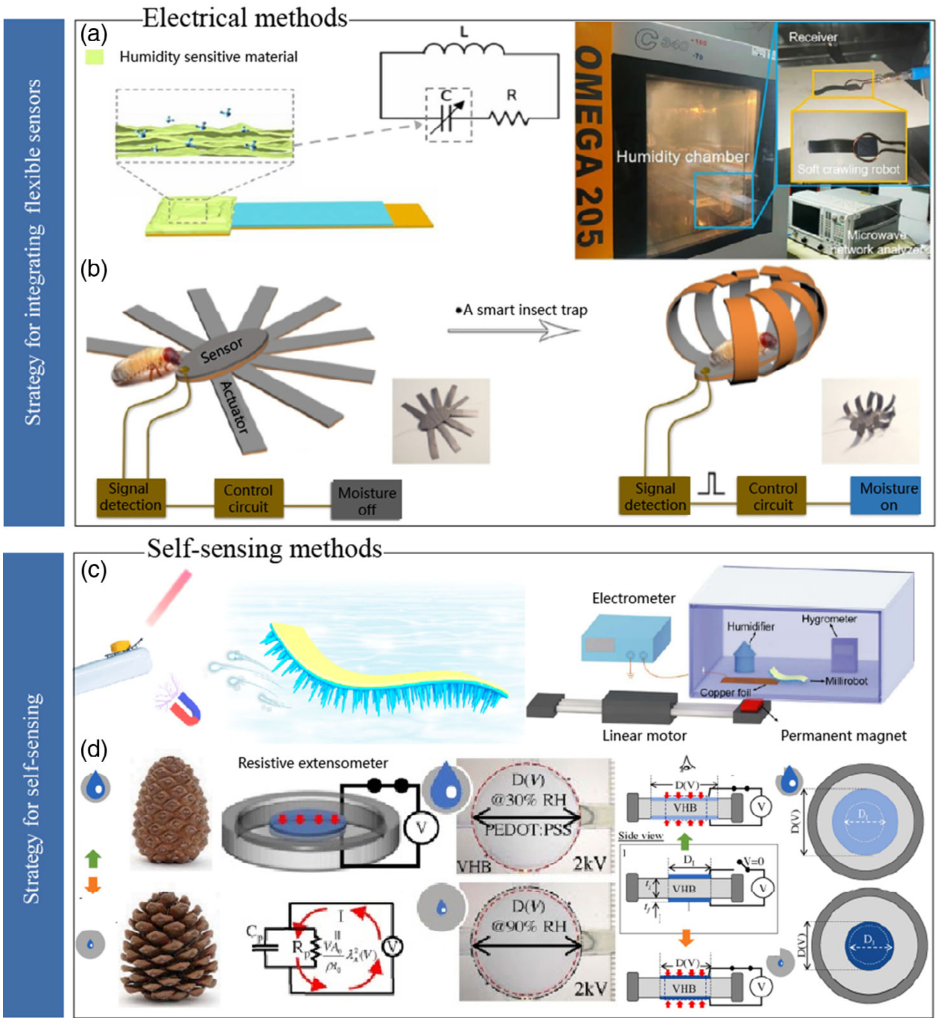

Figure 7. Demonstration of soft robot with humidity sensing. a) Active material-based relative humidity sensor is integrated into a soft inchworm robot for humidity sensing. Reproduced with permission.[135] Copyright 2022, American Chemical Society (ACS). b) Soft intelligent insect trap device with humidity self-sensing function. Reproduced with permission.[136] Copyright 2022, Elsevier. c) TENG millirobot for humidity sensing. Reproduced with permission.[137] Copyright 2021, MDPI. d) Humidity sensor incorporating a DEA capable of operating in high humidity environments. Reproduced with permission.[138] Copyright 2021, Elsevier.

seamless integration of multiple ionic conductive and fluidic features into an elastic matrix to produce SSAs with desired bioinspired sensing and actuation capabilities. The multimaterial manufacturing platform enables complex sensing patterns to be easily integrated into soft actuating systems to achieve closed-loop feedback control.

3. Closed-Loop Control Tasks of Soft Robots

Soft robots are inherently safe and flexible to a range of tasks due to the passive adaptation of their elastic body to the objects they interact with. The inherent material compliance of soft robots can protect both the robot and the environment from damage in a nonstructural environment.[3] This property makes soft robots attractive in environments such as human-robot interaction (HRI) and robotics operations where safety around vulnerable objects may be necessary.[139,140] Although soft robots have such excellent intrinsic characteristics, there are great difficulties in the design of closed-loop controllers. Some studies have used open-loop control schemes to meet the practical application requirements of soft robots. For example, from a practical point of view, some motion control of soft robots can be realized through the rational design of soft robot mechanisms and feedforward controllers based on ML technology.[141] It is possible to track preprogrammed tasks with soft robots executed through an open-loop control strategy, which is not suitable for tasks with high-precision requirements, such as minimally invasive surgery, positioning, and tracking. Therefore, closed-loop control for soft robots is needed, which has the advantages of anti-interference capability (suppression of uncertainty and automatic adjustment), reduced accuracy requirements for the forward path, and insensitivity-specific nonlinear effects. The design of accurate closed-loop controllers for soft robots is still an ongoing research topic, and it is worth noting that difficulties in sensing are an important reason for these challenges.[142] Thus, solving the problem of sensor-based closed-loop control of soft robots is crucial and urgently needed.

Smart materials and stretchable sensors have great potential to enable soft robots to interact intelligently with their environment. In addition, proprioceptive and exteroceptive information obtained through sensing is essential for a variety of general robot control tasks. The type of sensor modality to be used, the control strategy, and the response from the body all depend on the soft robot's task. The classification of tasks is determined by clarifying the main body through the flow of information and energy in closed-loop control.

3.1. Motion

Precise motion control is one of the proprioceptive sensors' most fundamental manipulation tasks. In a closed-loop motion task, the information flow path is the controller–actuator–sensor–controller. Energy flows from the controller to the actuator, so the main body is the actuator. Here, the goal of control is to estimate the shape of the body so that the body remains stable while performing the behavior. The proprioceptive sensors can be further classified according to their use for motion control. The first category is the indirect variable measurement of actuators, such as the internal drive pressure measurement of fluid actuators[143] and the current, voltage, or temperature of electrically driven actuators (self-sensing feedback).[59,144] These indirect variable measurements respond to the input value of the actuator, and sensors are usually used and integrated into the actuator mechanisms for internal variables. For example, Wirekoh et al.[86] chose a control scheme for simplicity to control sFPAM using its embedded sensors. In this control method, the embedded sensor signals were sent to a custom amplifier circuit to measure small changes in the resistance of the sFPAM. This amplification circuit was used to implement a sliding mode controller and implemented a proportional control scheme that alternated between a large and small proportional gain for both force and position depending on the size of the error between the current state and desired state. However, since the valves are bulky and expensive, it is difficult to precisely control the pressure or flow rate of air inside each actuator.[145]

Another category is the measurement of external variables such as curvature, torsion, and tension, which provide direct information about the deformation state of the actuator. As sensors for these variables should be mounted on the soft robot actuator structure, closed-loop control of soft robots is achieved by developing soft sensors and integrating sensor and actuator manufacturing methods.[54,104,146] The early work was achieved by the controller compensating for the elasticity of the actuator connection to gain precise motion control.[147] In a recent work, soft robots with integrated sensors for bending sensing and force sensing have been demonstrated for position closed-loop motion control[148] and force closed-loop motion control,[149] respectively. Liu et al.[148] developed a somatosensory thin-film soft-body crawling robot driven by artificial muscles with position closed-loop control. An arch-shaped membrane skeleton with a twisted fiber artificial muscle connected to the membrane skeleton was coated with strain sensors to detect body deformation. A controller is designed to implement position closed-loop motion control based on the deformation of the body detected by the stretch sensor as input (**Figure 8**a). Yang et al.[150] fabricated a soft robotic finger using a multi-intelligent material substrate composed of SMP and conductive elastomeric thermoplastic polyurethane (TPU) by 3D printing to achieve controllability of flexibility and closed-loop control of the position. In particular, the actuation of different knuckles was controlled by temperature-regulated changes in the elastic modulus of the SMP material around the glass transition temperature (T_g), and the bending sensing of the finger was achieved using the piezoresistive effect of the conductive TPU. Then, theoretical modeling of finger position feedback and stiffness modulation is performed and the feasibility of closed-loop control of the finger position of the soft robot is experimentally verified. Wang et al.[66] developed an artificial muscle with tensile and torsional effects using twisted natural rubber fibers and coating them with snap-fit carbon nanomaterials. The muscle was used in a soft crawling robot to control the movement by measuring changes in the resistance of the artificial muscle to connect or disconnect electrical currents for a force closed-loop control (Figure 8b). It is worth noting that the availability of both position and force feedback functions can help improve the maneuverability of perceptive soft robots. For example, Zhou et al.[151] proposed a design method for a proprioceptive bellows actuator based on 3D-printed conductive materials and 3D-printed deformable structures. The conductive bellows exhibited effective resistance variation and structural deformation, and the conductive bellows-based design of the proprioceptive bellows actuator achieved effective position feedback and real-time output force estimation. This work provides a promising solution to the challenge of perceptive soft robots requiring integrated actuation and sensing to perform complex motion closed-loop tasks.

Materials known to be capable of autonomous oscillation in biological systems (e.g., heartbeat) provide ideas for developing soft robots with autonomous motion and have been demonstrated in some soft robots with closed-loop control through self-sensing.[152,153] Ge et al.[152] described a way to create a thermal–mechanical–thermal feedback loop for a polymer actuator based on a thermal phase change (Figure 8c). This thermally driven solid polymer produced continuous motion by sensing and responding to its temperature without switching to temperature rise/fall. Inspired by soft structures that have the intrinsic sensory stimulus–response of biological organs, Karipoth et al.[153] proposed a magnetically driven soft robot based on a soft body structure that provides intrinsic strain sensing through the "seamless embedding" of graphite paste-based sensor materials. The graphite paste-based sensor material provides immediate feedback regarding deformation, and the cyclic motion of the soft worm-like robot utilizes the hyperextension of the developed strain sensor to achieve precise closed-loop feedback control (Figure 8d). These results demonstrate new possibilities for using soft robots with self-sensing capabilities in applications such as delicate surgery inside the body.

3.2. Manipulation

Robotic manipulation involves controlling the movement of the body to alter the state of an external object to the desired set point

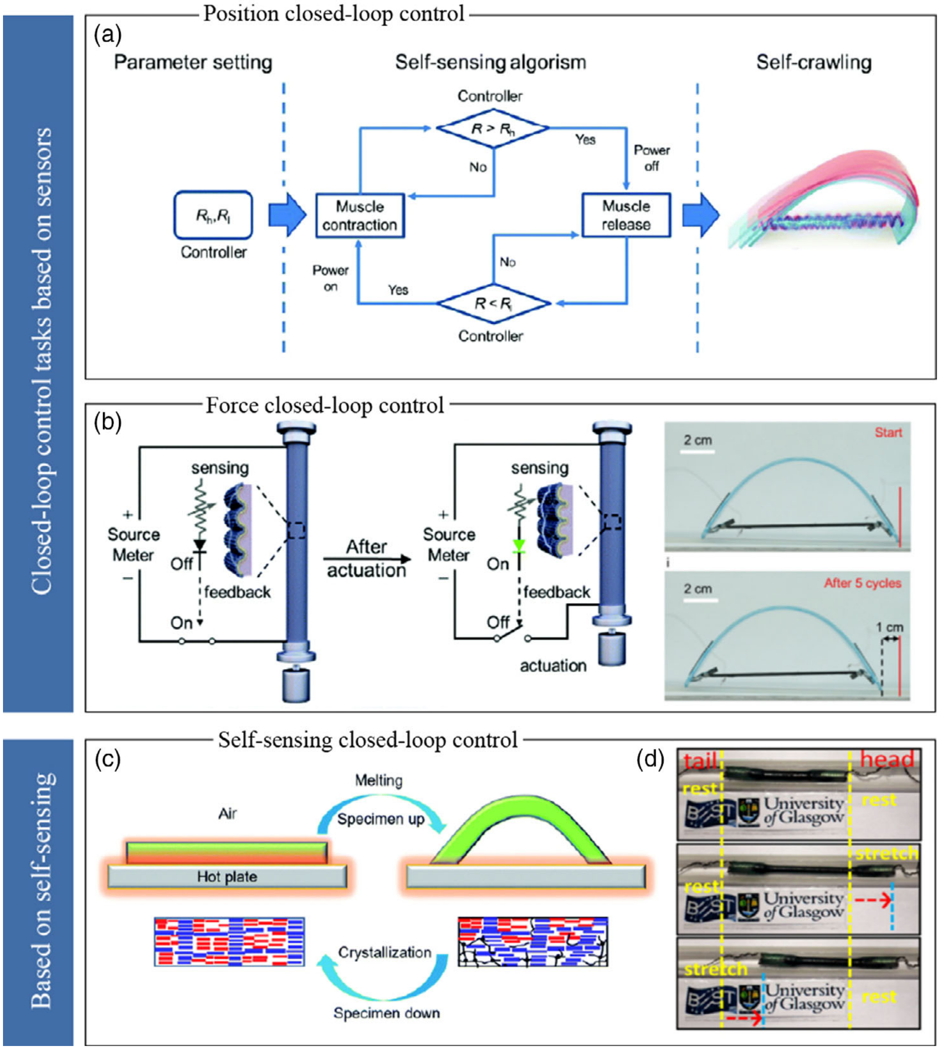

Figure 8. Motion tasks based on closed-loop control of soft robots. a) Somatosensory thin-film soft crawling robot driven by artificial muscles, with closed-loop control of motion by position. Reproduced with permission.[148] Copyright 2021, Royal Society of Chemistry (RSC). b) Artificial muscle with sensing is used to build a soft crawling robot, controlled by closed-loop control of forces. Reproduced with permission.[66] Copyright 2020, Royal Society of Chemistry (RSC). c) Motion and principles of a polymeric crawling soft robot based on a thermal–mechanical–thermal feedback loop with thermal-phase change. Reproduced with permission.[152] Copyright 2017, Royal Society of Chemistry (RSC). d) Magnetically driven soft robot equipped with stretching self-sensing for precise closed-loop feedback control by stretching. Reproduced with permission.[153] Copyright 2022, Wiley-VCH.

using internal actuators.[19] This is a widespread task in industry and is often based on the control of visual feedback—visual servo. Many related studies apply visual feedback information directly to the controller.[154] In the closed-loop manipulation task, the information flow path is controller–actuator–environment–sensor–controller. Energy flows from the actuator to the environment, so the main body is the environment. Here, the goal of control is to estimate the state of the body–environment interaction to keep the manipulation stable. Closed-loop power of manipulation relies on sensory feedback of the deformation state of the actuator and its contact with the surrounding environment. For soft robots, different drive mechanisms and a wide range of physical structures allow for various sensing strategies.

The soft robot's feedback control during the manipulation task is based on both proprioception and exteroception. From the perspective of sensing, manipulation has two closed-loop control steps. The first step is a proprioception closed-loop control based on sensors for controlling the feedback of the deformation state of the actuator. The role of proprioception is mainly to obtain state information of the internal actuator, which depends on flexible strain sensors. However, closed-loop control based on proprioception is difficult to achieve for continuum soft robots with flexible stretch sensors considering the special mechanism of continuum robots. Although some theoretical models of soft continuum robotic systems have been proposed as a basis for closed-loop control, few studies have been able to tackle model-based manipulation tasks. Mo et al.[155] reported a study on the use of a tendon-driven continuum robot to deform soft objects to accommodate constrained objects. A visual predictive controller (VPC) with a reference trajectory was used to ensure smooth operation. A linear extended state observer (ESO) is further designed to measure the state of the robot so that the controller can compensate for the estimation errors (**Figure 9**a). The second step is a sensor-based exteroception closed-loop control for obtaining environmental information and feedback on the state of the interface for interaction with the environment. A control system needs to be connected between the actuating system and the sensing system to process the environmental information from the sensing system on the one hand and to control the actuator according to the results of the information processing, on the other hand, forming a closed-loop control. As energy flows to the actuator, the stability of the actuator is of deep concern. One of the most basic manipulation tasks involving tactile sensors is grasp adaption. To perform robust grasping, a multifingered robotic hand should be able to adapt its grasping configuration, that is, how to grasp the object, to maintain grasping stability. Such a change in grasp configuration is called grasp adaptation.[156] Grasp adaptation depends on the controller, the employed sensory feedback, and the types of uncertainties inherent to the problem. Early works were built on real-time feedback on the state of the soft robot's grasping process[146] (real-time feedback control has remained a priority until now) and estimated normal and tangential forces on the hand to detect slip and react accordingly.[157] Closed-loop control based on haptic sensing provides great convenience for adaptive gripping. Chen et al.[158] proposed two simple sensors were used in a soft pneumatic gripper (SPG) control system to give it an adaptive gripping capability similar to innervation. The control system is characterized by two sensors, where the pneumatic sensor can detect the gripping force and the bending sensor can detect the bending degree by testing the pressure versus size. The adaptive gripping control process is shown in Figure 9b. The test results show that the SPG can maintain a stable gripping state for a long time based on the size-sensing recognition capability. Guo et al.[159] developed an intelligent, shape-adaptive pneumatic electroadhesive actuator (PneuEA) handling system that combines two soft touch sensors with an electro-adhesive pneumatic soft gripper. Information about the contact state of the two tactile sensors sensing the soft gripper is used to control the opening of the pneumatic valve to form a closed-loop control (Figure 9c). The PneuEA gripper is capable of gripping and placing not only flat and flexible materials but also delicate objects. This work is expected to expand the applications for soft gripper adaptive gripping and motorized adhesive technology. Recent results used learning-based methods for slip onset prediction with adjustment and grasp failure detection with adjustment because of the ability of these methods to handle complex multimodal sensory information[160] and their generalizability.[161]

One of the most complex manipulation tasks for soft robots is in-hand manipulation. Dexterous in-hand manipulation usually requires precise planning and control of finger movements based on models of objects and fingers during robotic execution. This is due to the complex contact interactions between the fingers and the object and the minimal passive adaptation to object changes. This imposes stringent requirements on actuators, controllers, and sensors. In-hand manipulation advances in soft robots are mainly limited to nonlocal sensing feedback.[162] Even though, external vision tracking systems have achieved significant progress in-hand manipulation using external vision tracking systems.[160] However, control strategies trained using vision alone are scene dependent and require large training data.[19] Reinforcement learning (RL) can potentially find effective control strategies, but it is often infeasible to train RL using physically soft-bodied robots.[163] To accelerate research on the control and RL of soft-body robotic systems, Graule et al.[164] introduced a software toolbox that can help train and evaluate controllers for continuum robots. Further studies have been proposed on the use of haptic sensing in-hand manipulation to improve grasping robustness. Notably, in a recent work, Jamil et al.[165] designed an inductive soft body pneumatic gripper using hybrid power. A rigid optical fiber with low optical loss was used for optical signal transmission to measure the curvature deformation and the contact force on a specific part of the finger. The curvature and contact force are passed as inputs to a proportional integral differential (PID) control program to control the force applied by the actuator (Figure 9d). The results show that the actuator has good tracking performance and can reject disturbances, due to the robustness of the gripper's PID control.

Biologically superior manipulation capabilities depend on the sensory movements of the biological neuromuscular system. It is valuable to achieve multifunctionally and locally sensing soft robots to achieve capabilities close to natural organisms. Zhao et al.[166] reported a soft-body sensory actuation material that uses a conductive and photothermally responsive hydrogel that combines piezoresistive and pressure-sensing functions. This two-in-one functional hydrogel exhibits both the extrinsic sensation of perceiving the environment and the proprioception of sensing its deformation in real time while being actuated with nearly infinite DOF. When connected to a control circuit, the muscle-like material achieves self-sensing closed-loop control (Figure 9e).

3.3. Reaction

Soft robots perform various tasks often within unstructured scenarios and need to face different external disturbances and stimuli. In a closed-loop response task, the information flow path is controller–actuator–environment–sensor–controller, with energy flowing from the environment to the actuator, so the body is the actuator. Here, the goal of control is to estimate and respond to the external environment's forces to ensure the body's stability in action and the safety of the external agent. Soft robots need to react to active mechanics imposed by external agents to perform tasks safely and stably.[167] Covering the entire surface of the robot with microsensors capable of measuring local pressure and transmitting data over a network is an ideal solution to provide the robot with artificial skin to improve mobility and safety.[168] Another possible approach is the development of soft robots with self-sensing capabilities, where the actuators use their sensing capabilities for feedback control for rapid response and strategy selection after the reaction. Sun et al.[169] investigated the integrated sensing and actuation of twisted-and-coiled actuators (TCAs) with self-sensing functions. Closed-loop PI control of individual TCAs was achieved, and an innervated soft claw that

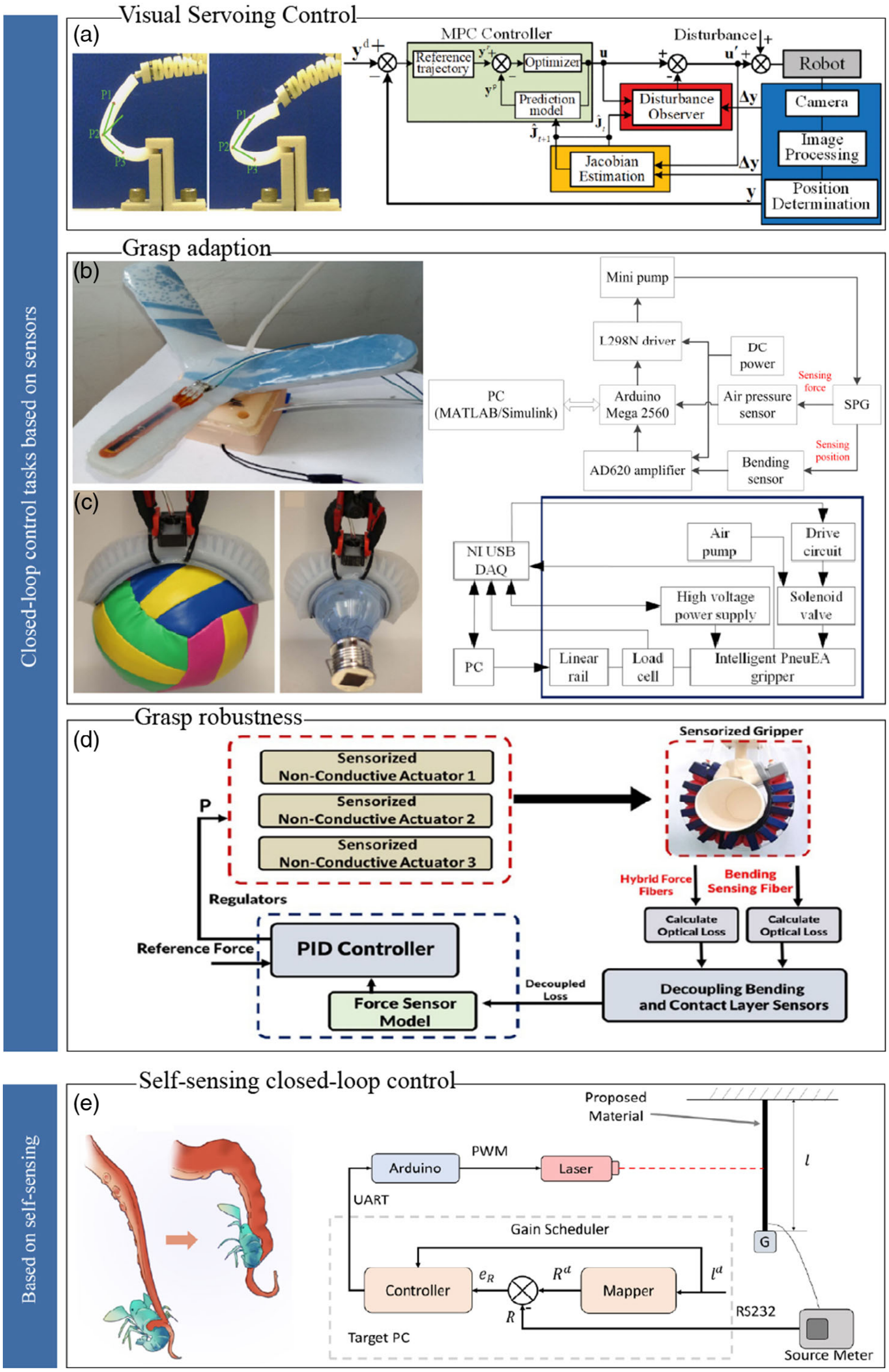

Figure 9. Manipulation tasks based on closed-loop control of soft robots. a) Continuum soft robot for performing visual servoing manipulation closed-loop tasks. Reproduced with permission.[155] Copyright 2021, Institute of Electrical and Electronics Engineers (IEEE). b) Two simple sensors are used in the soft pneumatic gripper to give it adaptive gripping capabilities. Reproduced with permission.[158] Copyright 2018, Elsevier. c) Sensory adaptive electric adhesive pneumatic soft gripper. Reproduced with permission.[159] Copyright 2018, Institute of Physics (IOP) Publishing. d) Pneumatic soft gripper with a built-in pressure sensor and fiber-optic stretch sensor performs stable manipulation through PID closed-loop control of force and position. Reproduced with permission.[165] Copyright 2021, Institute of Electrical and Electronics Engineers (IEEE). e) Conductively actuated and photothermally actuated hydrogel soft robot with piezoresistive stretch and pressure self-sensing. Reproduced with permission.[166] Copyright 2021, American Association for the Advancement of Science (AAAS).

responds to external loads without additional sensors was built (**Figure 10**a). The soft claw can automatically respond to stimuli generated by external agents and perform specified motions.

However, when the external agent is a human, which usually involves human–robot interaction, the security of the external agent is more important than the stability of the robot. The security, context prediction, and adaptation issues associated with human–robot interaction make the soft robot's response task more challenging, and distinct from the manipulation task.[170] In human–robot interaction scenarios, the reaction task can often be performed in parallel with the manipulation task to ensure the smooth execution of the task as well as the security of the external agent. Furthermore, at the control level, one of the main issues to be addressed by reactive tasks is how to dynamically, safely, and task consistently adapt, keeping in mind the overall plan and the respective constraint texts.[171] Wang et al.[172] proposed a self-sensing soft electrohydraulic pneumatic actuator (SEHPA) with a dual-drive mode. The self-sensing capability of the SEHPA can be used specifically to monitor and ensure accurate output. The SEHPA has the potential to be mounted on the fingertip and provide accurate tactile sensation once the manipulator touches an object through teleoperation (Figure 10b). The excellent response behavior and accurate haptic feedback prove to be a candidate in the field of teleoperation. It is worth noting that noncontact human–robot interaction response tasks play an important role in the field of soft robotics in addition to haptic tasks, and the feasibility of these response tasks has been demonstrated. For instance, Liu et al.[173] integrated a flexible bimodal smart skin based on TENG and LM sensing into soft robots for reacting the touchless and tactile stimuli. Furthermore, they proposed a closed-loop control method that enables soft robots to react to the humans' approaching–leaving actions so that humans can teach them movements via bare hand–eye coordination (Figure 10c).

The main challenges for large-area electronic skins for covering soft robots are higher mechanical deformation and robustness, improved skin compatibility, and higher device densities.[174] Recent research has demonstrated an intrinsically stretchable polymer transistor array with an unprecedented device density of 347 transistors per square centimeter. The transistor array constitutes intrinsically scalable skin electronics, including an active matrix for sensor arrays, as well as analog and digital circuit elements.[175] Then there is the challenge of organizing and calibrating many spatially distributed multimodal

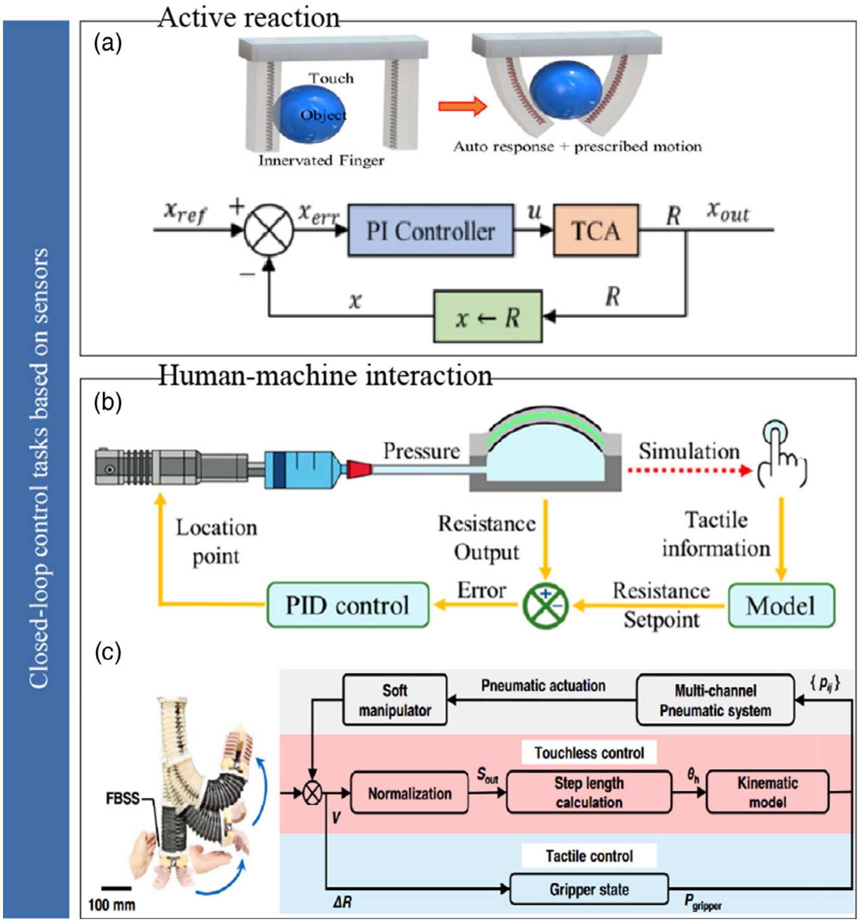

Figure 10. Reaction tasks based on closed-loop control of soft robots. a) Soft claws can automatically respond to stimuli with closed-loop feedback control. Reproduced with permission.[169] Copyright 2020, Institute of Electrical and Electronics Engineers (IEEE). b) Self-sensing SEHPA can provide closed-loop control of haptic feedback during HMI. Reproduced with permission.[172] Copyright 2022, MDPI. c) Soft manipulator with closed-loop control of touchless and tactile. Reproduced with permission.[173] Copyright 2022, Springer Nature.

haptic sensing elements. The latest and comprehensive whole-body haptic sensing study was able to self-organize and self-calibrate 1260 multimodal sensing units and implement a hierarchical task manager consisting of a fusion of a balance controller, a self-collision avoidance system, and a skin compliance controller.[176]

3.4. Exploration

The exploration task is a process of autonomous body movement of the robot based on control and sensory feedback. In the closed-loop exploration task, the information flow path is controller–actuator–environment–sensor–controller. Energy flows from the environment to the sensor, so the body is the sensor. Here, the goal of control is the extraction of features of the environment by the sensor for planning the following behavior of the body. Exploration is the process of voluntary motion of the body based on the somatosensory feedback for identifying environmental properties.[177] The feedback is performed not only on sensory data but also on complex processed sensory data.[178] According to the processing complexity of sensory data in feature extraction, environmental properties can be divided into low-level features and mid-level tasks.

Environmental properties of interest can be low-level features such as surface texture,[179] contact force,[180] or temperature.[115] Exploiting low-level features relies on the direct utilization of sensor data. Therefore, they only require simple closed-loop control and data-processing algorithms, such as support vector machine (SVM).[181] For instance, Yu et al.[179] described an ingeniously constructed and simply fabricated soft pneumatic actuator with self-sensing capability for force and vibration feedback. This SenAct embeds a stable, fast-responding capacitive sensor that can simultaneously generate output force and monitor changes in capacitance. SenAct features lightweight, soft, fast-responding, and repeatable self-sensing and closed-loop control to recreate precise force and vibration feedback based on an external force or vibration signals to generate tactile feedback and thereby obtain target object geometric information of the target object (**Figure 11**a). The environmental attributes of interest can also be mid-level tasks such as object classification[182] or object recognition.[181,183] Mid-level tasks require complex processing of sensory data and therefore require relatively complex data processing algorithms, including SVM[184] and more advanced neural networks such as convolutional neural networks (CNNs).[183,185] For example, Jin et al.[184] reported an innovative soft-robotic gripper system based on TENG sensors to capture the continuous motion and tactile information for the soft gripper. The tactile sensors can perceive the contact position and the sensory information collected during the operation of the soft gripper is further trained by the SVM algorithm to identify diverse objects (Figure 11b). Based on the above work, Sun et al.[110] reported a smart soft robotic manipulator consisting of TENG tactile sensors and a PVDF pyroelectric temperature sensor, and a three-layer 1D-CNN was constructed for data feature extraction and automatic recognition to verify the sensing ability of the proposed intelligent manipulator system. Recently, Huang et al.[183] proposed a framework for variable-stiffness object recognition using tactile information collected by force-sensitive resistors on a three-finger soft gripper. A 3D palpation process was used to generate a spatiotemporal tactile image. A CNN and a Naive Bayes classifier were used to identify objects. The detection of shapes and sizes of hard objects underneath soft tissues is considered extremely important for breast and testicular cancer early detection, a field where soft robots can shine with inexpensive and ubiquitous devices.

Achieving full autonomy in exploration requires active exploration, which is a higher-level process than mid-level tasks that select the best action to better sense information.[19] The first step toward active exploration control architecture is considered to be tactile servoing.[186] This includes tracking or maintaining a touched object, tracking an object's pose, and tactile object exploration. For example, Li et al.[187] presented a novel hierarchical control framework on tactile servoing with visual-servoing approaches to allow for surface exploration of unknown objects. The framework was divided into three layers: a joint-level layer, a tactile-servoing layer, and a visual-servoing layer. The tactile-servoing layer provided "blind" surface exploration skills, maintaining desired contact patterns and acquiring a tactile point cloud. The visual layer monitored and controlled the actual object pose, providing high-level fingertip motion commands that were merged with the tactile-servoing control commands. Common to all the actions was a tight feedback loop maintaining optimal object contact using tactile-servoing controllers. Furthermore, tactile servoing provides closed-loop control of exploratory movements of an unknown object using tactile sensors for feedback. Additional tactile information obtained during the process was then used to estimate the compliance of the object.[188] The next step to develop active exploration strategies is that they run simultaneously and are regulated by the tactile feature extraction process.[19] For example, Low et al.[189] presented a versatile soft robotic gripper whose capability was optimized by integrating vision and tactile sensing facilities for food handling. On the one hand, a vision module was developed to identify food samples and the pose of each food item. An object detection algorithm based on You Only Look Once (YOLOv3) was applied in the vision system and a pretrained weight file was used as a CNN feature extractor on the dataset. On the other hand, tactile sensors were integrated into a real-time grip pose exploration technique (grip pose comparator) to automatically reconfigure and search for a stable pose to handle food samples of different shapes and sizes. The sequence of robot controllers comprised robot arm controller, gripper controller, and closed-loop force feedback system (Figure 11c). The next challenge in this area is to further develop exploration methods for active tactile learning based on the tactile feature extraction process to efficiently learn and characterize objects based on their physical properties (shape, stiffness, mass, surface texture, etc.) of unknown objects. The prior knowledge gained in active tactile learning is used to guide soft robots to make decisions to acquire information more efficiently in unknown environments to achieve optimal local or even global exploration strategies.[190–193]

4. Challenges and Future Perspectives

The approaches to provide perception capabilities for intelligent soft robots show differences in the applicability for differing soft

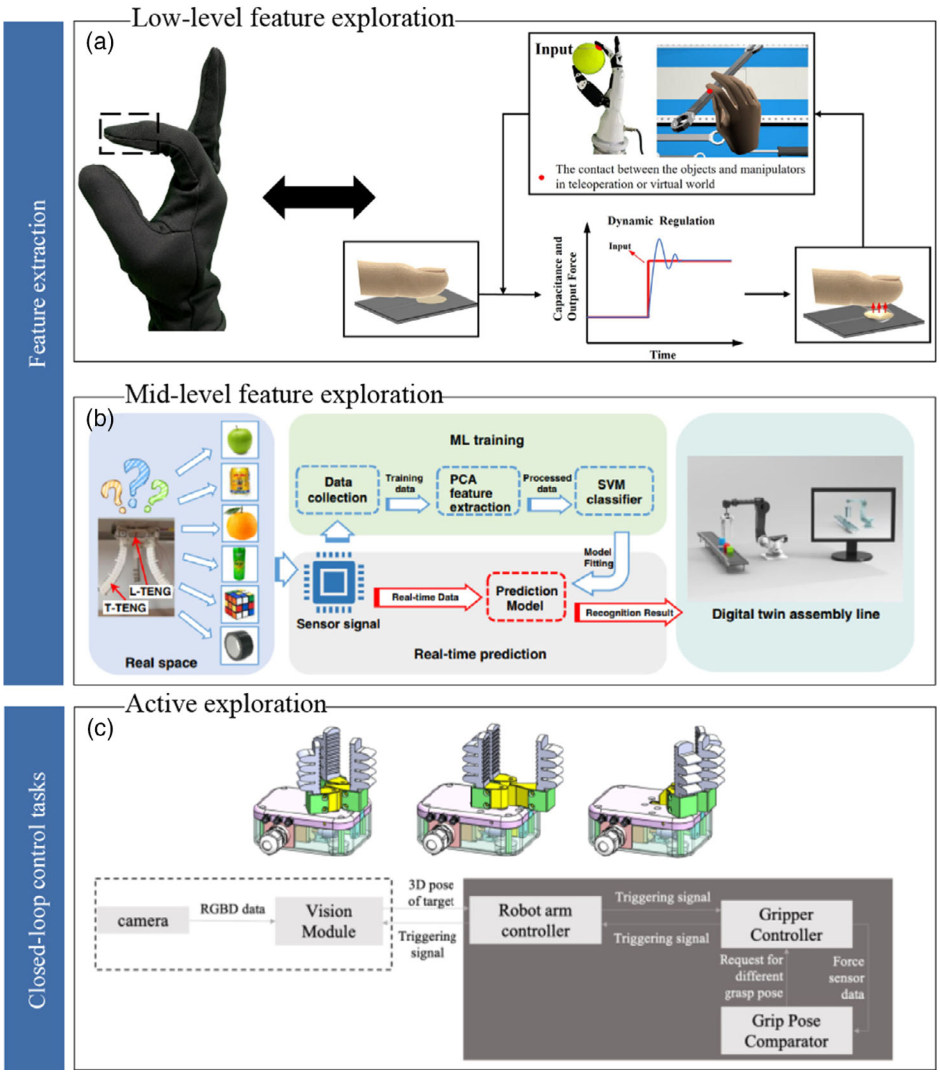

Figure 11. Exploration tasks based on feature attraction and closed-loop control of soft robots. a) Soft pneumatic self-sensing actuator with precise force and vibration feedback. Reproduced with permission.[179] Copyright 2022, Elsevier. b) Soft-robotic gripper system based on TENG sensors to identify diverse objects. Reproduced with permission.[184] Copyright 2020, Springer Nature. c) Soft robotic gripper system by integrating vision and tactile-sensing facilities for active exploration. Reproduced with permission.[189] Copyright 2021, Institute of Electrical and Electronics Engineers (IEEE).

robots in addition to being promising within a specific sensing range and accuracy as summarized in **Table 1** and **2**. Despite these efforts, many challenges remain, and we have highlighted some of the most important ones below. 1) The challenge of proprioception is to develop proprioceptive sensors with high stretchability, high sensitivity, and high dynamic range. Soft robots experience strains of varying sizes (e.g., large bending and stretching deformations and small twisting deformations) and complex deformations (multiple deformation complexes), and key challenges include increasing the stretchability of the shape-sensing skin and improving the resolution of the sensor to detect small curvatures. Second, the challenge also lies in the introduction of multimodal proprioception, where the deformation of a soft robot is often a composite of multiple motions and is 3D rather than planar and single. One way of thinking is to obtain as much information as possible about the topographic variation of the soft robot body through multiple sensor bundles, and then use ML methods to analyze and decouple the large amount of data information, which will inevitably introduce a large amount of computational consumption. Once reliable soft robot proprioceptive solutions are available in this area, it is conceivable that shape feedback will enable controlled shape changes in robots. With current soft robots unable to morph into specific configurations, the next challenge is to refine closed-loop kinematics, shape control, and force control to allow soft robots to switch between morphology and corresponding motor gaits as needed. 2) The challenge for exteroception is the development of highly stretchable and high-bandwidth sensing arrays. Achieving full-spectrum environmental sensing often requires sensing arrays throughout the body, which challenges the stretchability of sensing arrays. In addition, different body regions have different bandwidth requirements, so high

Table 1. Summary of methods and their relative applicability for implementing proprioception on different types of soft robots discussed in this review (H: high, M: medium, L: low).

Proprioception	Methods	Sensors	Soft robot	Applicability	Ref.
Bending	Optical	Optical waveguide	Pneumatic prosthetic hand	H	[38]
	Microfluidic	Liquid metals	Pneumatic tentacle	L	[42]
	Electrical	Conductive elastomer	Pneumatic gripper	M	[54]
	Self-sensing	Resistive self-sensing	Electrothermal actuator	H	[59]
Twisting	Optical	Fiber optic	Pneumatic gripper	H	[71]
	Microfluidic	Fluid	Elastomeric finger	M	[72]
	Electrical	Hydrogel	Pneumatic finger	L	[74]
	Self-sensing	Inductive self-sensing	Twisted and coiled polymer muscle	H	[78]
Stretching	Optical	Optical waveguide	Pneumatic robot	H	[83]
	Microfluidic	Liquid metals	Pneumatic artificial muscle	H	[86]
	Electrical	Conductive nanomaterial	Soft robotic earthworm	M	[88]
	Self-sensing	Resistive self-sensing	Origami robot	H	[95]

Table 2. Summary of methods and their relative applicability for implementing exteroception on different types of soft robots discussed in this review (H: high, M: medium, L: low).

Exteroception	Methods	Sensors	Soft robots	Applicability	Ref.
Pressure	Microfluidic	Ionic conductive fluid	Pneumatic robotic gripper	H	[104]
	Electrical	Silver nanowires	Shape memory polymer gripper	M	[109]
	Self-sensing	Resistive self-sensing	Electrothermal polymer actuator	H	[113]
Temperature	Electrical	PEDOT:PSS nanowires	Pneumatic robotic gripper	L	[122]
		Hydrogel	Pneumatic robotic gripper	L	[124]
	Self-sensing	Pyroelectric self-sensing	Light-driven thin-film robot	H	[125]
Humidity	Electrical	Graphene oxide	Light-driven crawling robot	H	[135]
	Self-sensing	TENG self-sensing	NIR light or magnetic field-driven crawling robot	H	[137]

bandwidth is required. Second, other exteroception capabilities (e.g., gas sensing, light sensing, magnetic sensing) are required to be introduced into soft robots, and these types of sensors have been proposed but still need further application in soft robots. Multimodal exteroception helps soft robots acquire environmental information more efficiently. This further increases the difficulty of information processing and computational models to extract useful information from the sensor array are the next challenges. However, the details of how to develop and implement such algorithms are not yet clear, for example, how to select the most efficient algorithm for classification, regression, and detection tasks for different signal inputs; the use of neural networks in different situations; and the balance between efficiency and reliability are all issues that need to be addressed. 3) The challenges of closed-loop control of soft robots can be categorized by their tasks. Current soft robots cannot be morphed into specific configurations for motion tasks. The key challenge is providing comprehensive shape feedback through integrating multiple proprioceptive functions to allow the robot to switch control between morphology and corresponding motion gaits as needed. For manipulation tasks, the next challenge is the fusion of proprioceptive and exteroceptive multisensor information based on the controlled shape of the soft robot. Furthermore, the introduction of exteroceptive multimodality (including sensing pressure, shear, and vibration, and even detecting the presence of chemical and biological markers in the environment) will greatly enhance the manipulation capabilities of soft robots, which will be available for a wide range of applications, including hazardous environment manipulation, disaster response, and manufacturing. For response tasks, haptic responses may require minimal spatial discrimination. The challenge is to develop sensing arrays throughout the body for low-level control to help soft robots respond to external stimuli promptly while contributing to the safety of human–robot interaction. Notably, introducing noncontact sensing methods (frictional electrical, magnetic, temperature, light, gas, etc.) into soft robots can help further enhance the responsiveness of soft robots. For exploration tasks, exploration may require the highest spatial resolution as evidenced by the dense distribution of mechanoreceptors at human fingertips, and the key challenge lies in the interpretation and learning of information through knowledge gained from active haptic exploration. This relies on the improvement of information processing capabilities. Solving these problems requires collaboration across interdisciplinary areas, such as computer and data science, materials science, control science, and neuroscience. The result will be soft robots that understand themselves, their environment, and their interactions with humans better, resulting in more intelligent soft robots and richer, more efficient experiences for humans.

5. Conclusion

In this review, we discussed soft robots with proprioceptive and exteroceptive functions and summarized the closed-loop control tasks based on these sensory feedbacks. These sensing capabilities are the basis for developing autonomous, intelligent soft robots. We analyzed two strategies for developing perceptive soft robots: 1) by integrating flexible/stretchable sensors into soft robots and 2) by designing and fabricating self-sensing soft robots with functional materials capable of both actuation and sensing. Self-sensing soft robots have the advantage of a seamless fusion of actuation and sensing functions. However, the coupling of actuation and sensing also poses great challenges in data analysis and information extraction. In the context of the two strategies, we classified perceptive soft robots based on sensing functions, including proprioception (bending perception, twisting perception, and stretching perception) and exteroception (pressure perception, temperature perception, and humidity perception). In addition, we summarized design ideas and implementation methods for perceptive soft robots with different closed-loop control tasks (motion, manipulation, reaction, and exploration).

Lately, researchers have developed soft robots with sensing capabilities that mimic natural organisms. We believe this biomimicking approach will become the dominant trend in the future advancement of perceptive robotics. The next step in this direction will most likely focus on the integration and fusion of multimodal perceptive functions in soft robots for more stable and reliable closed-loop control and the incorporation of customized ML to further improve the perceptive capabilities of soft robots. In the long run, soft robots comparable to natural systems will be around in our daily life, capable of exploring the unknown world like living creatures and working closely with humans.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (no. 61903317), the Guangdong-Hongkong Joint Funding Program (no. 2021A0505110015), the Guangdong Basic and Applied Basic Research Foundation (no. 2022A1515011523), the Science and Technology Innovation Council of Shenzhen (nos. KQTD20170810105439418 and JCYJ20200109114237902), and the funding from the Shenzhen Institute of Artificial Intelligence and Robotics for Society (no. AC01202101106).

Conflict of Interest

The authors declare no conflict of interest.

Keywords

closed-loop control, exteroception, proprioception, sensory feedback, soft robots

Received: October 5, 2022
Revised: November 22, 2022
Published online:

[1] M. H. Dickinson, C. T. Farley, R. J. Full, M. A. R. Koehl, R. Kram, S. Lehman, *Science* **2000**, *288*, 100.
[2] J. C. Case, E. L. White, R. K. Kramer, *Soft Robot.* **2015**, *2*, 80.
[3] T. Arnold, M. Scheutz, *Soft Robot.* **2017**, *4*, 81.
[4] D. Rus, M. T. Tolley, *Nature* **2015**, *521*, 467.
[5] S. Kim, C. Laschi, B. Trimmer, *Trends Biotechnol.* **2013**, *31*, 287.
[6] M. Wehner, R. L. Truby, D. J. Fitzgerald, B. Mosadegh, G. M. Whitesides, J. A. Lewis, R. J. Wood, *Nature* **2016**, *536*, 451.
[7] E. W. Hawkes, L. H. Blumenschein, J. D. Greer, A. M. Okamura, *Sci. Robot.* **2017**, *2*, eaan3028.
[8] M. Li, A. Pal, A. Aghakhani, A. Pena-Francesch, M. Sitti, *Nat. Rev. Mater.* **2021**, *7*, 235.
[9] T. M. Bieze, F. Largilliere, A. Kruszewski, Z. Zhang, R. Merzouki, C. Duriez, *Soft Robot.* **2018**, *5*, 348.
[10] P. Wu, W. Jiangbei, F. Yanqiong, *Soft Robot.* **2018**, *5*, 71.
[11] H. Wang, M. Totaro, L. Beccai, *Adv. Sci.* **2018**, *5*, 1800541.
[12] Z. Xu, C. Chi, B. Burchfiel, E. Cousineau, S. Feng, S. Song, arXiv:2203.01197, **2022**.
[13] C. S. Sherrington, *Psychol. Bull.* **1907**, *4*, 198.
[14] J. C. Case, E. L. White, R. K. Kramer, *Smart Mater. Struct.* **2016**, *25*, 45018.
[15] S. Han, H. Peng, Q. Sun, S. Venkatesh, K. Chung, S. C. Lau, Y. Zhou, V. A. L. Roy, *Adv. Mater.* **2017**, *29*, 1700375.
[16] M. D. Mitchell, F. E. Hurley, C. D. Onal, *IEEE 17th Int. Conf. Autom. Science and Engineering (CASE)*, IEEE, Piscataway, NJ **2021**, p. 215.
[17] M. Cianchetti, F. Renda, A. Licofonte, C. Laschi, *4th IEEE RAS & EMBS Int. Conf. Biomedical Robotics and Biomechatronics (BioRob)*, IEEE, Piscataway, NJ **2012**, p. 634.
[18] M. Ilami, H. Bagheri, R. Ahmed, E. O. Skowronek, H. Marvi, *Adv. Mater.* **2021**, *33*, 2003139.
[19] B. Shih, D. Shah, J. Li, T. G. Thuruthel, Y. L. Park, F. Iida, Z. Bao, R. Kramer-Bottiglio, M. T. Tolley, *Sci. Robot.* **2020**, *5*, eaaz9239.
[20] W. Dou, G. Zhong, J. Cao, Z. Shi, B. Peng, L. Jiang, *Adv. Mater. Technol.* **2021**, *6*, 2100018.
[21] B. Ma, C. Xu, L. Cui, C. Zhao, H. Liu, *ACS Appl. Mater. Interfaces* **2021**, *13*, 5574.
[22] K. Kruusamäe, A. Punning, A. Aabloo, K. Asaka, *Actuators* **2015**, *4*, 17.
[23] J. van der Weijde, B. Smit, M. Fritschi, C. van de Kamp, H. Vallery, *IEEE ASME Trans. Mechatron.* **2017**, *22*, 1268.
[24] S. Katta, M. Krieg, M. B. Goodman, *Annu. Rev. Cell Dev. Biol.* **2015**, *31*, 347.
[25] D. Alatorre, D. Axinte, A. Rabani, *IEEE T. Robot.* **2022**, *38*, 526.
[26] A. Tsay, T. J. Allen, U. Proske, M. J. Giummarra, *Neurosci. Biobehav. Rev.* **2015**, *52*, 221.
[27] H. C. Bastian, *Brain* **1887**, *10*, 1.
[28] U. Proske, S. C. Gandevia, *Physiol. Rev.* **2012**, *92*, 1651.
[29] Q. Zhao, J. W. C. Dunlop, X. Qiu, F. Huang, Z. Zhang, J. Heyda, J. Dzubiella, M. Antonietti, J. Yuan, *Nat. Commun.* **2014**, *5*, 4293.
[30] Q. Ji, Z. Jing, J. Shen, Y. Hu, L. Chang, L. Lu, M. Liu, J. Liu, Y. Wu, *Adv. Intell. Syst.* **2021**, *3*, 2000240.
[31] J. Mu, C. Hou, B. Zhu, H. Wang, Y. Li, Q. Zhang, *Sci. Rep.* **2015**, *5*, 1.
[32] S. Taccola, F. Greco, E. Sinibaldi, A. Mondini, B. Mazzolai, V. Mattoli, *Adv. Mater.* **2015**, *27*, 1668.
[33] C. Wang, K. Sim, J. Chen, H. Kim, Z. Rao, Y. Li, W. Chen, J. Song, R. Verduzco, C. Yu, *Adv. Mater.* **2018**, *30*, 1706695.
[34] H. Zhao, J. Jalving, R. Huang, R. Knepper, A. Ruina, R. Shepherd, *IEEE Robot. Autom. Mag.* **2016**, *23*, 55.

[35] J. Chen, J. Zhang, Z. Luo, J. Zhang, L. Li, Y. Su, X. Gao, Y. Li, W. Tang, C. Cao, Q. Liu, L. Wang, H. Li, *ACS Appl. Mater. Interfaces* **2020**, *12*, 22200.
[36] J. C. Yeo, H. K. Yap, W. Xi, Z. Wang, C. Yeow, C. T. Lim, *Adv. Mater. Technol.* **2016**, *1*, 1600018.
[37] S. S. Banerjee, I. Arief, R. Berthold, M. Wiese, M. Bartholdt, D. Ganguli, S. Mitra, S. Mandal, J. Wallaschek, A. Raatz, G. Heinrich, A. Das, *Adv. Mater. Technol.* **2021**, *25*, 101219.
[38] H. Zhao, K. O'Brien, S. Li, R. F. Shepherd, *Sci. Robot.* **2016**, *1*, eaai7529.
[39] K. K. Kim, I. H. Ha, S. H. Ko, *14th Int. Conf. Ubiquitous Robot. Ambient Intell.*, IEEE, Jeju, Korea (South) **2017**, p. 62.
[40] S. Li, H. Zhao, R. F. Shepherd, *MRS Bull.* **2017**, *42*, 138.
[41] Y. Tao, G. Gu, L. Zhu, *IEEE Int. J. Intell. Rob. Appl.* **2017**, *1*, 451.
[42] Z. Xie, F. Yuan, Z. Liu, Z. Sun, E. M. Knubben, L. Wen, *IEEE ASME Trans. Mechatron.* **2020**, *25*, 1841.
[43] S. Cheraghi, M. A. Taher, H. Karimi-Maleh, *J. Food Compos. Anal.* **2017**, *62*, 254.
[44] S. Russo, T. Ranzani, H. Liu, S. Nefti-Meziani, K. Althoefer, A. Menciassi, *Soft Robot.* **2015**, *2*, 146.
[45] C. B. Cooper, K. Arutselvan, Y. Liu, D. Armstrong, Y. Lin, M. R. Khan, J. Genzer, M. D. Dickey, *Adv. Funct. Mater.* **2017**, *27*, 1605630.
[46] M. Su, R. Xie, Y. Zhang, X. Kang, D. Huang, Y. Guan, H. Zhu, *Appl. Sci.* **2019**, *9*, 2999.
[47] M. Amjadi, K. Kyung, I. Park, M. Sitti, *Adv. Funct. Mater.* **2016**, *26*, 1678.
[48] L. Wang, Y. Chen, L. Lin, H. Wang, X. Huang, H. Xue, J. Gao, *Chem. Eng. J.* **2019**, *362*, 89.
[49] Y. Zheng, Y. Li, K. Dai, Y. Wang, G. Zheng, C. Liu, C. Shen, *Compos. Sci. Technol.* **2018**, *156*, 276.
[50] Y. Liu, D. Zhang, *Compos. Sci. Technol.* **2016**, *137*, 102.
[51] M. Vural, A. M. Behrens, O. B. Ayyub, J. J. Ayoub, P. Kofinas, *ACS Nano* **2015**, *9*, 336.
[52] J. Morrow, H. Shin, C. Phillips-Grafflin, S. Jang, J. Torrey, R. Larkins, S. Dang, Y. Park, D. Berenson, in *IEEE Int. Conf. Robot. Autom. (ICRA)*, IEEE, Piscataway, NJ **2016**, p. 5024.
[53] H. Liu, H. Zhang, W. Han, H. Lin, R. Li, J. Zhu, W. Huang, *Adv. Mater.* **2021**, *33*, 2004782.
[54] S. Mousavi, D. Howard, F. Zhang, J. Leng, C. H. Wang, *ACS Appl. Mater. Interfaces* **2020**, *12*, 15631.
[55] R. Tabassian, V. H. Nguyen, S. Umrao, M. Mahato, J. Kim, M. Porfiri, I. K. Oh, *Adv. Sci.* **2019**, *6*, 1901711.
[56] A. Punning, M. Kruusmaa, A. Aabloo, *Sens. Actuators, A* **2007**, *136*, 656.
[57] K. Kruusamäe, P. Brunetto, S. Graziani, A. Punning, G. Di Pasquale, A. Aabloo, *Polym. Int.* **2010**, *59*, 300.
[58] K. Kruusamäe, A. Punning, A. Aabloo, K. Asaka, *Actuators* **2015**, *4*, 17.
[59] Y. Cao, J. Dong, *IEEE ASME Trans. Mechatron.* **2021**, *26*, 854.
[60] H. Zhao, R. Hu, P. Li, A. Gao, X. Sun, X. Zhang, X. Qi, Q. Fan, Y. Liu, X. Liu, M. Tian, G. Tao, L. Qu, *Nano Energy* **2020**, *76*, 104926.
[61] C. Larson, B. Peele, S. Li, S. Robinson, M. Totaro, L. Beccai, B. Mazzolai, R. Shepherd, *Science* **2016**, *351*, 1071.
[62] R. Xu, A. Yurkewich, R. V. Patel, *IEEE Robot. Autom. Lett.* **2016**, *1*, 1052.
[63] K. Masuya, K. Tahara, *IEEE Robot. Autom. Lett.* **2021**, *6*, 4883.
[64] M. Zou, S. Li, X. Hu, X. Leng, R. Wang, X. Zhou, Z. Liu, *Adv. Funct. Mater.* **2021**, *31*, 2007437.
[65] M. Yang, L. P. Cooper, N. Liu, X. Wang, M. P. Fok, *Opt. Express* **2020**, *28*, 35158.
[66] R. Wang, Y. Shen, D. Qian, J. Sun, X. Zhou, W. Wang, Z. Liu, *Mater. Horiz.* **2020**, *7*, 3305.
[67] M. Amjadi, K. Kyung, I. Park, M. Sitti, *Adv. Funct. Mater.* **2016**, *26*, 1678.
[68] A. Abbas, J. Zhao, in *IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, IEEE, Piscataway, NJ **2017**, p. 482.
[69] I. M. Van Meerbeek, C. M. De Sa, R. F. Shepherd, *Sci. Robot.* **2018**, *3*, eaau2489.
[70] K. C. Galloway, Y. Chen, E. Templeton, B. Rife, I. S. Godage, E. J. Barth, *Soft Robot.* **2019**, *6*, 671.
[71] M. Yang, L. P. Cooper, N. Liu, X. Wang, M. P. Fok, *Opt. Express* **2020**, *28*, 35158.
[72] K. Lin, A. Gamboa-Gonzalez, M. Wehner, *Electronics* **2021**, *10*, 3166.
[73] Y. Wang, W. Qin, X. Hu, Z. Liu, Z. Ren, H. Cao, B. An, X. Zhou, M. Shafiq, S. Yin, Z. Liu, *Sens. Actuators B Chem.* **2022**, *368*, 132228.
[74] S. Wang, Z. Sun, Y. Zhao, L. Zuo, *Sens. Actuators, A* **2021**, *331*, 113006.
[75] Z. Sun, S. Wang, Y. Zhao, Z. Zhong, L. Zuo, *Adv. Intell. Syst.* **2020**, *4*, 2200089.
[76] T. G. Thuruthel, E. Falotico, F. Renda, C. Laschi, *Bioinspir. Biomim.* **2017**, *12*, 66003.
[77] D. R. Higueras-Ruiz, M. W. Shafer, H. P. Feigenbaum, *Sci. Robot.* **2021**, *6*, abd5383.
[78] J. van der Weijde, H. Vallery, R. Babuška, *Soft Robot.* **2019**, *6*, 621.
[79] D. Bombara, S. Fowzer, J. Zhang, *Soft Robot.* **2022**, *9*, 72.
[80] C. Lamuta, S. Messelot, S. Tawfick, *Smart Mater. Struct.* **2018**, *27*, 55018.
[81] P. E. Roland, H. Ladegaard-Pedersen, *Brain* **1977**, *100*, 671.
[82] J. Morrow, H. Shin, C. Phillips-Grafflin, S. Jang, J. Torrey, R. Larkins, S. Dang, Y. Park, D. Berenson, in *IEEE Int. Conf. Robot. Autom. (ICRA)*, IEEE, Piscataway, NJ **2016**, p. 5024.
[83] T. Kim, S. Lee, T. Hong, G. Shin, T. Kim, Y. Park, *Sci. Robot.* **2020**, *5*, eabc6878.
[84] P. A. Xu, A. K. Mishra, H. Bai, C. A. Aubin, L. Zullo, R. F. Shepherd, *Sci. Robot.* **2019**, *4*, eaaw6304.
[85] D. Alatorre, D. Axinte, A. Rabani, *IEEE T. Robot.* **2022**, *38*, 526.
[86] J. Wirekoh, L. Valle, N. Pol, Y. Park, *Soft Robot.* **2019**, *6*, 768.
[87] Y. Zhou, B. He, Z. Yan, Y. Shang, Q. Wang, Z. Wang, *Sensors* **2018**, *18*, 569.
[88] R. Goldoni, Y. Ozkan-Aydin, Y. Kim, J. Kim, N. Zavanelli, M. Mahmood, B. Liu, F. L. Hammond, D. I. Goldman, W. Yeo, *ACS Appl. Mater. Interfaces* **2020**, *12*, 43388.
[89] Y. Gao, Q. Li, R. Wu, J. Sha, Y. Lu, F. Xuan, *Adv. Funct. Mater.* **2019**, *29*, 1806786.
[90] H. Chong, J. Lou, K. M. Bogie, C. A. Zorman, S. J. Majerus, *IEEE T. Biomed. Circ. S.* **2019**, *13*, 1451.
[91] M. A. Mcevoy, N. Correll, *Science* **2015**, *347*, 1261689.
[92] G. Z. Yang, J. Bellingham, P. E. Dupont, P. Fischer, L. Floridi, R. Full, N. Jacobstein, V. Kumar, M. Mcnutt, R. Merrifield, B. J. Nelson, B. Scassellati, M. Taddeo, R. Taylor, M. Veloso, Z. L. Wang, R. Wood, *Sci. Robot.* **2018**, *3*, eaar7650.
[93] R. Liu, S. Wang, H. Yang, C. Shi, *IEEE Sens. J.* **2021**, *21*, 23880.
[94] Y. Yang, H. Zhu, J. Liu, H. Lu, Y. Ren, M. Y. Wang, *Polymers* **2022**, *14*, 2265.
[95] H. Yang, B. S. Yeow, Z. Li, K. Li, T. H. Chang, L. Jing, Y. Li, J. S. Ho, H. Ren, P. Y. Chen, *Sci. Robot.* **2019**, *4*, eaax7020.
[96] D. Rus, M. T. Tolley, *Nat. Rev. Mate.* **2018**, *3*, 101.
[97] A. B. Vallbo, R. S. Johansson, *Hum. Neurobiol.* **1984**, *3*, 3.
[98] J. M. Yau, S. S. Kim, P. H. Thakur, S. J. Bensmaia, *J. Neurophysiol.* **2016**, *115*, 631.
[99] S. Sundaram, *Science* **2020**, *370*, 768.
[100] Z. Si, W. Yuan, *IEEE Robot. Autom. Lett.* **2022**, *7*, 2361.
[101] J. Yin, V. J. Santos, J. D. Posner, *Sens. Actuators, A* **2017**, *264*, 289.
[102] S. Wang, J. Xu, W. Wang, G. N. Wang, R. Rastak, F. Molina-Lopez, J. W. Chung, S. Niu, V. R. Feig, J. Lopez, *Nature* **2018**, *555*, 83.
[103] S. Sundaram, P. Kellnhofer, Y. Li, J. Zhu, A. Torralba, W. Matusik, *Nature* **2019**, *569*, 698.

[104] R. L. Truby, M. Wehner, A. K. Grosskopf, D. M. Vogt, S. G. M. Uzel, R. J. Wood, J. A. Lewis, *Adv. Mater.* **2018**, *30*, 1706383.
[105] H. F. Arab, H. Jin, T. Yokota, T. Someya, N. V. Thakor, *Sci. Adv.* **2020**, *6*, a412.
[106] B. S. Homberg, R. K. Katzschmann, M. R. Dogar, D. Rus, *Autom. Robot.* **2019**, *43*, 681.
[107] B. Oh, Y. G. Park, H. Jung, S. Ji, W. H. Cheong, J. Cheon, W. Lee, J. U. Park, *Soft Robot.* **2020**, *7*, 564.
[108] Z. Shen, X. Zhu, C. Majidi, G. Gu, *Adv. Mater.* **2021**, *33*, 2102069.
[109] Y. Roh, M. Kim, S. M. Won, D. Lim, I. Hong, S. Lee, T. Kim, C. Kim, D. Lee, S. Im, G. Lee, D. Kim, D. Shin, D. Gong, B. Kim, S. Kim, S. Kim, H. K. Kim, B. K. Koo, S. Seo, J. S. Koh, D. Kang, S. Han, *Sci. Robot.* **2021**, *6*, eabi6774.
[110] Z. Sun, M. Zhu, Z. Zhang, Z. Chen, Q. Shi, X. Shan, R. C. H. Yeow, C. Lee, *Adv. Sci.* **2021**, *8*, 2100230.
[111] J. Guo, C. Xiang, J. Rossiter, *Mater. Des.* **2018**, *156*, 586.
[112] B. Ma, C. Xu, L. Cui, C. Zhao, H. Liu, *ACS Appl. Mater. Interfaces* **2021**, *13*, 5574.
[113] P. Zhou, J. Lin, W. Zhang, Z. Luo, L. Chen, *Adv. Sci.* **2022**, *9*, 2104270.
[114] J. A. Boulant, J. B. Dean, *Annu. Rev. Physiol.* **1986**, *48*, 639.
[115] J. Cai, M. Du, Z. Li, *Adv. Mater. Technol.* **2022**, 2101182.
[116] V. B. Nam, D. Lee, *Nanomaterials* **2021**, *11*,576.
[117] Q. Wang, M. Gao, L. Zhang, Z. Deng, L. Gui, *Sensors* **2019**, *19*,314.
[118] J. Wu, X. Yang, H. Ding, Y. Wei, Z. Wu, K. Tao, B. R. Yang, C. Liu, X. Wang, S. Feng, X. Xie, *Adv. Electron. Mater.* **2020**, *6*, 2000451.
[119] T. Q. Trung, S. Ramasundaram, B. Hwang, N. Lee, *Adv. Mater.* **2016**, *28*, 502.
[120] S. Jeon, S. Lim, T. Q. Trung, M. Jung, N. Lee, *Proc. IEEE* **2019**, *107*, 2065.
[121] Z. Liu, Y. Wang, Y. Ren, G. Jin, C. Zhang, W. Chen, F. Yan, *Mater. Horiz.* **2020**, *7*, 919.
[122] W. Yang, M. Xie, X. Zhang, X. Sun, C. Zhou, Y. Chang, H. Zhang, X. Duan, *ACS Appl. Mater. Interfaces* **2021**, *13*, 55756.
[123] L. Peng, Y. Zhang, J. Wang, Q. Wang, G. Zheng, Y. Li, Z. Chen, Y. Chen, L. Jiang, C. Wong, *Nano Energy* **2022**, *99*, 107367.
[124] Z. Liu, Y. Wang, Y. Ren, G. Jin, C. Zhang, W. Chen, F. Yan, *Mater. Horiz.* **2020**, *7*, 919.
[125] X. Q. Wang, K. H. Chan, Y. Cheng, T. Ding, T. Li, S. Achavananthadith, S. Ahmet, J. S. Ho, G. W. Ho, *Adv. Mater.* **2020**, *32*, 2000351.
[126] F. W. Silva, S. L. Elliot, *Ecol. Evol.* **2016**, *6*, 3672.
[127] Y. Huang, X. Zeng, W. Wang, X. Guo, C. Hao, W. Pan, P. Liu, C. Liu, Y. Ma, Y. Zhang, X. Yang, *Sens. Actuators, A* **2018**, *278*, 1.
[128] Y. Dong, J. Wang, X. Guo, S. Yang, M. O. Ozen, P. Chen, X. Liu, W. Du, F. Xiao, U. Demirci, B. Liu, *Nat. Commun.* **2019**, *10*, 1.
[129] L. Liu, Y. Li, R. Wang, C. Yin, Q. Dong, H. Hing, C. Kim, M. J. Welsh, *Nature* **2007**, *450*, 294.
[130] H. Farahani, R. Wagiran, M. N. Hamidon, *Sensors* **2014**, *14*, 7881.
[131] B. S. Shim, W. Chen, C. Doty, C. Xu, N. A. Kotov, *Nano Lett.* **2008**, *8*, 4151.
[132] U. Lange, T. Hirsch, V. M. Mirsky, O. S. Wolfbeis, *Electrochim. Acta* **2011**, *56*, 3707.
[133] W. A. Daoud, J. H. Xin, Y. S. Szeto, *Sens. Actuators B Chem* **2005**, *109*, 329.
[134] M. Zhu, Q. Shi, T. He, Z. Yi, Y. Ma, B. Yang, T. Chen, C. Lee, *ACS Nano* **2019**, *13*, 1940.
[135] R. Wang, L. Han, C. Wu, Y. Dong, X. Zhao, *ACS Appl. Mater. Interfaces* **2022**, *14*, 6138.
[136] J. Ma, Y. Zhang, Y. Liu, D. Han, J. Mao, J. Zhang, W. Zhao, H. Sun, *Sci. Bull.* **2022**, *67*, 501.
[137] S. Tian, S. Li, Y. Hu, W. Wang, A. Yu, L. Wan, J. Zhai, *Sensors* **2021**, *21*, 1972.
[138] M. Shrestha, Z. Lu, G. Lau, *Sens. Actuators B Chem.* **2021**, *329*, 129268.
[139] T. Arnold, M. Scheutz, *Soft Robot.* **2017**, *4*, 81.
[140] L. Pinto, D. Gandhi, Y. Han, Y. Park, A. Gupta. *Eur. Conf. Comput. Vis.* **2016**, 3.
[141] M. Giorelli, F. Renda, M. Calisti, A. Arienti, G. Ferri, C. Laschi, *IEEE T. Robot.* **2015**, *31*, 823.
[142] F. Xu, H. Wang, Z. Liu, W. Chen, Y. Wang, *Soft Robot.* **2021**, *9*, 690.
[143] H. K. Yap, H. Y. Ng, C. Yeow, *Soft Robot.* **2016**, *3*, 144.
[144] R. Zhang, P. Iravani, P. Keogh, *Sens. Actuators, A* **2017**, *264*, 123.
[145] J. Wang, A. Chortos, *Adv. Intell. Syst.* **2022**, 2100165.
[146] R. Adam Bilodeau, E. L. White, R. K. Kramer, in *IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, IEEE, Piscataway, NJ **2015**, p. 2324.
[147] W. Felt, K. Y. Chin, C. D. Remy, *Soft Robot.* **2017**, *4*, 261.
[148] Z. Liu, R. Zhang, Y. Xiao, J. Li, W. Chang, D. Qian, Z. Liu, *Mater. Horiz.* **2021**, *8*, 1783.
[149] O. M. Wani, H. Zeng, A. Priimagi, *Nat. Commun.* **2017**, *8*, 1.
[150] Y. Yang, Y. Chen, Y. Li, Z. Wang, Y. Li, *Soft Robot.* **2017**, *4*, 338.
[151] J. Zhou, Y. Chen, X. Chen, Z. Wang, Y. Li, Y. Liu, *IEEE Robot. Autom. Lett.* **2020**, *5*, 1867.
[152] F. Ge, Y. Zhao, *Chem. Sci.* **2017**, *8*, 6307.
[153] P. Karipoth, A. Christou, A. Pullanchiyodan, R. Dahiya, *Adv. Intell. Syst.* **2022**, *4*, 2100092.
[154] Y. Nakabo, M. Ishikawa, in *Proc. on 1998 IEEE Int. Conf. Robot. Autom.* IEEE, Piscataway, NJ **1998**.
[155] F. Xu, H. Wang, Z. Liu, W. Chen, Y. Wang, *Soft Robot.* **2022**, *9*, 690.
[156] M. Li, Y. Bekiroglu, D. Kragic, A. Billard, in *IEEE/RSJ Int. Conf. Intell. Robot. Syst.,* IEEE, Piscataway, NJ **2014**, 3339.
[157] N. Wettels, V. J. Santos, R. S. Johansson, G. E. Loeb, *Adv. Robot.* **2012**, *22*, 829.
[158] Y. Chen, S. Guo, C. Li, H. Yang, L. Hao, *Robot. Autonm. Syst.* **2018**, *104*, 14.
[159] J. Guo, K. Elgeneidy, C. Xiang, N. Lohse, L. Justham, J. Rossiter, *Smart Mater. Struct.* **2018**, *27*, 55006.
[160] O. M. Andrychowicz, B. Baker, M. Chociej, R. Józefowicz, B. Mcgrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, J. Schneider, S. Sidor, J. Tobin, P. Welinder, L. Weng, W. Zaremba, *IEEE Int. J. Robot. Res.* **2020**, *39*, 3.
[161] Y. C. M. K. Levine, in *IEEE Int. Conf. Robot. Autom. (ICRA)*, IEEE, Piscataway, NJ **2017**, p. 3381.
[162] S. Abondance, C. B. Teeple, R. J. Wood, *IEEE Robot. Autom. Lett.* **2020**, *5*, 5502.
[163] A. Cully, J. Clune, D. Tarapore, J. Mouret, *Nature* **2015**, *521*, 503.
[164] M. A. Graule, T. P. Mccarthy, C. B. Teeple, J. Werfel, R. J. Wood, *IEEE Robot. Autom. Lett.* **2022**, *7*, 4071.
[165] B. Jamil, G. Yoo, Y. Choi, H. Rodrigue, *IEEE Robot. Autom. Lett.* **2021**, *6*, 8694.
[166] Y. Zhao, C. Y. Lo, L. Ruan, C. H. Pi, C. Kim, Y. Alsaid, I. Frenkel, R. Rico, T. C. Tsao, X. He, *Sci. Robot.* **2021**, *6*, eabd5483.
[167] H. Iwata, S. Sugano, in *Proc. on 2002 IEEE Int. Conf. Robot. Autom.* IEEE, Piscataway, NJ, **2002**.
[168] M. Makihata, M. Muroyama, S. Tanaka, T. Nakayama, Y. Nonomura, M. Esashi, *Sensors* **2018**, *18*, 2374.
[169] J. Sun, J. Zhao, in *IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, IEEE, Piscataway, NJ **2020**, p. 8795.
[170] P. Polygerinos, N. Correll, S. A. Morin, B. Mosadegh, C. D. Onal, K. Petersen, M. Cianchetti, M. T. Tolley, R. F. Shepherd, *Adv. Eng. Mater.* **2017**, *19*, 1700016.
[171] S. Haddadin, E. Croft, , Springer, Cham, **2016**, p. 1835.
[172] H. Wang, X. Cheng, P. Huang, M. Yu, J. Ma, S. Peng, Y. Cheng, Y. Yu, W. Yang, P. Wang, Z. Jiao, *Actuators* **2022**, *11*, 74.
[173] W. Liu, Y. Duo, J. Liu, F. Yuan, L. Li, L. Li, G. Wang, B. Chen, S. Wang, H. Yang, Y. Liu, Y. Mo, Y. Wang, B. Fang, F. Sun, X. Ding, C. Zhang, L. Wen, *Nat. Commun.* **2022**, *13*, 1.

[174] J. Xu, S. Wang, G. N. Wang, C. Zhu, S. Luo, L. Jin, X. Gu, S. Chen, V. R. Feig, J. W. To, S. Rondeau-Gagne, J. Park, B. C. Schroeder, C. Lu, J. Y. Oh, Y. Wang, Y. H. Kim, H. Yan, R. Sinclair, D. Zhou, G. Xue, B. Murmann, C. Linder, W. Cai, J. B. Tok, J. W. Chung, Z. Bao, *Science* **2017**, *355*, 59.

[175] S. Wang, J. Xu, W. Wang, G. N. Wang, R. Rastak, F. Molina-Lopez, J. W. Chung, S. Niu, V. R. Feig, J. Lopez, T. Lei, S. Kwon, Y. Kim, A. M. Foudeh, A. Ehrlich, A. Gasperini, Y. Yun, B. Murmann, J. B. H. Tok, Z. Bao, *Nature* **2018**, *555*, 83.

[176] E. Dean-Leon, J. R. Guadarrama-Olvera, F. Bergner, G. Cheng, in *IEEE Int. Conf. Robot. Autom. (ICRA)*, Piscataway, NJ **2019**, p. 5404.

[177] G. E. Loeb, G. A. Tsianos, J. A. Fishel, N. Wettels, S. Schaal, *Prog. Brain Res.* **2011**, *192*, 129.

[178] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, J. J. Leonard, *IEEE T. Robot.* **2016**, *32*, 1309.

[179] M. Yu, X. Cheng, S. Peng, Y. Cao, Y. Lu, B. Li, X. Feng, Y. Zhang, H. Wang, Z. Jiao, P. Wang, L. Zhao, *Mater. Design* **2022**, *223*, 111149.

[180] J. Yang, D. Tang, J. Ao, T. Ghosh, T. V. Neumann, D. Zhang, Y. Piskarev, T. Yu, V. K. Truong, K. Xie, Y. C. Lai, Y. Li, M. D. Dickey, *Adv. Funct. Mater.* **2020**, *30*, 2002611.

[181] J. Gandarias, J. Gómez-De-Gabriel, A. García-Cerezo, *Sensors* **2018**, *18*, 692.

[182] M. M. Zhang, M. D. Kennedy, M. A. Hsieh, K. Daniilidis, in *IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, Piscataway, NJ **2016**, p. 4931.

[183] J. Huang, A. Rosendo, *Soft Robot.* **2022**, https://doi.org/10.1089/soro.2021.0105.

[184] T. Jin, Z. Sun, L. Li, Q. Zhang, M. Zhu, Z. Zhang, G. Yuan, T. Chen, Y. Tian, X. Hou, C. Lee, *Nat. Commun.* **2020**, *11*, 1.

[185] Z. H. Guo, H. L. Wang, J. Shao, Y. Shao, L. Jia, L. Li, X. Pu, Z. L. Wang, *Sci. Adv.* **2022**, *8*, 5201.

[186] Q. Li, C. Schürmann, R. Haschke, H. J. Ritter, in *Robot: Sci. Syst.*, Universität Bielefeld, Berlin, Germany **2013**, https://pub.uni-bielefeld.de/record/2566437.

[187] Q. Li, R. Haschke, H. Ritter, in *IEEE-RAS 15th Int. Conf. Humanoid Robot.* IEEE, Piscataway, NJ **2015**, p. 610.

[188] Z. Su, J. A. Fishel, T. Yamamoto, G. E. Loeb, *Front. Neurorobot.* **2012**, *6*, 7.

[189] J. H. Low, P. M. Khin, Q. Q. Han, H. Yao, Y. S. Teoh, Y. Zeng, S. Li, J. Liu, Z. Liu, P. Valdivia, Y. Alvarado, I. Chen, B. C. K. Tee, C. H. Yeow, in *IEEE/ASME Trans. Mechatronics*, IEEE, Piscataway, NJ **2021**, p. 1.

[190] A. Maity, A. K. Raychaudhuri, B. Ghosh, *Sci. Rep.* **2019**, *9*, 7777.

[191] W. Zhang, Z. Wu, J. Hu, Y. Cao, J. Guo, M. Long, H. Duan, D. Jia, *Sens. Actuators B Chem.* **2020**, *304*, 127233.

[192] G. H. Lee, H. Moon, H. Kim, G. H. Lee, W. Kwon, S. Yoo, D. Myung, S. H. Yun, Z. Bao, S. K. Hahn, *Nat. Rev. Mater.* **2020**, *5*, 149.

[193] M. Ha, G. S. Cañón Bermúdez, T. Kosub, I. Mönch, Y. Zabila, E. S. Oliveros Mata, R. Illing, Y. Wang, J. Fassbender, D. Makarov, *Adv. Mater.* **2021**, *33*, 2005521.

Zhuofan Lin is currently studying for a Master's degree at Shenzhen University. He received his bachelor's degree from the Dalian Maritime University in marine engineering. His research interests are in smart materials, flexible electronics, and soft robots.

Ziya Wang is currently an assistant professor of physics and optoelectronic engineering at Shenzhen University. She received her B.S. and Ph.D. in physics from University of Science & Technology Beijing. Her research interests are in smart functional materials, soft sensors and electronics, and robotic tactile perception.

Wenyu Zhao is currently a Doctorate at The Chinese University of Hong Kong, Shenzhen. He received his bachelor's degree from the University of Science and Technology Beijing in materials science and engineering and master's degree at Ecole Centrale de Lyon, France, in nanomaterials and engineering. His research focuses on the flexible force sensor, ionic hydrogel, and 3D printing technologies.

Yingtian Xu received his Bachelor's degree in mechanical engineering from Tianjin University and his M.S. in robotics from Johns Hopkins University. He is currently working toward his Ph.D. in tactile sensing and sensor-based robot control at the Chinese University of Hong Kong, Shenzhen.

Xiaopu Wang works as an associate researcher at Shenzhen Institute of Artificial Intelligence and Robotics for Society (AIRS). At the same time, she also serves as an adjunct assistant professor at the Chinese University of Hong Kong-Shenzhen (CUHK-SZ). She has been working on biomedical microrobots since her doctoral study at ETH Zurich. Her work includes both fundamental research and application exploration of microrobots. Currently, she is mainly working on the functionalization of microrobots for biomedical applications. Her research interests include 3D printing, photopolymerization, additive manufacturing, soft actuators, etc.

Tianwei Zhang is an associate research scientist at Shenzhen Institute of Artificial Intelligence and Robotics for Society. He received a doctoral degree from the Department of Mechano-Informatics, The University of Tokyo. He received a master's degree in electronic science and technology from Peking University, China, in 2013. His research interests are robot vision and motion planning. He has published several articles in ICRA/IROS/RAL.

Zhenglong Sun received a B.Eng. in biomedical engineering and M.Eng. and Ph.D. in Mechatronic System and Design from the Nanyang Technological University (NTU). Currently, he is an assistant professor at the Chinese University of Hong Kong, Shenzhen. His research interests include medical/surgical robots, haptic sensing and feedback, and human–machine interaction. He has published over 70 journal and conference papers.

Lan Lin is currently studying for a Master's degree at Shenzhen University. She received her bachelor's degree at East China Normal University in computer science and technology. Her main research interests are in the fields of algorithms in tactile data process.

Zhengchun Peng received his B.S. in mechanical engineering from Beijing Institute of Technology, China, and Ph.D. in MEMS from the Georgia Institute of Technology, USA. He then joined Intel Corp. as a senior R&D engineer, developing wafer sort and e-test technologies for 14 nm and 10 nm processors. He is currently a distinguished professor at Shenzhen University. His main research interests are in the fields of micro/nanosensors, flexible/stretchable electronics and their application in robotics, human–machine interface, and healthcare.