Electronic Skins for Intelligent Soft Robots

Benjamin Shih[1], Dylan Shah[2], Jinxing Li[3], Thomas G. Thuruthel[4], Yong-Lae Park[5], Fumiya Iida[4], Zhenan Bao[3], Rebecca Kramer-Bottiglio[2], Michael T. Tolley[1*]

[1] Department of Mechanical and Aerospace Engineering, University of California, San Diego, USA
[2] Department of Mechanical Engineering & Materials Science, Yale University, USA
[3] Department of Chemical Engineering & Material Science and Engineering, Stanford University, USA
[4] Department of Engineering, University of Cambridge, UK,
[5] Department of Mechanical and Aerospace Engineering, Seoul National University, South Korea

[*] To whom correspondence should be addressed; E-mail: tolley@ucsd.edu

As robots grow increasingly prevalent in real-world environments, sensory systems capable of sensing complex deformations and environmental interactions are needed for robust control. Soft robotics has emerged as a field of study that seeks to replace rigid components in traditional robots with materials that are compliant. It has garnered interest for real-world applications due

to intrinsic safety embedded at the material level, deformable materials capable of shape and behavioral changes, and conformable physical contact for manipulation. Yet, with the introduction of soft and stretchable materials to robotic systems comes a myriad of challenges for sensor integration, including multi-modal sensing capable of stretching, embedment of high-resolution but large-area sensor arrays, and sensor fusion with an increasing volume of data. This review presents and discusses recent developments in skin-based sensing for soft robots, from hardware and fabrication techniques to machine learning techniques that translate robot perception into action planning.

Introduction

Skin plays an essential role for biological systems as a barrier between an organism's external environment and its internal components. Embedded within its layers are a dense network of mechanical, chemical, vibrational, temperature, and pain receptors, which work in coordination to enable somatosensation in skin. These capabilities would also be incredibly useful for robots. Electronic skin (e-skin) research was originally motivated in part by a desire to understand biological sensing, but the lessons learned can help improve the design of robotic systems. To sense, plan, and act, robots require a variety of sensors embedded throughout their bodies so that they can obtain information about their environment.

The field of soft robotics (*1*) studies the use of flexible and compliant materials as components for building robots, instead of traditionally rigid components like metals. Soft robots often draw inspiration from nature, which has evolved organisms that are capable of operating in unstructured environments. In contrast, current robotic systems are usually confined to structured lab or warehouse environments. Additionally, natural environments typically contain a large number of objects of varying material properties that further complicate tasks such as object interaction and locomotion.

The overlap between e-skins, soft robotics, and machine learning is continually growing, and recent advances are summarized in Fig. 1. Soft actuation has improved significantly in capabilities (Fig. 1C) and soft sensors and e-skins exhibit a wide range of complexities (Fig. 1A). Several recent advances have combined principles from each field, often physically manifesting in the form of sensorized fingers and grippers (Fig. 1B). Many of the next substantial breakthroughs in the field may come from further integration of sensors and actuators as roboticists move toward designing systems that rival the abilities of biological organisms.

Several reviews have covered related topics on electronic skins and perception in soft robots including reviews on: design and fabrication of electronic skins (*27, 28*); wearable sensors (*29*); e-skins for interactive robots (*30, 31*); and future directions in sensing and perception for soft robots (*32, 33*). This review focuses on the emerging confluence of e-skins and machine learning, with a focus on how roboticists can combine recent developments from the two fields to build autonomous, deployable soft robots, integrated with capabilities for informative touch and

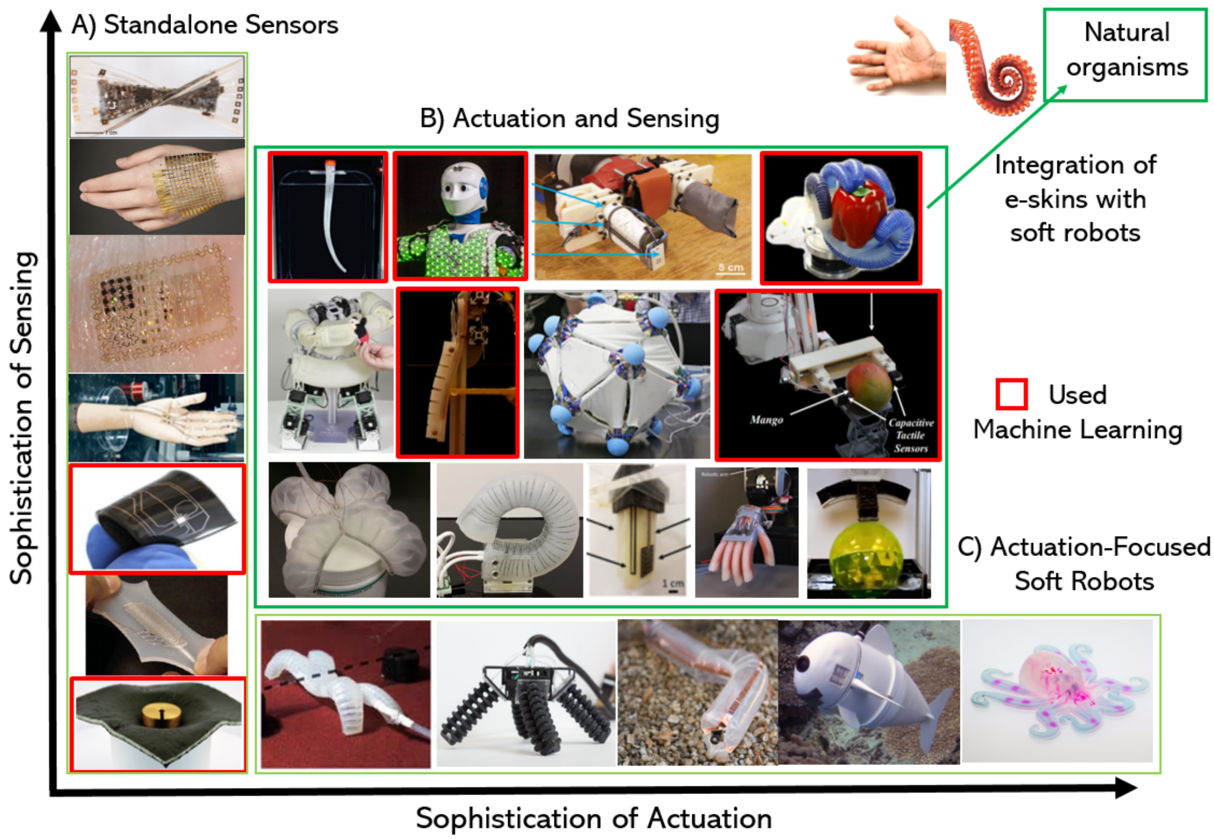

Figure 1: **Trends in the intersections between e-skins, soft robotics, and machine learning.** **(A)** A range of e-skins and soft sensors that increase in complexity, from bottom to top, by metrics including density, resolution, and fabrication (*2–8*). **(B)** Soft robots and e-skins that merge actuation and sensing (*9–21*), from left to right and top to bottom. **(C)** A range of soft robots, from left to right, focused primarily on actuation and mechanisms (*22–26*). Red boxes indicate work that has leveraged machine learning in the processing of their sensor information. The field of soft robotics will benefit in many ways from the integration of high-resolution, high-throughput e-skins into soft robots. In the future, the technologies presented here are expected to approach or even exceed the capabilities of what is found in nature and biology.

proprioception to stand up to the challenges of real-world environments. To limit the scope of this review, we consider a soft robot skin to be skin sensors directly mounted on the surface (e.g. (*34*)) or embedded in a thin layer beneath the surface of the body of a soft robot (e.g. (*16*)).

To highlight the opportunities at the intersection of e-skin and soft robotics research, we cover a variety of interdisciplinary topics ranging from fabrication to learning to control. The topics are split into tools (Section 1) and applications (Section 2): Section 1.1 reviews recent developments in the design and fabrication of e-skins. Next, Section 1.2 examines how soft robots currently perform skin-based sensing. Section 1.3 presents techniques from machine learning that soft robots can use to process and interpret the information from their e-skins. Section 2.1 analyzes trends in shape sensing, a desirable application of the tactile information that e-skins can provide. Section 2.2 synthesizes the e-skins into the robotics framework of sense, plan, and act, and examines how e-skins can advance the state of soft robotics via comprehensive tactile information. Finally, we describe the gaps and future outlook for bringing together the fields of soft robotics and electronic skins in Section 3.

We believe that the future consists of a society in which robots are tightly integrated with humanity. This includes in-home, assistive robots that can sense and understand gestures such as a pat on the back, collaborative robots that work alongside humans, and exploratory robots that can navigate the unpredictable real world. Building toward tangible robotic embodiment requires the development of deployable, high-resolution sensor skins, algorithms for interpreting sensor information, and reliable feedback control for soft robots.

1 Interdisciplinary Tools

1.1 Electronic Skins - From Flexible and Stretchable Electronics, to Integrated and Embedded Sensors

Compared to rigid robots, the high mechanical compliance of soft robots enables safer and more efficient human-robot interaction (HRI) since they can seamlessly interact with the human body (*39*). Further advancement of soft robots requires high-performance electronics and sensors that can stretch continuously with their bodies. Recent research in artificial skin has mainly focused on making individual sensor devices with better performance, such as sensitivity, stretchability, and reliability over many use cycles (Fig. 2). To realize fully biomimetic skin for soft robotics, artificial skin should contain sensor arrays that are stretchable, can cover large areas with a high spatiotemporal resolution, and possess multiple functions that mimic diverse receptors of the human skin (Fig. 2A). These features should enable robots to use data-driven methods to extract rich information about their environment.

Increasing sensor density and quantity normally requires a larger number of interconnecting wires. To reduce this burden, sensor arrays are normally designed in a matrix form. For example, a recently-developed tactile glove comprising of 548 force sensors was constructed using readily available materials and simple fabrication tools (Fig. 2B) (*35*). This sensor array

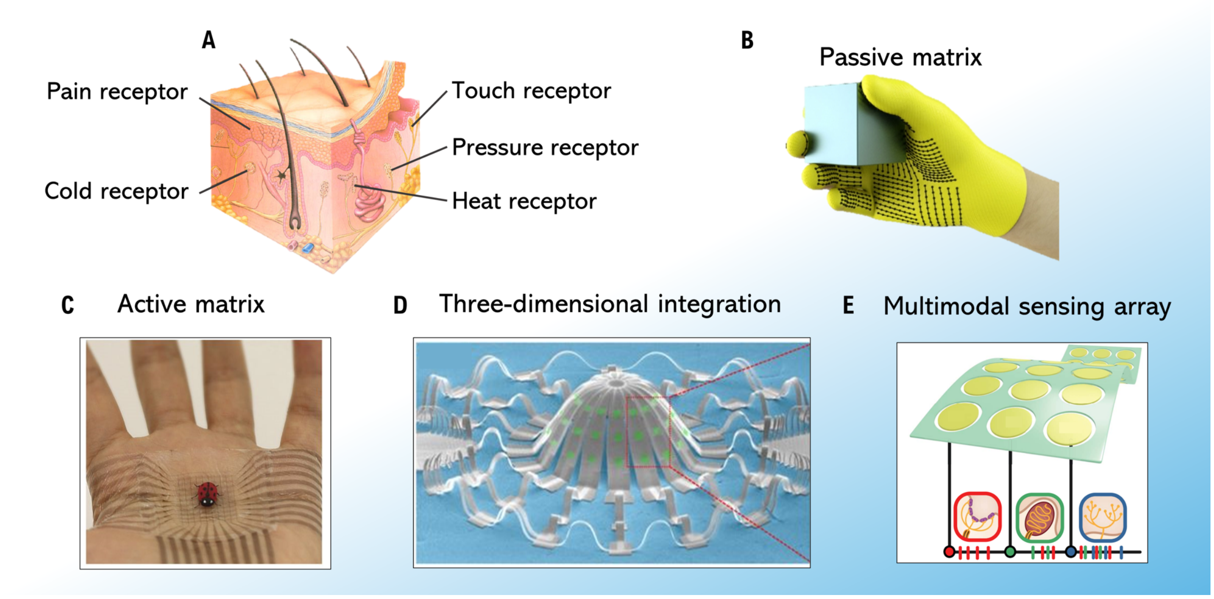

Figure 2: **Sensor arrays enable electronic skins to extract large quantities of information about their environment.** **(A)** Human skin with various receptors used to sense stimuli. **(B)** A scalable tactile glove containing a passive matrix of 548 force sensors for the collection of large data sets (*35*). **(C)** 2D sensor array used to generate a profile of pressure intensity from experimental mapping of the pixel signals using an active matrix (*36*). **(D)** A 3D array of electronic sensors assembled from 2D electronics (*37*). **(E)** Multimodal sensor array that can capture both pressure and temperature information (*38*). The icons at the bottom represent biological analogies: Merkel disks, Meissner corpuscle, and free nerves.

recorded a large-scale dataset of tactile maps (about 135,000 frames) which was used to identify objects using convolutional neural networks. This work highlights the ability of large-scale datasets collected by a high-density sensor array to enable not just a sense of touch but also the intelligent extraction of information from touch. Increasing the sensor density simply by scaling down a passive matrix architecture will reduce the amplitude of analog signals, while increasing crosstalk between interconnects. If multiple sensors are sampled simultaneously, each line will produce electromagnetic noise which will corrupt the signals being carried on neighboring conductive traces. Furthermore, the large number of addressing lines will be difficult to manage as the number of sensors increase significantly. These problems can be addressed with an active matrix that pairs each sensor with a transistor to provide local signal amplification and allow sensors to take turns transmitting information (*40–43*).

Active matrices with multiplexed signal transduction typically consume less power than passive matrices because they require fewer sampling lines and do not need external circuitry (*44*). However, stretchable e-skins could allow better coverage of curved robot surfaces while allowing sensing of complex texture information through detection of deformation and vibration, mimicking biological skin. Recent advancements in organic electronics by Wang et al. led to the creation of an intrinsically stretchable transistor array with 347 transistors per square centimeter (*45*). Their proof-of-concept demonstration illustrated that such a conformable active matrix could accurately map the force applied on each sensor. These capabilities indicate that stretchable active matrices containing soft sensors and transistors are a promising step toward soft robotic skin with high resolution and high data fidelity.

Making multi-layered sensor arrays in a three-dimensional (3D) lattice can further increase the sensor areal density and allow greater integration of different sensor modalities. Just as receptors in biological skin are embedded at various depths, engineers can embed sensors that are sensitive to different stimuli in different spatial locations. For example, pressure, shear, and strain sensors can be distributed in different layers of the e-skin to achieve optimized sensitivity. Huang et al. demonstrated that stretchable electronics integrated in 3D can be built with a layer-by-layer method using transfer printing of pre-designed stretchable circuits on elastomers with vertical interconnects (*8*). This stretchable human-machine interface had a four-layer design that offered multi-modal sensing and had integrated circuits for wireless data transfer. Using strain-engineering methods, two-dimensional (2D) structures can also be assembled into 3D electronic systems with sensing capabilities. Semiconductor materials can play critical roles in this context, through demonstrations of complex, mechanically assembled 3D systems for light-imaging capabilities that can encompass measurements of the direction, intensity and angular divergence properties of incident light.

3D printing has also been used to directly print sensors in soft robots to improve both exteroceptive and interoceptive capabilities (*46*). This work highlights how a 3D integration framework enables a higher integration density on stretchable substrates than single-layer approaches and allows new functionalities that would be difficult to implement with conventional layer-by-layer designs.

Processing complex tactile information from a sensor array requires efficient signaling and sampling methods. In human skin, stimulation of the receptors is converted into a series of voltage pulses sent to the nerves. This inspired researchers to develop artificial receptors and afferent nerves to convert tactile information to digital pulses at the site of sensation (*5, 47*). The signal could potentially be perceived by a user's nerves and brain, thus directly linking the human brain with soft robotic prosthetics. For example, Kim et al. recently developed a flexible artificial afferent nerve that can effectively collect pressure information from arrays of pressure sensors, and convert them to action potentials to activate muscles (*48*).

Biological skin contains receptor networks that can detect various stimuli, such as vibration, humidity, and temperature. Several studies on e-skin sensor arrays focused on the classification of a single type of information, such as force, shape, or direction-of-motion. The next generation of electronic skins should integrate multimodal sensor arrays to capture richer sensory information than their predecessors. Recently, Lee et al. reported a neuromimetic architecture that enabled simultaneous transmission of both tactile and thermotactile information (Fig. 2E) (*38*). The pressure- and temperature-sensitive transducers can both be communicated through the pulse signatures by a single electrical conductor. As a biomimetic signaling method, this approach is promising for reducing computational requirements when a robot is covered with thousands of sensors. Multimodal sensing could also be achieved through integration of multiple stretchable optical fibers, which has been shown to be effective at, for example, localizing and estimating force in soft actuators (*49*).

Overall, many innovations are required for realizing high-density and multifunctional sensor arrays for soft robots. A close collaboration between roboticists and materials scientists is needed to develop high performance, stretchable conductors for electrodes and interconnections, and stretchable semiconductors for building active matrices and signal amplifiers. Different sensing modalities and integration architectures should also be explored. Finally, hardware and algorithms for data processing should be taken into account during the design of sensory systems and their performance should be evaluated on a holistic range of practical robotic tasks.

1.2 Skin-Based Sensing for Soft Robots

As sensors are increasingly integrated into soft robots, we can imagine a conceptual plane which categorizes research based on the sophistication of actuation and sensing independently (Fig. 1). Standalone sensors lie on the y-axis; some consist of simpler strain sensors (the bottom three images in (Fig. 1A) (*2–4*)) while others have more sophisticated sensing schemes including distributed or multimodal sensing (the top four images in (Fig. 1A) (*5–8*)). The x-axis, representing actuation-focused soft robots, shows examples of increasingly complex soft systems that can walk (*22, 23*), grow (*24*), swim (*25*), and operate autonomously on chemical fuel (*26*) (Fig. 1C). Finally, many recent works have begun exploring the intersection of the actuation and sensing (Fig. 1B). Several of them embedded strain sensors for state estimation or tactile sensing in a finger-like structure (*9–18*) while the others mounted their skins externally (*19–21*). As both areas progress, we envision further integration of increasingly sophisticated actuation and sensing, extending into the top-right quadrant of the conceptual plane.

Access to higher-resolution data about touch will increase the ability of soft robots to perceive the complex deformations that they experience during tasks including locomotion and manipulation. Today's discrete sensors—which are built with high sensitivity and selectivity—can be tailored to sense deformation modes in a localized region or known environment with high confidence (*20, 50*). However, this sensing paradigm is insufficient in dynamic or unknown environments that experience significant deformation, as robots do not yet have the level of sophistication of human skin receptors or the human brain to collect a large range of information. In addition, many robots are unable to process the volume of information to accurately determine the environment or object being sensed. The transition from discrete to continuous sensing and the transition from structured to unconstrained environments both require electronic skins that can rapidly collect and process large amounts of information. The added complexity from both transitions compounds the processing required to interpret the signals.

In part because of the wide range of skills and expertise than span e-skins, soft robotics, and machine learning, current developments in skin-based sensing for soft robots focus on rapid manufacturability. Because the designs in soft robotics emphasize deployability, this often comes at the tradeoff of the high-resolution and sensitivity that can typically be found in e-skins. There are several designs of skin-like sensors that have been used in soft robotics and they operate based on a variety of principles. Many of these sensors contain conductive and stretchable materials to produce resistive or capacitive strain sensors (*2, 16, 51, 52*). Other groups used optical devices like cameras and optical fibers to sense deformations within an actuator (*53–55*). Several of these existing sensors are well-suited for measuring characteristics like strain, pressure, and bending but do not enable the high sensor densities or resolutions that have been demonstrated in e-skins. Soft robots would benefit from integration with e-skins, such as the skin-like sensor arrays that have been deployed in medical applications or directly on skin (*6, 47, 56–58*).

Currently, soft skin-like sensors have been deployed in several ways. Some groups used their sensors as wearables; Menguc et al. used liquid metal sensors to measure human gaits (*59*) using a sensor fabrication process first presented by Park et al. (*3*). The resistance of these sensors increases as the embedded microchannels inside the elastomer matrix are stretched due to the increased length and decreased area of their bulk liquid-metal channels. Others incorporated their sensors with robots: Boutry et al. paired a shear force sensor with a robot arm to allow robotic hand control (*60*); Booth et al. demonstrated reconfigurable, actuatable e-skins which could control the motion of deformable inanimate objects from their surface (*21*); and Zhao et al. embedded optical sensors within soft pneumatic fingers, which they then integrated with a Baxter robot (*17*). Skin-based sensing capabilities are continuing to improve and we expect to build further towards biology-like systems (top right corner of Fig. 1).

1.3 Machine Learning for Soft E-Skins

As e-skins increase in resolution, their signals could be processed to detect higher-order deformation modes and higher-level notions about the environment, such as material type. However,

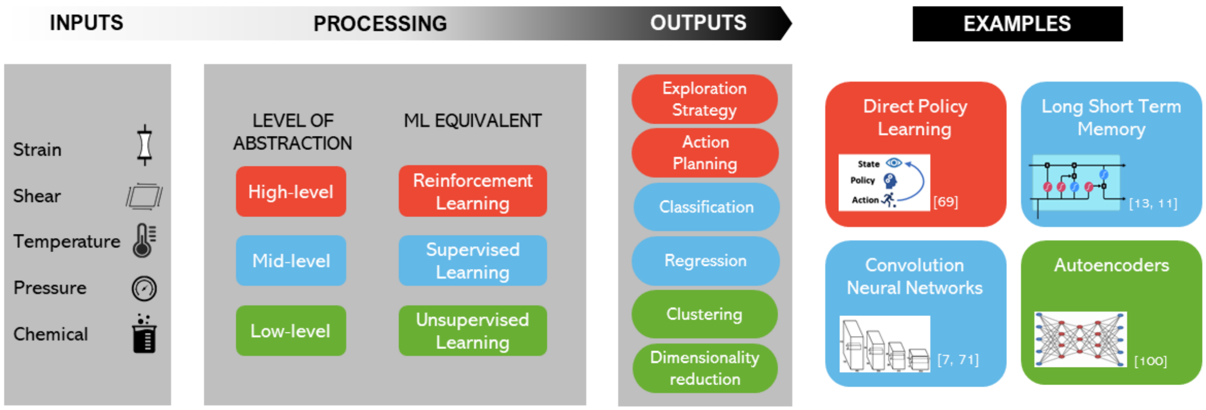

Figure 3: **Machine learning techniques can be used to process raw sensory information at any level of abstraction to aid in robot perception and action planning.** The level of abstraction depends on the task and the most effective type of learning architecture depends on the quality and structure of the sensor signals. Higher-level processes can include parallel execution of lower-level processes that can have an independent and traditional architecture. End-to-end architectures (e.g. (*61*)) without mid-level and low-level pipelines would likely be faster and more effective, but are computationally expensive to develop.

obtaining this information requires algorithms that can extract useful information from large quantities of data. To handle the vast amount of data that e-skins can provide, machine learning is emerging as a versatile tool for making sense of large quantities of data (Fig. 3). For example, Piacenza et al. obtained high-resolution data from a robotic fingertip and used ridge regression to process this data to estimate the locations of indentations (*62*). Similarly, Larson et al. used convolutional neural networks to learn deformations on a sensor array that can interpret human touch in soft interfaces (*63*). At the level of abstraction of the entire robotic system, Van Meerbeek et al. tested various learning algorithms to estimate the twist and bend angles in sensorized foam, finding that k nearest neighbors (kNN) outperformed other common algorithms including support vector machines (SVM) and multilayer perceptrons (MLP) (*55*). In addition, Kim et al., Soter et al., Thuruthel et al., and Kim et al., focused on recurrent neural networks, which have been shown to be advantageous for learning patterns in time series data (*9, 12, 64, 65*).

Due to the complexity of the mapping between raw sensory information and relevant functional abstractions, information theory and machine learning will play a large role in bringing tactile sensing to human-like performance levels. In particular, the sub-field of reinforcement learning will be important for developing closed-loop control for tactile feedback. Suitable algorithms and architectures for analogous tasks in soft robotics can be developed by drawing inspiration from, and mimicking biological processes. For example, in computer vision and machine learning, the hierarchical nature of visual processing (corresponding to compositional functions) (*66*) has recently enabled deep neural networks to achieve human-like performance across a variety of visual processing tasks (*67*). Processing signals from arrays of tactile sensors may benefit from similar techniques as both can be represented as matrices.

Tactile exploration can benefit from recent developments in learning-based simultaneous localization and mapping (SLAM) algorithms. Notably, Mirowski et al. used an asynchronous advantage actor-critic algorithm for navigating in a complex environment and additionally solved auxiliary prediction tasks which made the reinforcement learning (RL) problem faster and more data efficient (*68*). Chen et al. showed a direct policy learning algorithm with spatial memory and bootstrapped with human-mediated imitation learning without explicit task rewards (*69*). In the absence of continuous reward functions, actor-critic algorithms are preferred since they require fewer samples.

Similarly, tactile manipulation tasks can use insights from learning-based manipulation controllers. A general trend observed in such works is the success of model-based RL (*70*) or learning by demonstration (*71*), approaches that leverage techniques from control theory or human knowledge, respectively. There have been successful solutions for the direct learning of control policies for dexterous manipulation, but this relied upon the availability of an accurate simulation environment (*72*). Until robot simulators can model soft-body dynamics that reliably transfer to real robot hardware, such approaches are difficult to apply to soft robots and deformable objects. For specific simple tasks, it might be easier to find a direct policy than to fit a general-purpose model of the system dynamics (*73*).

2 Towards Applications and Future Directions

2.1 Shape Sensing

While environmental sensing helps a robot understand its surroundings, having a self-model of the robot's body is important for planning trajectories and actions within that environment. For robots primarily composed of rigid components, the geometry of each segment remains the same throughout the robot's lifetime, and relative rotations or translations of links provide enough additional information to fully specify the overall changes in shape. However, for soft robots, individual segments can continuously change their shapes — via both intentional and unintentional deformation modes — which complicates modeling and sensing schemes. Complementing recent work on soft sensing (*32*), the direct sensing of surface deformations would enhance the functionality of soft robots.

One approach to sensing the shape of soft robots involves pairing a model with a relatively low number of sensors, typically on the same order of magnitude as the number of controllable degrees of freedom in the system. A great deal of progress has been made in modeling manipulators that can be parameterized by a curve in 3D space (*74*). These models have even been coupled with sensing mechanisms to enable closed-loop control of continuum manipulators (*75*). Some approaches embed sensors into other soft robotic components, such as bending actuators, to achieve closed-loop control in a low-dimensional task space (*76*).

The primary drawback of this type of approach is that when other unplanned deformation

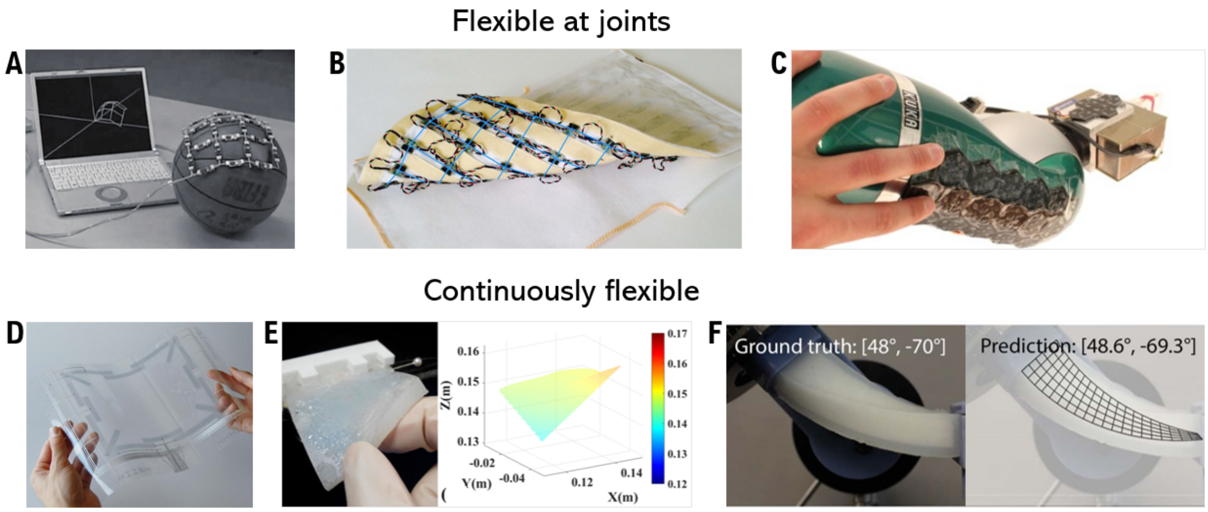

Figure 4: **E-skins that can sense their shape in 3D.** Recent advances in shape-sensing e-skins use several sensing modalities. (**A-C**) Accelerometers and/or magnetometers on rigid printed circuit boards (PCBs) can rotate relative to each other and reconstruct their shape at discrete points. (**A**) "3D capture sheet" (*79*), (**B**) sensor network with accelerometers and magnetometers (*80*), (**C**) hexagonal PCBs with integrated accelerometers (*50*). (**D-F**) Continuously flexible devices can sense deformation throughout their surface and estimate their resulting shape. Data-driven methods were then used in these examples to estimate the continuous shape of the e-skin. (**D**) Piezo-electric bend sensors on PET (*81*). (**E**) Fiber Bragg gratings in silicone (*82*). (**F**) Plastic optical fibers in silicone foam (*55*).

modes are introduced, such as buckling, or a change of material properties through damage or natural material aging, the models accumulate error. Additionally, it is unclear how to generalize these advances to reconfigurable soft robots (*77*) or robots that have more complex morphologies. For example, recent simulations suggest that there are a wide range of soft robot morphologies that could produce useful locomotion, including quadrupedal shapes and various oddly-shaped blobs (*78*). All these classes of robots would benefit from sensing mechanisms with fewer assumptions about the robot's mechanical properties.

The ideal shape sensing system could stretch with the robot's surface without impacting its kinematics or dynamics, sense shape without external components, and be thin. E-skins designed for wearable applications should accommodate the strains of approximately 55-75% experienced by biological skin (*47*), and a similar range should be suitable for most soft robotic applications, although different robots experience different surface strains. While a perfect solution for shape-sensing of soft robots does not currently exist, recent advances in the field of flexible shape-sensing e-skins (Fig. 4) have the potential to greatly improve the capabilities of soft robots.

In contrast to that of soft skins, most work on shape-sensing e-skins treats the skin as an inextensible sheet of rigid elements joined by known axes of rotation (Fig. 4A-C). The primary challenge is thus estimating the relative orientation between sections with known geometries, to determine the spatial locations of discrete points within the sheet. In one early study, Hoshi and Shinoda arranged 24 printed circuit board (PCB) "nodes" into a mesh and estimated inter-node rotations using accelerometers and magnetometers (*79*) (Fig. 4A). Building upon this work, Mittendorfer et al. developed rigid sensorized hexagonal PCBs that could be integrated into semi-flexible sheets and wrapped around robots (*50*) (Fig. 4B). The nodes contained accelerometers similar to the work by Hoshi (*79*) and had similar assumptions (PCBs are free to rotate but cannot be stretched), but rotations between neighboring PCBs were calculated by obtaining at least two orientations of the skin per skin shape and solving a constrained Procrustes problem for aligning matrices of datapoints in real-time. Hermanis et al. then used a gridlike arrangement of accelerometers and gravitometers on a flexible fabric sheet (*80*) (Fig. 4C). The sheets were demonstrated in a dynamic state estimation task where a user wore a shirt equipped with the shape-sensing sheets while bending and crouching.

In contrast to the discrete-sampling methods mentioned above, other approaches leverage techniques from machine learning and statistics to process various sensing signals and extract a continuous estimate of the shape of the skins (Fig. 4D-F). This kind of data-driven technique will be increasingly useful as the sensory spatial density increases, as discussed throughout this review. For instance, Rendl et al. used regularized least squares to process data from 16 piezoelectric bend sensors on a plastic sheet (polyethylene terephthalate - PET) to approximate the shape of the sheet as a combination of several shape primitives (*81*) (Fig. 4D). This created a flexible system that could sense the bent state of the sheet with a roughly centimeter-level accuracy over an approximately A4-sized sheet. Another study used relatively inextensible optical fiber Bragg gratings arranged in a circle on the top and bottom of a silicone e-skin (*82*) (Fig. 4E). The relation between the strains on the fiber and the shape of the sheet was extracted from training data using a feed-forward artificial neural network containing one hidden layer for computation between the input and output layers. In a similar spirit, an array of optical fibers were twisted through an elastomeric foam and their outputs were sent to several machine learning algorithms (including kNN, SVM, neural networks, and decision trees) to predict the mode of deformation and angle of deformation of their structure (*55*) (Fig. 4F). These approaches all dealt well with a limited set of deformations and in principle should work for a wider range of deformations when paired with a more expressive (deeper) network. However, none of these existing works can mechanically accommodate large in-plane strains, primarily due to the inextensibility of the optical fibers used.

2.2 Closing the Loop: Towards Feedback Control of Soft Robots

When it comes to interacting with unstructured environments, one advantage of soft robotics is that the intrinsic material compliance can protect both the robot and the environment from damage. This property makes soft robots appealing in contexts such as HRI and robotic manipulation, where safety around fragile objects can be important (*39, 83*). Pairing with e-skins has great potential to enable soft robots to interact intelligently with their environment.

Additionally, tactile information obtained through skin is vital for a variety of general robotic control tasks. The type of sensor modality to be used, the processing algorithm, and the response from the body all depend on the task at hand (*84*). These tasks can be divided into three broad categories depending on the flow of information or energy and the primary system of concern (Fig. 5).

Manipulation

Robotic manipulation involves altering the state of an external object to a desired set-point using internal actuators. The role of tactile sensors is mainly to obtain state information of the external object. As energy flows to the environment, stability of the object is of high concern. Grasp force optimization and stabilization is one of the most basic manipulation tasks involving tactile sensors (*87*). Early works were built on estimation of normal and tangential forces on the hand to detect slip and react accordingly (*88*). Recent works used learning-based methods for slip-onset prediction with adjustment and grasp-failure detection with adjustment, due to the ability of these methods to handle complex multi-modal sensory information (*89*) and their generalizability (*90*).

Other manipulation studies used low-dimensional sensor space representations to improve performance in certain situations. Herke et al. used autoencoders to generate a low-dimensional representation of their complex and continuous tactile data (*91*). Control policies learned using this latent space representation required fewer roll-outs and were more robust to noise. Another study was on calibration and self-modelling of a fully sensorized body for whole-body manipulation (*92*). Recent work has shown that this process can be fully automated using control signal information and other sensor modalities including inertial measurement units (*93*).

Perhaps the most complex manipulation task is in-hand manipulation, which imposes strict requirements upon the body, brain and sensors (*94*). Current progress in in-hand manipulation using tactile sensors is primarily limited to rolling circular objects (*61*). On the other hand, notable developments in in-hand manipulation have been achieved with external visual tracking systems (*72*). However, control policies trained using vision alone are scene dependent and require large quantities of training data, motivating further research into using tactile sensing during in-hand manipulation.

Exploration

Tactile exploration is the process of voluntary motion of the body based on the somatosensory feedback for identifying environmental properties (*95*). The environmental property of interest could be low-level features like surface texture (*96, 97*), temperature (*98*) or mid-level tasks like object classification (*99, 100*). However, to be fully autonomous, the higher-level process of selecting the best actions for obtaining better sensory information, also known as active exploration, has to be considered. This is not trivial, as the concept of an objective function and a reward function becomes difficult to define.

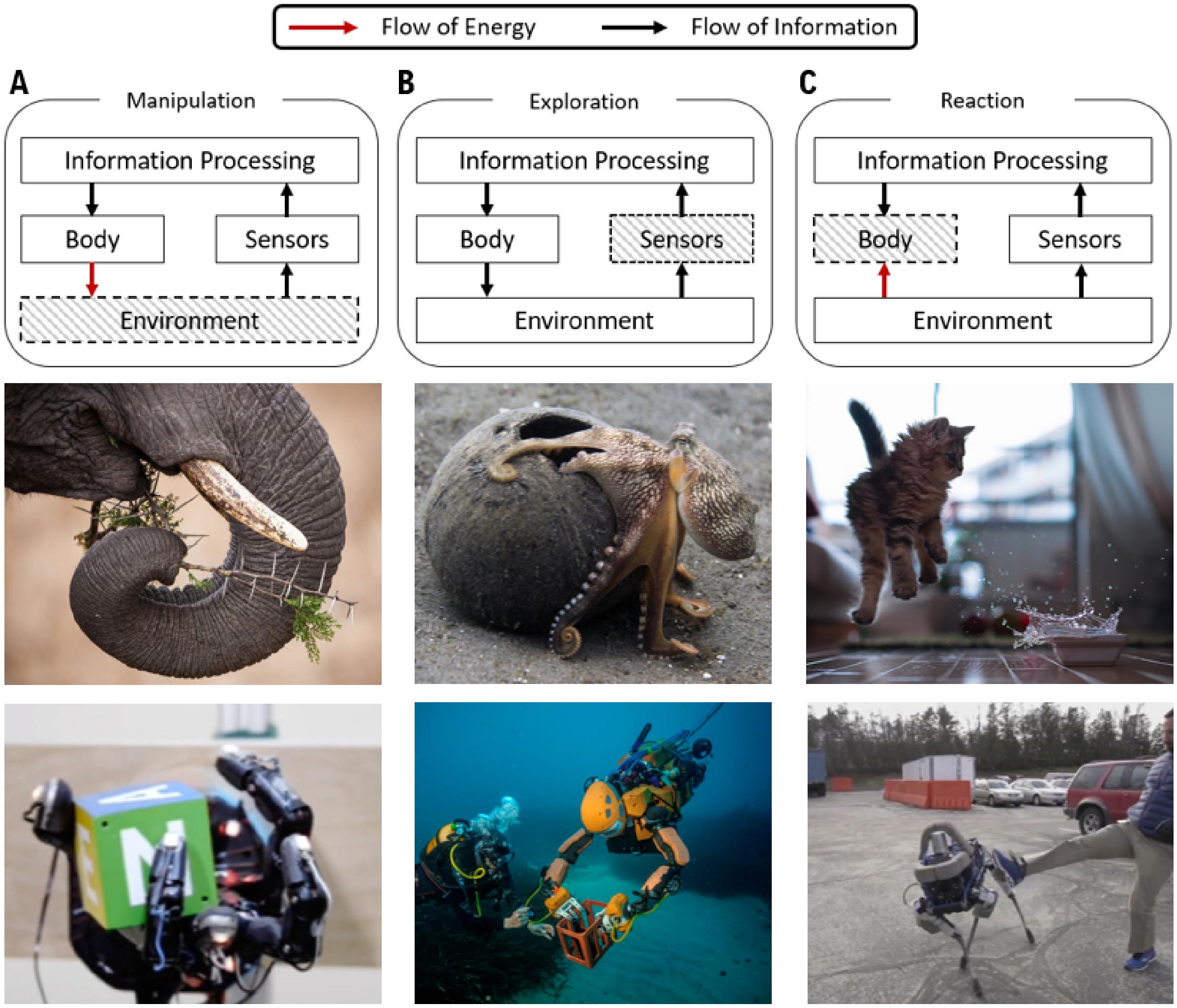

Figure 5: **Closed-loop tasks where tactile sensing is essential.** These tasks primarily differ on the system that determines the objective (denoted by the hashed boxes). The middle row consists of biological demonstrations of the tasks. The bottom row contains examples (*72, 85, 86*) of these capabilities in current rigid robots, which we expect to further improve in parallel with the integration of electronic skins, soft robotics, and machine learning. Note that the presented division is not strict, and real-world tasks often involve a combination of all three elementary tasks. **(A)** Manipulation involves altering the state of an external object to a desired set-point using internal actuators. **(B)** Exploration involves motion of the body to account for uncertainties in the environment, based on somatosensory feedback. **(C)** Reaction involves estimating and responding to environmental cues such that the body remains in a desired state.

It is currently conjectured that human exploration is driven by a combination of extrinsic and intrinsic reward variables (*101*). Extrinsic rewards are task specific, like classification of objects, whereas intrinsic rewards are task-independent and hence more general, like curiosity-driven exploration. Experiments suggest that humans primarily employ six types of exploratory movements when exploring objects to determine their properties (*102*). Hence, there have been studies on acquiring these specialized closed-loop policies based on intrinsic rewards like curiosity (*103*) or extrinsic rewards like texture discrimination ability (*104*). To achieve efficient exploration with soft robots, a combination of tactile and proprioceptive feedback will likely be useful for effectively implementing such reward functions.

A first step towards an autonomous tactile exploration control architecture, referred to as tactile servoing by the authors, was proposed by Li et al. (*105*). By framing the control objective as the problem of following a trajectory in the sensor feature-space, various autonomous sensory exploration strategies emerged. The emergent exploration strategies include maintaining contact with an object, edge tracking, and shape exploration of an unknown object. Exploration has also been framed as a force and pose control problem on an unknown object using tactile sensors for feedback (*106*). Additional tactile information obtained during the process was then used to estimate the compliance of the object. Recent works integrated active exploration with object discrimination (*107*). However, the mid-level processes were independent from the high-level exploration strategy and the proposed algorithm was therefore relatively inefficient and slow. The next challenge in this area is to develop exploration strategies that run simultaneously and are regulated by the tactile feature extraction process. Such an algorithm would allow robots equipped with e-skins to efficiently process their sensory information to make informed decisions on how to move within the world to gather information and achieve at least locally optimal exploration strategies.

Reaction

Whole-body tactile skins are required for reacting to active environmental forces applied by external agents (*108*). Here, the control objective is to estimate and react to external forces such that the body remains stable while executing a behavior. Often, the safety of the external agent—typically a human—becomes a higher priority than the robot stability (*109*). As reaction typically involves HRI, additional challenges arise from safety, context prediction and adaptation (*110, 111*). Otherwise, closed-loop reaction using tactile sensing is similar to the closed-loop manipulation problem and is often implemented in parallel with manipulation tasks as in the case of slip detection (*112*).

The main challenges in whole-body sensing are the organization and calibration of a large number of spatially distributed multi-modal tactile sensing elements (*113*). Spatial calibration can be manually performed or automated using robot kinematics and action inference techniques (*114*). Data driven methods are also promising for end-to-end models without an explicit kinematic/dynamic calibration (*115*). The most recent and comprehensive whole-body tactile sensing research was able to self-organize and self-calibrate 1,260 multi-modal sensing units, and implement a hierarchical task manager comprised of the fusion of a balance controller, a self-collision avoidance system, and a skin compliance controller (*116*).

3 Conclusions, Gaps, and Outlook

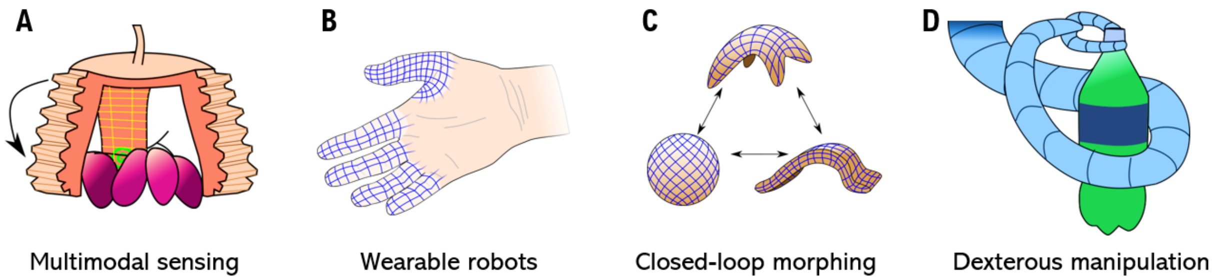

Figure 6: **Tactile sensing and proprioception will enable soft robots to operate effectively in numerous challenging domains.** **(A)** Multimodal sensing would be useful during manipulation, for detecting gripper states, object properties, and events such as contact and slip. **(B)** E-skins with an integrated human-robot interface could enable seamless assistive wearable robots and intuitive teleoperation of anthropomorphic robots. **(C)** When paired with the appropriate actuators, shape sensing would enable closed-loop changes of shape. **(D)** Closed-loop control algorithms would enable soft robots equipped with e-skins to succeed when performing complex tasks, including in-arm manipulation.

The fields of e-skins and soft robotics have both experienced rapid progress in recent years, demonstrating success in a wide range of domains. However, integrating advances from both fields to produce intelligent, autonomous soft robots is a challenging task which will require advances in several key areas (Fig. 6). Here, we outline major open questions in this area and identify areas of research which could provide solutions.

Open Questions and Future Directions

Design and fabrication The primary future challenges of developing sensor arrays for soft robots will be to design stretchable sensory arrays with wide bandwidth and high dynamic range, resolution, and sensitivity. In addition, multimodal sensing would be useful for increasing robots' knowledge of their environment, leading to richer HRI (6A-B). Sensing of pressure, shear, vibration, and even detecting the presence of chemical and biological markers in the environment would be useful for a wide range of applications including manipulation, disaster response, and manufacturing. Recent efforts on integrating bacteria cells into soft robots have made it possible to directly detect and display chemical information on soft robots (*18*). Another major design challenge is choosing how many sensors to integrate into a skin, and deciding how to place those intelligently. Resources are limited and require careful allocation. Where should sensors be placed along the skin's primary plane, and at what distance from the skin's surface? Are there "optimal" sensor distributions?

Machine learning and information processing Advancing the intelligence of soft robots will also require the community to develop computational models that can extract useful information from sensor arrays. However, the details of how to develop and implement such algorithms are unclear. What algorithms can most efficiently accomplish tasks in classification, regression, and fault detection? If neural networks are used, what architectures are easiest to train? Are there trade-offs between efficiency and reliability? Answering these questions will necessitate collaboration between computer and data scientists, materials engineers, and neuroscientists. The final result will be robots that are more aware of themselves, their environment, and their interactions with humans, yielding richer and more productive experiences for human end-users.

Affective touch is a crucial form of non-verbal communication that humans use daily, and is one application that would benefit from the combination of e-skins, soft robotics, and machine learning. In contrast, most robots currently are unable to understand gestures like a pat on the back, because they either do not have the sensors necessary to measure the interaction or because they are not able to make sense of the affective contact.

Shape sensing Despite the recent progress in shape-sensing e-skins, it is unclear how to extend these advances to the wide range of soft robots presented in the literature. Soft robots experience large strains and complex deformations—how can stretchability be introduced into shape-sensing skins? How can resolution be increased to detect small local curvatures?

Once the field has reliable solutions for soft robot proprioception, it is conceivable that shape feedback would enable controlled shape-change in robots. Current soft robots do not have much ability to morph into specific configurations, yet even simple shape-change has led to innovative solutions for a wide range of tasks, such as obstacle avoidance (*34*), rolling locomotion (*117*), underwater locomotion (*118*) and camouflage (*119*). Larger shape-change could result in robots which switch between morphologies and corresponding locomotion gaits on-demand (Fig. 6C).

Feedback control Using sensorized skins to close-the-loop has the potential to improve soft robots' ability to react to their environment, locomote, explore, and manipulate objects using their deformable bodies (Fig. 6D). The use of soft tactile sensors for closed-loop control is still in its nascency. The few relevant studies in this area use low-dimensional soft strain sensors for closed-loop kinematic or force control (*76, 120, 121*). This is surprising given the wealth of literature on soft sensing technologies and considering the intended application of these sensors (*32*). One reason for this discrepancy could be that soft sensors were originally developed for wearable devices and therefore used only for state estimation. Another reason could be the stiff performance expectations placed on soft sensors. Although it would be useful to develop drift-free, linear sensors with high gauge factors, biology suggests that workarounds are possible. For example, the human tactile sensing is hysteretic, nonlinear, time varying, and slow. Nature adapts to these drawbacks by developing hyper-redundant sensing networks and intelligent data processing techniques (*122*).

Along the same lines, various sensor design strategies can be discovered by looking into nature. Tactile exploration likely requires the highest spatial resolution (around 2 mm), as evident from the dense mechanoreceptor distribution at the human fingertip (*123, 124*). On the other end of the spectrum, tactile reaction likely requires the lowest spatial resolution, as suggested by the poor spatial resolution across other parts of the body. Tactile manipulation lies in between, with an expected spatial resolution of 5 mm (*125*).

The type and distribution of mechanoreceptors across the body also suggests the type of sensor technologies that would be useful for a particular task. It is clear that humans employ distinct sensors for static and dynamic cues. Low-bandwidth mechanoreceptors (10-50 Hz), can be found mainly in the fingertip, and would be essential for tactile exploration (*126*). Higher bandwidth mechanoreceptors (50-400 Hz), that respond to the vibrations induced during object slippage, are distributed primarily at the palm of the hand (*127*). The response and sensing area of the mechanoreceptors are strongly dependent on the skin morphology. Hence, it is vital to consider the design of the body and the motion capabilities for mimicking the dynamic receptors in our body.

Other insights can be gained by extending such an analysis to invertebrate biological organisms, such as octopuses. An octopus has a large number of receptors, primarily chemoreceptors, located on each sucker. Additionally, the octopus has strain receptors associated with its muscles and a relatively large brain for processing its receptor information. Despite these capabilities, it has a poor proprioceptive sense and cannot estimate the overall shape and location of external objects it is handling. There is local proprioceptive feedback in each arm for low-level control, but the only feedback to the central nervous system comes through vision (*128*). Wells et al. conjectured that in flexible animals, motor control is hierarchical and proprioceptive information must be utilized locally (*129*). Contrary to popular belief, the performance of the octopus in manipulation tasks is poor. Therefore, it might be necessary to incorporate rigid components in fully-soft robots, if they are to be used for tactile-based closed-loop control tasks.

Outlook

In recent years, the concept of soft-bodied robots has rapidly grown in popularity. Researchers have developed many interesting forms of actuation that more closely mimic the functionality and capabilities found in nature. The next step for the field is to develop biologically-inspired tactile sensing for soft-bodied robots that can safely interact with—and explore—their environments. Current work concentrates on the design and fabrication of soft robots and sensors and explores how machine learning can enhance soft robot perception. In the short term, the field can focus on deployable, high-resolution sensor skins, algorithms for processing the dense sensor information, and reliable feedback control for soft robots. The future consists of robots that can touch and feel with the sensitivity and perception of natural systems.

References

1. D. Rus and M. T. Tolley, "Design, fabrication and control of soft robots," *Nature*, vol. 521, no. 7553, p. 467, 2015.

2. H. A. Sonar, M. C. Yuen, R. Kramer-Bottiglio, and J. Paik, "An any-resolution pressure localization scheme using a soft capacitive sensor skin," in *2018 IEEE International Conference on Soft Robotics (RoboSoft)*, pp. 170–175, Apr. 2018.

3. Y.-L. Park, B.-R. Chen, and R. J. Wood, "Design and fabrication of soft artificial skin using embedded microchannels and liquid conductors," *IEEE Sensors Journal*, vol. 12, no. 8, pp. 2711–2718, 2012.

4. T. Hellebrekers, O. Kroemer, and C. Majidi, "Soft magnetic skin for continuous deformation sensing," *Advanced Intelligent Systems*, vol. 1, no. 4, p. 1900025, 2019.

5. B. C.-K. Tee, A. Chortos, A. Berndt, A. K. Nguyen, A. Tom, A. McGuire, Z. C. Lin, K. Tien, W.-G. Bae, H. Wang, P. Mei, H.-H. Chou, B. Cui, K. Deisseroth, T. N. Ng, and Z. Bao, "A skin-inspired organic digital mechanoreceptor," *Science*, vol. 350, pp. 313–316, Oct. 2015.

6. D.-H. Kim, N. Lu, R. Ma, Y.-S. Kim, R.-H. Kim, S. Wang, J. Wu, S. M. Won, H. Tao, A. Islam, *et al.*, "Epidermal electronics," *Science*, vol. 333, no. 6044, pp. 838–843, 2011.

7. M. Kaltenbrunner, T. Sekitani, J. Reeder, T. Yokota, K. Kuribara, T. Tokuhara, M. Drack, R. Schwödiauer, I. Graz, S. Bauer-Gogonea, *et al.*, "An ultra-lightweight design for imperceptible plastic electronics," *Nature*, vol. 499, no. 7459, p. 458, 2013.

8. Z. Huang, Y. Hao, Y. Li, H. Hu, C. Wang, A. Nomoto, T. Pan, Y. Gu, Y. Chen, T. Zhang, *et al.*, "Three-dimensional integrated stretchable electronics," *Nature Electronics*, vol. 1, no. 8, p. 473, 2018.

9. G. Soter, A. Conn, H. Hauser, and J. Rossiter, "Bodily aware soft robots: integration of proprioceptive and exteroceptive sensors," in *2018 IEEE international conference on robotics and automation (ICRA)*, pp. 2448–2453, IEEE, 2018.

10. L. Chin, J. Lipton, M. C. Yuen, R. Kramer-Bottiglio, and D. Rus, "Automated recycling separation enabled by soft robotic material classification," in *2019 2nd IEEE International Conference on Soft Robotics (RoboSoft)*, pp. 102–107, IEEE, 2019.

11. R. Deimel and O. Brock, “A novel type of compliant and underactuated robotic hand for dexterous grasping,” *The International Journal of Robotics Research*, vol. 35, no. 1-3, pp. 161–185, 2016.

12. T. G. Thuruthel, B. Shih, C. Laschi, and M. T. Tolley, “Soft robot perception using embedded soft sensors and recurrent neural networks,” *Science Robotics*, vol. 4, no. 26, p. eaav1488, 2019.

13. L. Scimeca, P. Maiolino, D. Cardin-Catalan, A. P. del Pobil, A. Morales, and F. Iida, “Non-destructive robotic assessment of mango ripeness via multi-point soft haptics,” in *2019 International Conference on Robotics and Automation (ICRA)*, pp. 1821–1826, IEEE, 2019.

14. R. A. Bilodeau, E. L. White, and R. K. Kramer, “Monolithic fabrication of sensors and actuators in a soft robotic gripper,” in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 2324–2329, IEEE, 2015.

15. N. Farrow and N. Correll, “A soft pneumatic actuator that can sense grasp and touch,” in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 2317–2323, IEEE, 2015.

16. B. Shih, D. Drotman, C. Christianson, Z. Huo, R. White, H. I. Christensen, and M. T. Tolley, “Custom soft robotic gripper sensor skins for haptic object visualization,” in *2017 IEEE/RSJ IROS*, pp. 494–501, IEEE, 2017.

17. H. Zhao, K. OBrien, S. Li, and R. F. Shepherd, “Optoelectronically innervated soft prosthetic hand via stretchable optical waveguides,” *Science Robotics*, vol. 1, no. 1, p. eaai7529, 2016.

18. K. B. Justus, T. Helleb rekers, D. D. Lewis, A. Wood, C. Ingham, C. Majidi, P. R. LeDuc, and C. Tan, “A biosensing soft robot: Autonomous parsing of chemical signals through integrated organic and inorganic interfaces,” *Science Robotics*, vol. 4, no. 31, p. eaax0765, 2019.

19. A. Alspach, J. Kim, and K. Yamane, “Design of a soft upper body robot for physical human-robot interaction,” in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, pp. 290–296, IEEE, 2015.

20. P. Mittendorfer, E. Dean, and G. Cheng, “3D spatial self-organization of a modular artificial skin,” in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3969–3974, Sept. 2014.

21. J. W. Booth, D. Shah, J. C. Case, E. L. White, M. C. Yuen, O. Cyr-Choiniere, and R. Kramer-Bottiglio, “Omniskins: Robotic skins that turn inanimate objects into multifunctional robots,” *Science Robotics*, vol. 3, no. 22, p. eaat1853, 2018.

22. R. F. Shepherd, F. Ilievski, W. Choi, S. A. Morin, A. A. Stokes, A. D. Mazzeo, X. Chen, M. Wang, and G. M. Whitesides, "Multigait soft robot," *Proceedings of the national academy of sciences*, vol. 108, no. 51, pp. 20400–20403, 2011.

23. D. Drotman, S. Jadhav, M. Karimi, P. Dezonia, and M. T. Tolley, "3D printed soft actuators for a legged robot capable of navigating unstructured terrain," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 5532–5538, IEEE, 2017.

24. E. W. Hawkes, L. H. Blumenschein, J. D. Greer, and A. M. Okamura, "A soft robot that navigates its environment through growth," *Science Robotics*, vol. 2, no. 8, p. eaan3028, 2017.

25. R. K. Katzschmann, J. DelPreto, R. MacCurdy, and D. Rus, "Exploration of underwater life with an acoustically controlled soft robotic fish," *Science Robotics*, vol. 3, no. 16, p. eaar3449, 2018.

26. M. Wehner, R. L. Truby, D. J. Fitzgerald, B. Mosadegh, G. M. Whitesides, J. A. Lewis, and R. J. Wood, "An integrated design and fabrication strategy for entirely soft, autonomous robots," *Nature*, vol. 536, no. 7617, p. 451, 2016.

27. S. Wagner, S. P. Lacour, J. Jones, I. H. Pai-hui, J. C. Sturm, T. Li, and Z. Suo, "Electronic skin: architecture and components," *Physica E: Low-dimensional Systems and Nanostructures*, vol. 25, no. 2-3, pp. 326–334, 2004.

28. J. Case, M. Yuen, M. Mohammed, and R. Kramer, "Sensor skins: An overview," in *Stretchable Bioelectronics for Medical Devices and Systems*, pp. 173–191, Springer, 2016.

29. M. Amjadi, K.-U. Kyung, I. Park, and M. Sitti, "Stretchable, skin-mountable, and wearable strain sensors and their potential applications: a review," *Advanced Functional Materials*, vol. 26, no. 11, pp. 1678–1698, 2016.

30. N. Yogeswaran, W. Dang, W. T. Navaraj, D. Shakthivel, S. Khan, E. O. Polat, S. Gupta, H. Heidari, M. Kaboli, L. Lorenzelli, *et al.*, "New materials and advances in making electronic skin for interactive robots," *Advanced Robotics*, vol. 29, no. 21, pp. 1359–1373, 2015.

31. R. Dahiya, N. Yogeswaran, F. Liu, L. Manjakkal, E. Burdet, V. Hayward, and H. Jörntell, "Large-area soft e-skin: The challenges beyond sensor designs," *Proceedings of the IEEE*, vol. 107, no. 10, pp. 2016–2033, 2019.

32. H. Wang, M. Totaro, and L. Beccai, "Toward perceptive soft robots: Progress and challenges," *Advanced Science*, vol. 5, no. 9, p. 1800541, 2018.

33. K. Chin, T. Hellebrekers, and C. Majidi, "Machine learning for soft robotic sensing and control," *Advanced Intelligent Systems*, 2020.

34. D. S. Shah, M. C. Yuen, L. G. Tilton, E. J. Yang, and R. Kramer-Bottiglio, “Morphing robots using robotic skins that sculpt clay,” *IEEE Robotics and Automation Letters*, vol. 4, pp. 2204–2211, Apr. 2019.

35. S. Sundaram, P. Kellnhofer, Y. Li, J.-Y. Zhu, A. Torralba, and W. Matusik, “Learning the signatures of the human grasp using a scalable tactile glove,” *Nature*, vol. 569, no. 7758, p. 698, 2019.

36. K. Takei, T. Takahashi, J. C. Ho, H. Ko, A. G. Gillies, P. W. Leu, R. S. Fearing, and A. Javey, “Nanowire active-matrix circuitry for low-voltage macroscale artificial skin,” *Nature materials*, vol. 9, no. 10, p. 821, 2010.

37. W. Lee, Y. Liu, Y. Lee, B. K. Sharma, S. M. Shinde, S. D. Kim, K. Nan, Z. Yan, M. Han, Y. Huang, *et al.*, “Two-dimensional materials in functional three-dimensional architectures with applications in photodetection and imaging,” *Nature communications*, vol. 9, no. 1, pp. 1–9, 2018.

38. W. W. Lee, Y. J. Tan, H. Yao, S. Li, H. H. See, M. Hon, K. A. Ng, B. Xiong, J. S. Ho, and B. C. Tee, “A neuro-inspired artificial peripheral nervous system for scalable electronic skins,” *Science Robotics*, vol. 4, no. 32, p. eaax2198, 2019.

39. T. Arnold and M. Scheutz, “The tactile ethics of soft robotics: designing wisely for human–robot interaction,” *Soft robotics*, vol. 4, no. 2, pp. 81–87, 2017.

40. J. Viventi, D.-H. Kim, L. Vigeland, E. S. Frechette, J. A. Blanco, Y.-S. Kim, A. E. Avrin, V. R. Tiruvadi, S.-W. Hwang, A. C. Vanleer, *et al.*, “Flexible, foldable, actively multiplexed, high-density electrode array for mapping brain activity in vivo,” *Nature neuroscience*, vol. 14, no. 12, p. 1599, 2011.

41. D.-H. Kim, J.-H. Ahn, W. M. Choi, H.-S. Kim, T.-H. Kim, J. Song, Y. Y. Huang, Z. Liu, C. Lu, and J. A. Rogers, “Stretchable and foldable silicon integrated circuits,” *Science*, vol. 320, no. 5875, pp. 507–511, 2008.

42. T. Someya, Y. Kato, T. Sekitani, S. Iba, Y. Noguchi, Y. Murase, H. Kawaguchi, and T. Sakurai, “Conformable, flexible, large-area networks of pressure and thermal sensors with organic transistor active matrixes,” *Proceedings of the National Academy of Sciences*, vol. 102, no. 35, pp. 12321–12325, 2005.

43. T. Sekitani, Y. Noguchi, K. Hata, T. Fukushima, T. Aida, and T. Someya, “A rubberlike stretchable active matrix using elastic conductors,” *Science*, vol. 321, no. 5895, pp. 1468–1472, 2008.

44. X. Ren, K. Pei, B. Peng, Z. Zhang, Z. Wang, X. Wang, and P. K. Chan, “A low-operating-power and flexible active-matrix organic-transistor temperature-sensor array,” *Advanced Materials*, vol. 28, no. 24, pp. 4832–4838, 2016.

45. S. Wang, J. Xu, W. Wang, G.-J. N. Wang, R. Rastak, F. Molina-Lopez, J. W. Chung, S. Niu, V. R. Feig, J. Lopez, *et al.*, “Skin electronics from scalable fabrication of an intrinsically stretchable transistor array,” *Nature*, vol. 555, no. 7694, p. 83, 2018.

46. B. Shih, C. Christianson, K. Gillespie, S. Lee, J. Mayeda, Z. Huo, and M. T. Tolley, “Design considerations for 3D printed, soft, multimaterial resistive sensors for soft robotics,” *Frontiers in Robotics and AI*, vol. 6, p. 30, 2019.

47. A. Chortos, J. Liu, and Z. Bao, “Pursuing prosthetic electronic skin,” *Nature materials*, vol. 15, no. 9, p. 937, 2016.

48. Y. Kim, A. Chortos, W. Xu, Y. Liu, J. Y. Oh, D. Son, J. Kang, A. M. Foudeh, C. Zhu, Y. Lee, *et al.*, “A bioinspired flexible organic artificial afferent nerve,” *Science*, vol. 360, no. 6392, pp. 998–1003, 2018.

49. P. A. Xu, A. Mishra, H. Bai, C. Aubin, L. Zullo, and R. Shepherd, “Optical lace for synthetic afferent neural networks,” *Science Robotics*, vol. 4, no. 34, p. eaaw6304, 2019.

50. P. Mittendorfer and G. Cheng, “3D surface reconstruction for robotic body parts with artificial skins,” in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 4505–4510, Oct. 2012.

51. R. K. Kramer, C. Majidi, R. Sahai, and R. J. Wood, “Soft curvature sensors for joint angle proprioception,” in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, pp. 1919–1926, IEEE, 2011.

52. J. T. Muth, D. M. Vogt, R. L. Truby, Y. Mengüç, D. B. Kolesky, R. J. Wood, and J. A. Lewis, “Embedded 3D printing of strain sensors within highly stretchable elastomers,” *Advanced Materials*, vol. 26, no. 36, pp. 6307–6312, 2014.

53. A. Alspach, J. Kim, and K. Yamane, “Design and fabrication of a soft robotic hand and arm system,” in *2018 IEEE International Conference on Soft Robotics (RoboSoft)*, pp. 369–375, Apr. 2018.

54. J. Jung, M. Park, D. W. Kim, and Y.-L. Park, “Optically sensorized elastomer air chamber for proprioceptive sensing of soft pneumatic actuators,” *IEEE Robotics and Automation Letters*, 2020.

55. I. Van Meerbeek, C. De Sa, and R. Shepherd, “Soft optoelectronic sensory foams with proprioception,” *Science Robotics*, vol. 3, no. 24, p. eaau2489, 2018.

56. G. Schwartz, B. C.-K. Tee, J. Mei, A. L. Appleton, D. H. Kim, H. Wang, and Z. Bao, “Flexible polymer transistors with high pressure sensitivity for application in electronic skin and health monitoring,” *Nature communications*, vol. 4, p. 1859, 2013.

57. J. Byun, Y. Lee, J. Yoon, B. Lee, E. Oh, S. Chung, T. Lee, K.-J. Cho, J. Kim, and Y. Hong, "Electronic skins for soft, compact, reversible assembly of wirelessly activated fully soft robots," *Science Robotics*, vol. 3, no. 18, p. eaas9020, 2018.

58. H. Jeong, L. Wang, T. Ha, R. Mitbander, X. Yang, Z. Dai, S. Qiao, L. Shen, N. Sun, and N. Lu, "Modular and reconfigurable wireless e-tattoos for personalized sensing," *Advanced Materials Technologies*, p. 1900117, 2019.

59. Y. Mengüç, Y.-L. Park, H. Pei, D. Vogt, P. M. Aubin, E. Winchell, L. Fluke, L. Stirling, R. J. Wood, and C. J. Walsh, "Wearable soft sensing suit for human gait measurement," *The International Journal of Robotics Research*, vol. 33, no. 14, pp. 1748–1764, 2014.

60. C. M. Boutry, M. Negre, M. Jorda, O. Vardoulis, A. Chortos, O. Khatib, and Z. Bao, "A hierarchically patterned, bioinspired e-skin able to detect the direction of applied pressure for robotics," *Science Robotics*, vol. 3, no. 24, p. eaau6914, 2018.

61. H. Van Hoof, T. Hermans, G. Neumann, and J. Peters, "Learning robot in-hand manipulation with tactile features," in *2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids)*, pp. 121–127, IEEE, 2015.

62. P. Piacenza, S. Sherman, and M. Ciocarlie, "Data-driven super-resolution on a tactile dome," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1434–1441, 2018.

63. C. Larson, J. Spjut, R. Knepper, and R. Shepherd, "A deformable interface for human touch recognition using stretchable carbon nanotube dielectric elastomer sensors and deep neural networks," *Soft robotics*, vol. 6, no. 5, pp. 611–620, 2019.

64. D. Kim, J. Kwon, B. J. Jeon, and Y.-L. Park, "Adaptive calibration of soft sensors using optimal transportation transfer learning for mass production and long-term usage," *Advanced Intelligent Systems*, 2020.

65. D. Kim, J. Kwon, S. Han, Y.-L. Park, and S. Jo, "Deep full-body motion network (dfmnet) for a soft wearable motion sensing suit," *IEEE/ASME Transactions on Mechatronics*, 2018.

66. M. Riesenhuber and T. Poggio, "Hierarchical models of object recognition in cortex," *Nature neuroscience*, vol. 2, no. 11, p. 1019, 1999.

67. Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE transactions on pattern analysis and machine intelligence*, vol. 35, no. 8, pp. 1798–1828, 2013.

68. P. Mirowski, R. Pascanu, F. Viola, H. Soyer, A. J. Ballard, A. Banino, M. Denil, R. Goroshin, L. Sifre, K. Kavukcuoglu, *et al.*, "Learning to navigate in complex environments," *arXiv preprint arXiv:1611.03673*, 2016.

69. T. Chen, S. Gupta, and A. Gupta, "Learning exploration policies for navigation," *arXiv preprint arXiv:1903.01959*, 2019.

70. J. Fu, S. Levine, and P. Abbeel, "One-shot learning of manipulation skills with online dynamics adaptation and neural network priors," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 4019–4026, IEEE, 2016.

71. A. Rajeswaran, V. Kumar, A. Gupta, G. Vezzani, J. Schulman, E. Todorov, and S. Levine, "Learning complex dexterous manipulation with deep reinforcement learning and demonstrations," *arXiv preprint arXiv:1709.10087*, 2017.

72. M. Andrychowicz, B. Baker, M. Chociej, R. Jozefowicz, B. McGrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, *et al.*, "Learning dexterous in-hand manipulation," *arXiv:1808.00177*, 2018.

73. D. P. Bertsekas, *Dynamic programming and optimal control*, vol. 1. Athena scientific, 1995.

74. J. Burgner-Kahrs, D. C. Rucker, and H. Choset, "Continuum robots for medical applications: A survey," *IEEE Transactions on Robotics*, vol. 31, pp. 1261–1280, Dec. 2015.

75. T. George Thuruthel, Y. Ansari, E. Falotico, and C. Laschi, "Control strategies for soft robotic manipulators: A survey," *Soft Robotics*, Jan. 2018.

76. J. Morrow, H. Shin, C. Phillips-Grafflin, S. Jang, J. Torrey, R. Larkins, S. Dang, Y.-L. Park, and D. Berenson, "Improving soft pneumatic actuator fingers through integration of soft sensors, position and force control, and rigid fingernails," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 5024–5031, May 2016.

77. S. Y. Kim, R. Baines, J. Booth, N. Vasios, K. Bertoldi, and R. Kramer-Bottiglio, "Reconfigurable soft body trajectories using unidirectionally stretchable composite laminae," *Nature Communications*, vol. 10, p. 3464, Aug. 2019.

78. N. Cheney, R. MacCurdy, J. Clune, and H. Lipson, "Unshackling evolution: evolving soft robots with multiple materials and a powerful generative encoding," in *Proceedings of the 15th annual conference on Genetic and evolutionary computation*, pp. 167–174, ACM, 2013.

79. T. Hoshi and H. Shinoda, "3D shape measuring sheet utilizing gravitational and geomagnetic fields," in *2008 SICE Annual Conference*, pp. 915–920, Aug. 2008.

80. A. Hermanis, R. Cacurs, and M. Greitans, "Acceleration and magnetic sensor network for shape sensing," *IEEE Sensors Journal*, vol. 16, pp. 1271–1280, Mar. 2016.

81. C. Rendl, D. Kim, S. Fanello, P. Parzer, C. Rhemann, J. Taylor, M. Zirkl, G. Scheipl, T. Rothlnder, M. Haller, and S. Izadi, "Flexsense: A transparent self-sensing deformable surface," in *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, UIST '14, (New York, NY, USA), pp. 129–138, ACM, 2014. event-place: Honolulu, Hawaii, USA.

82. T. L. T. Lun, K. Wang, J. D. L. Ho, K. Lee, K. Y. Sze, and K. Kwok, "Real-time surface shape sensing for soft and flexible structures using fiber Bragg gratings," *IEEE Robotics and Automation Letters*, vol. 4, pp. 1454–1461, Apr. 2019.

83. L. Pinto, D. Gandhi, Y. Han, Y.-L. Park, and A. Gupta, "The curious robot: Learning visual representations via physical interactions," in *European Conference on Computer Vision*, pp. 3–18, Springer, 2016.

84. M. R. Cutkosky, R. D. Howe, and W. R. Provancher, "Force and tactile sensors," *Springer Handbook of Robotics*, pp. 455–476, 2008.

85. O. Khatib, X. Yeh, G. Brantner, B. Soe, B. Kim, S. Ganguly, H. Stuart, S. Wang, M. Cutkosky, A. Edsinger, *et al.*, "Ocean one: A robotic avatar for oceanic discovery," *IEEE Robotics & Automation Magazine*, vol. 23, no. 4, pp. 20–29, 2016.

86. M. Raibert, K. Blankespoor, G. Nelson, and R. Playter, "Bigdog, the rough-terrain quadruped robot," *IFAC Proceedings Volumes*, vol. 41, no. 2, pp. 10822–10825, 2008.

87. M. Li, Y. Bekiroglu, D. Kragic, and A. Billard, "Learning of grasp adaptation through experience and tactile sensing," in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3339–3346, Ieee, 2014.

88. N. Wettels, V. J. Santos, R. S. Johansson, and G. E. Loeb, "Biomimetic tactile sensor array," *Advanced Robotics*, vol. 22, no. 8, pp. 829–849, 2008.

89. F. Veiga, J. Peters, and T. Hermans, "Grip stabilization of novel objects using slip prediction," *IEEE transactions on haptics*, vol. 11, no. 4, pp. 531–542, 2018.

90. Y. Chebotar, M. Kalakrishnan, A. Yahya, A. Li, S. Schaal, and S. Levine, "Path integral guided policy search," in *2017 IEEE international conference on robotics and automation (ICRA)*, pp. 3381–3388, IEEE, 2017.

91. H. Van Hoof, N. Chen, M. Karl, P. van der Smagt, and J. Peters, "Stable reinforcement learning with autoencoders for tactile and visual data," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3928–3934, IEEE, 2016.

92. Y. Ohmura and Y. Kuniyoshi, "Humanoid robot which can lift a 30kg box by whole body contact and tactile feedback," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 1136–1141, IEEE, 2007.

93. P. Mittendorfer, E. Yoshida, and G. Cheng, "Realizing whole-body tactile interactions with a self-organizing, multi-modal artificial skin on a humanoid robot," *Advanced Robotics*, vol. 29, no. 1, pp. 51–67, 2015.

94. K. Hertkorn, M. A. Roa, and C. Borst, "Planning in-hand object manipulation with multifingered hands considering task constraints," in *2013 IEEE International Conference on Robotics and Automation*, pp. 617–624, IEEE, 2013.

95. G. E. Loeb, G. A. Tsianos, J. A. Fishel, N. Wettels, and S. Schaal, "Understanding haptics by evolving mechatronic systems," in *Progress in brain research*, vol. 192, pp. 129–144, Elsevier, 2011.

96. N. Jamali and C. Sammut, "Majority voting: Material classification by tactile sensing using surface texture," *IEEE Transactions on Robotics*, vol. 27, no. 3, pp. 508–521, 2011.

97. J. Sinapov, V. Sukhoy, R. Sahai, and A. Stoytchev, "Vibrotactile recognition and categorization of surfaces by a humanoid robot," *IEEE Transactions on Robotics*, vol. 27, no. 3, pp. 488–497, 2011.

98. H. Yousef, M. Boukallel, and K. Althoefer, "Tactile sensing for dexterous in-hand manipulation in roboticsa review," *Sensors and Actuators A: physical*, vol. 167, no. 2, pp. 171–187, 2011.

99. N. Jamali and C. Sammut, "Material classification by tactile sensing using surface textures," in *2010 IEEE International Conference on Robotics and Automation*, pp. 2336–2341, IEEE, 2010.

100. B. S. Homberg, R. K. Katzschmann, M. R. Dogar, and D. Rus, "Haptic identification of objects using a modular soft robotic gripper," in *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on*, pp. 1698–1705, IEEE, 2015.

101. J. Gottlieb, P.-Y. Oudeyer, M. Lopes, and A. Baranes, "Information-seeking, curiosity, and attention: computational and neural mechanisms," *Trends in cognitive sciences*, vol. 17, no. 11, pp. 585–593, 2013.

102. S. J. Lederman and R. L. Klatzky, "Hand movements: A window into haptic object recognition," *Cognitive psychology*, vol. 19, no. 3, pp. 342–368, 1987.

103. L. Pape, C. M. Oddo, M. Controzzi, C. Cipriani, A. Förster, M. C. Carrozza, and J. Schmidhuber, "Learning tactile skills through curious exploration," *Frontiers in neurorobotics*, vol. 6, p. 6, 2012.

104. J. A. Fishel and G. E. Loeb, "Bayesian exploration for intelligent identification of textures," *Frontiers in neurorobotics*, vol. 6, p. 4, 2012.

105. Q. Li, C. Schürmann, R. Haschke, and H. Ritter, "A control framework for tactile servoing," 2013.

106. Z. Su, J. A. Fishel, T. Yamamoto, and G. E. Loeb, "Use of tactile feedback to control exploratory movements to characterize object compliance," *Frontiers in neurorobotics*, vol. 6, p. 7, 2012.

107. M. Kaboli, K. Yao, D. Feng, and G. Cheng, "Tactile-based active object discrimination and target object search in an unknown workspace," *Autonomous Robots*, vol. 43, no. 1, pp. 123–152, 2019.

108. H. Iwata and S. Sugano, "Whole-body covering tactile interface for human robot coordination," in *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292)*, vol. 4, pp. 3818–3824, IEEE, 2002.

109. M. Frigola, A. Casals, and J. Amat, "Human-robot interaction based on a sensitive bumper skin," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 283–287, IEEE, 2006.

110. S. Haddadin and E. Croft, "Physical human–robot interaction," in *Springer handbook of robotics*, pp. 1835–1874, Springer, 2016.

111. D. Silvera-Tawil, D. Rye, and M. Velonaki, "Artificial skin and tactile sensing for socially interactive robots: A review," *Robotics and Autonomous Systems*, vol. 63, pp. 230–243, 2015.

112. G. Canepa, R. Petrigliano, M. Campanella, and D. De Rossi, "Detection of incipient object slippage by skin-like sensing and neural network processing," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 28, no. 3, pp. 348–356, 1998.

113. G. Cheng, E. Dean-Leon, F. Bergner, J. R. G. Olvera, Q. Leboutet, and P. Mittendorfer, "A comprehensive realization of robot skin: Sensors, sensing, control, and applications," *Proceedings of the IEEE*, vol. 107, no. 10, pp. 2034–2051, 2019.

114. A. Del Prete, S. Denei, L. Natale, F. Mastrogiovanni, F. Nori, G. Cannata, and G. Metta, "Skin spatial calibration using force/torque measurements," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 3694–3700, IEEE, 2011.

115. R. Calandra, S. Ivaldi, M. P. Deisenroth, E. Rueckert, and J. Peters, "Learning inverse dynamics models with contacts," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3186–3191, IEEE, 2015.

116. E. Dean-Leon, J. R. Guadarrama-Olvera, F. Bergner, and G. Cheng, "Whole-body active compliance control for humanoid robots with robot skin," in *2019 International Conference on Robotics and Automation (ICRA)*, pp. 5404–5410, IEEE, 2019.

117. E. Steltz, A. Mozeika, N. Rodenberg, E. Brown, and H. M. Jaeger, “JSEL: Jamming skin enabled locomotion,” in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 5672–5677, Oct. 2009.

118. M. Ishida, D. Drotman, B. Shih, M. Hermes, M. Luhar, and M. T. Tolley, “Morphing structure for changing hydrodynamic characteristics of a soft underwater walking robot,” *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 4163–4169, 2019.

119. J. H. Pikul, S. Li, H. Bai, R. T. Hanlon, I. Cohen, and R. F. Shepherd, “Stretchable surfaces with programmable 3D texture morphing for synthetic camouflaging skins,” *Science*, vol. 358, pp. 210–214, Oct. 2017.

120. H. A. Sonar, A. P. Gerratt, S. P. Lacour, and J. Paik, “Closed-loop haptic feedback control using a self-sensing soft pneumatic actuator skin,” *Soft robotics*, 2019.

121. J. Wirekoh, L. Valle, N. Pol, and Y.-L. Park, “Sensorized, flat, pneumatic artificial muscle embedded with biomimetic microfluidic sensors for proprioceptive feedback,” *Soft robotics*, vol. 6, no. 6, pp. 768–777, 2019.

122. R. S. Dahiya, G. Metta, M. Valle, and G. Sandini, “Tactile sensing - from humans to humanoids,” *IEEE transactions on robotics*, vol. 26, no. 1, pp. 1–20, 2009.

123. J. C. Stevens, “Aging and spatial acuity of touch,” *Journal of gerontology*, vol. 47, no. 1, pp. P35–P40, 1992.

124. R. S. Johansson and A. Vallbo, “Tactile sensibility in the human hand: relative and absolute densities of four types of mechanoreceptive units in glabrous skin,” *The Journal of physiology*, vol. 286, no. 1, pp. 283–300, 1979.

125. F. Mancini, A. Bauleo, J. Cole, F. Lui, C. A. Porro, P. Haggard, and G. D. Iannetti, “Whole-body mapping of spatial acuity for pain and touch,” *Annals of neurology*, vol. 75, no. 6, pp. 917–924, 2014.

126. Å. Vallbo and R. Johansson, “Properties of cutaneous mechanoreceptors in the human hand related to touch sensation,” *Human neurobiology*, vol. 3, no. 1, pp. 3–14, 1984.

127. R. S. Johansson and J. R. Flanagan, “Coding and use of tactile signals from the fingertips in object manipulation tasks,” *Nature Reviews Neuroscience*, vol. 10, no. 5, p. 345, 2009.

128. M. J. Wells, *Octopus: physiology and behaviour of an advanced invertebrate*. Springer Science & Business Media, 2013.

129. M. Wells, “Tactile discrimination of surface curvature and shape by the octopus,” *Journal of Experimental Biology*, vol. 41, no. 2, pp. 433–445, 1964.

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Competing Interests

The authors declare that they have no competing financial interests.

Correspondence

Correspondence and requests for materials should be addressed to M. T. Tolley (email: tolley@ucsd.edu).