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A Review on Sensor Technologies, Control Approaches, and Emerging Challenges in Soft Robotics

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ABSTRACT

The growing interest in soft robotics stems from the flexibility of soft systems and their unique capacity to adapt to complex tasks that are often unachievable with rigid robots. However, this adaptability comes with significant challenges, particularly in monitoring and controlling systems that possess potentially infinite degrees of freedom. This review offers an overview of the diverse sensing and control strategies employed in soft robotics. We offer an overview of sensor characteristics used in soft robots. These sensors are categorized according to the physical quantities they detect and their specific functions, illustrating their practical applications. Additionally, we provide a comprehensive classification of the literature based on the functional roles of control strategies in soft systems—such as motion control (e.g., pose and tip controllers) and force control for tasks like grasping, manipulation, and locomotion—highlighting the central importance of real-time sensory feedback. The survey also discusses key limitations and outlines promising directions to support the development of advanced sensing and control frameworks for next-generation soft robots.

1 | Introduction

Foundational work in robotics focused for several decades on discrete manipulators, consisting of rigid links connected by joints, with an end-effector that interacts with the environment [1]. These robots are known for their efficiency in performing repetitive tasks with precision and reliability. However, their rigid design limits their flexibility and adaptability within a given workspace, and their rigid materials pose safety risks in human interactions [2]. Soft robotics can overcome these limitations with their inherent flexibility and mechanical adaptability. Such robots, primarily composed of soft materials, exhibit hyper-redundant configurations with infinite degrees of freedom (DoF), which enables them to alter their configuration at any point along their length [3, 4]. Resembling the movements of snakes [5], elephant trunks [6], and octopus arms [7, 8], soft robots theoretically have infinite DoF, though not every DoF is actuated [6]. They have showcased their versatility in various domains such as terrestrial applications [9–13], aerial systems [14–16], and underwater operations [17–19]. For instance, soft robots have proven to be highly effective in underwater pipeline inspection, maintenance, and perception, since they are environmentally compatible, tolerate high pressures, and allow for easier fabrication [20–22]. Their attributes have also been leveraged in aerial manipulation tasks and collision recovery [16].

Soft robots possess highly intricate and deformable structures with infinite DoF, which complicate accurate monitoring of the shape and position of each segment of the soft robot compared to rigid robots [23, 24]. Early perception technology in this field was limited to basic devices such as strain gauges [25], resistive sensors [26], and cameras [27, 28]. These sensors can fall short in soft systems due to their lack of the necessary flexibility and stretchability to integrate with various soft bodies and their difficulty in providing accurate data across diverse environments. Moreover, the continuous state space of soft robots and their complex interactions with the environment introduce further challenges for control strategies, which underscore the need for advanced sensing systems that also preserve the inherent softness of the robots [29]. Notable advancements in sensor technology, such as electronic skins (e-skins) [30–32], self-powered, stretchable piezoelectric sensors [33–39], and advanced optical fibers [40–43], have been developed to address these challenges. Advanced sensors can also reduce the computational burden on the controller in soft robots by gathering data and continuously monitoring system states, providing real-time feedback required for training and refining control models.

Therefore, real-world performance can be impacted by the sensor and controller choices. The appropriate choice of sensor can allow for a reduction in redundancy required to achieve closed-loop control [23]. For biomimetic locomotion, research has propelled the use of both on-board and off-board sensing mechanisms depending on the requirements for specific applications [44, 45]. For applications where navigation of obstacles is important, soft robotics has used visual sensors to allow a Model-Free control scheme to plan and execute the motion [46]. In contrast, if the path is pre-determined biomimetic locomotion has been applied through the use of on-board strain sensors [47]. For biomedical applications of soft robotics, the choices of sensing methods and locomotion methods are closely tied due to the requirements for on-board components, regardless whether the device is surgical or wearable in nature [48]. As applications require physical contact, such as object manipulation, e-skins have been integrated to allow for appropriate grasping forces to be applied [49].

The use of soft materials in soft robots often results in hyper-redundant systems with complex nonlinear characteristics, posing substantial challenges in accurate modeling, motion prediction, and control design. These complexities emphasize the necessity for developing diverse modeling methods in the field [3]. For many years, conventional model-based control techniques were considered impractical for soft robotics, largely due to the complexity involved in capturing their dynamic behavior using continuum models [29]. This challenge may explain why, unlike in other domains—where model-based methods typically serve as a foundation later augmented by data-driven and machine learning approaches—soft robotics has followed the opposite trajectory, with early reliance on model-free strategies [29]. At first, control strategies for soft systems heavily relied on data-driven techniques. As the field expanded, model-based control methods and the latest trend of hybrid approaches, which combine model-free with model-based methods, were integrated to control the dynamics of soft robots [23, 50, 51]. The initial reliance on data-driven techniques also highlights the crucial role of sensors in soft robot control. This review provides a comprehensive examination of the interplay between sensing technologies and control strategies in soft robotics. It highlights how sensors are not only essential for state estimation and feedback but also play a foundational role in shaping the development of control approaches.

1.1 | Scope of the Review

This survey focuses on the integration of sensors in soft robotics and the development of control algorithms tailored to their highly deformable, compliant structures. It offers a detailed classification of sensors based on their measuring characteristics and functional roles, highlighting key features that enable effective sensing in soft robotic systems. On the control side, the article adopts a functionality-based perspective, organizing control strategies into motion and force control categories. The article further discusses how specific sensor-controller pairings support critical tasks such as pose tracking, locomotion, object manipulation, and environmental interaction. Finally, it addresses current limitations in sensing and control integration and outlines promising directions for overcoming these challenges.

A key distinction of this review compared to other works such as [23, 45, 52–56] lies in its approach to sensor classification and its emphasis on sensors' contribution to the control design of soft robotic systems. This review classifies sensors based on their measurands rather than using the conventional method of categorizing them by sensing technique. This classification method simplifies the understanding of how various sensors can be utilized for different sensing functions, particularly in relation to the control design for soft robots. It explains why certain technologies are favored for measuring a specific physical quantity, detailing the methods they use for measurement. It also highlights their crucial characteristics and facilitates the selection of appropriate sensors for specific applications. The survey encompasses both laboratory-fabricated and commercial sensors, regardless of whether they are rigid or stretchable, within the context of soft robots. For controls, this review emphasizes the interplay between sensor information and control strategy, and frames control not only in terms of architecture (e.g., model-based or data-driven) but also by the functional goals of the system, such as achieving precise motion or regulating interaction forces, rather than focusing on locomotion methods. This dual classification helps clarify how control algorithms are matched to sensing capabilities and task requirements in soft robotics.

The structure of this review is as follows: Section 2 provides an in-depth overview of the various sensors employed in soft robotics. Section 3 examines the control strategies relevant to soft robotic systems. Section 4 discusses current challenges in the field and explores future research directions. Finally, Section 5 presents concluding remarks.

2 | Sensors in Soft Robotics

In robotics, sensors serve a role analogous to biological sense organs, providing precise external data that informs and precedes any robotic action [2]. The quality and reliability of these sensors are crucial for effective control, especially in tasks such as navigation, object grasping, and manipulation, where they help reduce the risk of environmental damage [52]. However, integrating an effective sensor system into soft robots presents significant challenges [23]. To integrate electronics into soft robots, it is essential that all components—especially sensors embedded within the robot's structure—are flexible and highly deformable.

When rigid components are necessary, as is often the case in laboratory-scale research, they should be small relative to the local deformation of the soft body. Moreover, these components must possess properties that meet the specific demands of the intended task, making it critical to understand the key characteristics required for sensor selection. This section outlines these essential sensor characteristics, including sensitivity, resolution, hysteresis, linearity, accuracy, and precision.

Sensitivity refers to a sensor's ability to detect and quantify small changes in the measured physical quantity. It is defined as the rate of change of the sensor's output with respect to a change in the input stimulus. A higher sensitivity indicates that the sensor can produce a larger output signal for a given change in input, which is particularly important when detecting subtle variations. Generally, there is a trade-off between the sensing range of a sensor and its sensitivity; expanding the sensing range often compromises sensitivity. **Resolution** denotes the smallest detectable change in the input that the sensor can reliably measure. It represents the limit of granularity in the sensor's response. Another important characteristic is **hysteresis**, which describes the sensor's tendency to exhibit different output values for the same input, depending on whether the input is increasing or decreasing. This memory-like behavior creates a looped response curve and can affect the accuracy and repeatability of measurements. Soft sensors are also commonly affected by **drift**, which refers to a sensor's baseline changes over the course of time due to deformation beyond the elastic range. This behavior requires soft sensors to be frequently calibrated to ensure accurate readings. **Linearity** refers to how well the sensor's output corresponds proportionally to changes in the input across its operating range. A highly linear sensor produces an output that closely follows a straight-line relationship with the input. **Accuracy** and **precision** are also critical performance metrics. Accuracy indicates how close a sensor's readings are to the true or reference value, while precision reflects the consistency or repeatability of those readings under the same conditions. In other words, precision describes how closely repeated measurements cluster together. Accuracy is often quantified using the root mean square error (RMSE) between measured and actual values, whereas the standard deviation of the RMSE can be used to represent precision.

To ensure accuracy, precision, and compensation for errors, sensors should be calibrated or an application of continuous adaptive methods should be done at regular intervals throughout the working period. Common types of errors for sensors include hysteresis, drift, and linearity errors. Soft sensors differ from physical sensors in that there is no consensus on how to maintain soft sensors for long-term functionality [57]. Specific calibration methods are beyond the scope of this review, but additional details on this topic can be found in [58, 59].

Moving from sensor characteristics to their practical applications in soft robotics, it becomes evident that the unique properties of each sensor type dictate their suitability for various contexts. Therefore, it is crucial to understand the diverse array of sensing technologies used in soft robots, each with its operational principles and applications. Before classifying sensors based on the parameters they measure, it is useful to briefly recap the main technologies behind the working mechanisms of different sensors, as outlined below. The visual representation of these mechanisms can be found in Figure 1.

Magnetic sensors are designed to detect the presence and strength of magnetic fields [56]. Any change in the magnetic field results in a measurable voltage or other electrical property. Although they are not prone to hysteresis and are highly sensitive, they can be influenced by nearby magnets [52]. These sensors are commonly used in force, shape, and tactile sensing applications because changes in these physical properties can alter the magnetic field. Magnetic sensors employ different principles to detect magnetic fields. Among the different types of magnetic sensors, **Hall-effect sensors** operate by inducing a Hall voltage when a magnetic field is perpendicular to the current flow [56].

Capacitive sensors work by measuring changes in capacitance between two conductive plates when an object-such as a part of a soft robot-comes close to or touches them. These sensors are highly sensitive to position, proximity, and touch, making them ideal for detecting small changes in the environment or the robot's movements [56]. They typically possess low hysteresis, low drift, low cost, and high sensitivity [52]. They are commonly used in soft robotics to measure pressure and force because they can provide accurate readings even with slight deformations or applied forces [60].

Resistive sensors detect changes in electrical resistance that occur when the conductive material of the sensor is deformed, making them ideal for tactile sensing [56]. Resistive sensors are highly sensitive and can detect objects by sensing variations in pressure, texture, and shape [61]. However, these sensors are sometimes prone to hysteresis, meaning their output may lag behind the actual changes in the material being measured [52, 62]. These sensors can also be prone to resistance creep due to changes in the composite under a constant stress [63]. A notable subset of resistive sensors is **piezoresistive sensors**, like strain gauges, which also detect resistance changes using semiconductive materials. This use of semiconductors makes piezoresistive sensors generally lighter, more compact, and more responsive to subtle external stimuli than traditional resistive sensors [56, 64, 65].

Optical sensors are advanced sensors that operate by converting mechanical inputs into variations in light intensity [66, 67]. When light passes through an optical fiber, it changes based on the sensor's expansion or contraction. These changes in light are then processed to reflect alterations in the sensor's length. Although optical sensors can be bulky due to the need for components like light emitters and detectors, they offer several advantages. These include being sensitive, compact, lightweight, not requiring complex wiring, and being capable of withstanding high temperatures and pressures while remaining immune to electromagnetic interference. **Optical fiber sensors** use light emitting diodes (LEDs) or lasers as light emitters at one end and phototransistors or cameras as detectors at the other end [43]. These sensors are widely utilized for shape and strain sensing. **Fiber Bragg grating (FBG)** technology incorporates optical fibers embedded with a regular pattern, or grating, at the measurement point. The grating reflects a specific spectral frequency, which changes when the fiber is strained, allowing for precise

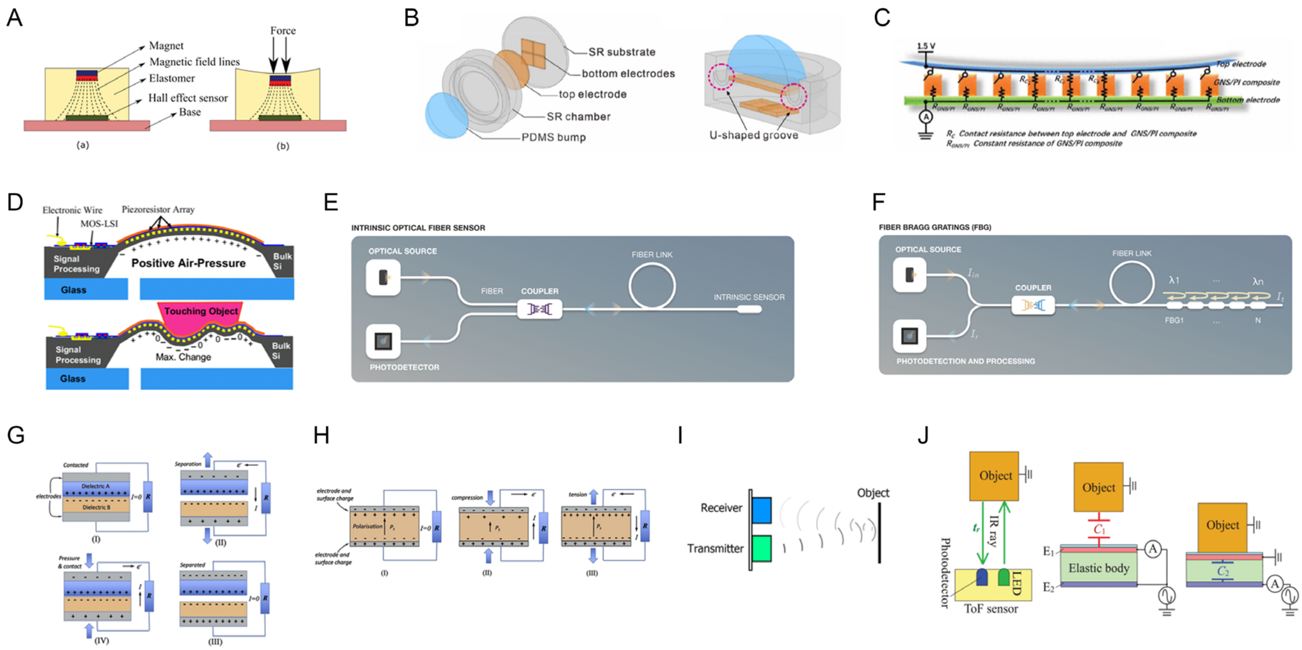

FIGURE 1 | Overview of sensing technologies and their underlying mechanisms: A) Magnetic sensor, detecting changes in the strength of magnetic fields Reproduced with permission, from [52]. Copyright 2022, IOP Publishing. B) Capacitive sensor, measuring capacitance variations between two conductive plates Reproduced with permission, from [52], [76]. Copyright 2022, IOP Publishing. C) Resistive sensor, detecting resistance changes in conductive materials Adapted with permissions, from [77]. Copyright 2022, IEEE.; D) Piezoresistive sensor, sensing changes in electrical resistance within semiconductive materials Reproduced with permissions, from [78], [67]. Copyright 2007, IEEE. ; E) Optical fiber sensor, monitoring light intensity changes in response to mechanical stimuli Reproduced with permissions, from [66]. Copyright 2022, MDPI.; F) Fiber Bragg grating sensor, measuring strain through wavelength shifts in an optical fiber Reproduced with permissions, from [66]. Copyright 2022, MDPI.; G) Triboelectric sensor, showcasing contact-separation for sensing and harvesting Adapted with permissions, from [73]. Copyright 2020, Elsevier. H) Piezoelectric sensor, producing an electrical charge when subjected to mechanical stress Adapted with permissions, from [73]. Copyright 2020, Elsevier. I) Ultrasonic sensor, determining distances by measuring the travel time of high-frequency sound waves Adapted with permission, from [79], [75]. Copyright 2018, IOP Publishing.; and J) Infrared ToF sensor, calculating distances based on the travel time of infrared light Reproduced with permissions, from [80]. Copyright 2021, IEEE.

strain measurement at that location. Fiber Bragg grating sensing systems are also highly effective for measuring deformations in soft robots due to their high accuracy in measuring curvature [56, 68].

Triboelectric sensors are advanced devices that use the triboelectric effect to convert mechanical energy into electrical power through friction [69]. This effect occurs when two different materials come into contact and then separate, transferring electrons between them. This electron transfer creates a charge imbalance, generating a voltage that can be captured and converted into electrical signals. As a result, mechanical energy from motion such as pressure, stretching, or sliding is converted into electrical energy. This generated voltage can be measured to detect various forms of mechanical motion, including touch, pressure, texture, and vibration [70–72]. Their dual capability to generate power from mechanical movements and perform sensing functions makes them particularly well-suited for soft robots operating in environments where external power sources are impractical, as they can harvest energy from the robot's movements or environmental vibrations [73].

Piezoelectric sensors operate based on the piezoelectric effect, which allows them to generate an electrical charge in response to pressure, strain, or other external stimuli [74]. This effect converts mechanical inputs into an electric voltage. One key advantage of piezoelectric sensors is their ability to generate electrical signals directly from mechanical stress, effectively making them self-powered and eliminating the need for an external power source [73].

Ultrasonic sensors are another sensing technology that emit high-frequency sound waves and calculate distance based on the time it takes for the echo to return after reflecting off an object [75]. These sensors are renowned for their low power consumption, less data complexity, low cost, and high accuracy in distance measurement. **Infrared time-of-flight (ToF) sensors** also work by emitting an infrared light pulse and measuring the time it takes for the light to travel to the object and return to the sensor. This ToF measurement allows for precise distance calculations.

Figure 1 depicts an overview of the previously described sensing technologies and their underlying mechanisms. Having summarized the different types of sensors and highlighted their key characteristics—where they excel and where they may fall short—we now move on to the core of this section: a survey of sensors categorized by their functionalities. The goal is to guide researchers in making informed decisions when selecting the most suitable sensor for their specific needs, thereby enhancing the performance of the soft robotic systems they are working with.

In the remainder of this section, we categorize sensors that measure quantities such as shape, strain, and distance as **motion sensors**, as they are primarily focused on detecting physical parameters related to movement. Figure 2 illustrates a

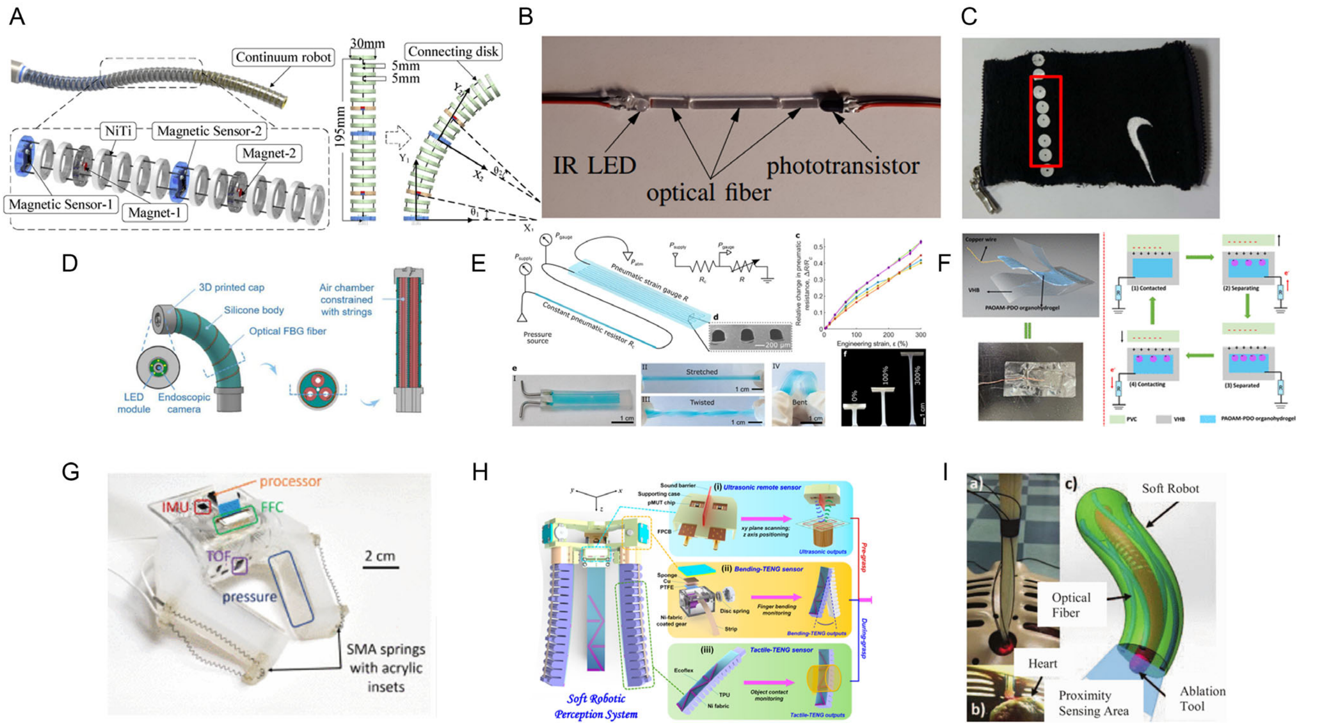

FIGURE 2 | Examples of various sensors for movement detection in soft robots. A) A general schematic of the 2-DOF continuum robot, incorporating two cylindrical permanent magnets and two three-axis magnetic sensors for measuring bending angles Reproduced with permissions, from [109]. Copyright 2018, Elsevier. B) Design of an optical fiber sensor for bending angle and curvature readings in a soft gripper Reproduced with permissions, from [92]. Copyright 2023, IEEE. C) A wristband embedded with a piezoelectric sensor for torsion measurement Adapted with permissions, from [96]. Copyright 2019, IEEE. D) Pneumatically driven robot with a helically wrapped optical fiber containing 16 multiplexed FBGs for real-time configuration feedback, equipped with an endoscopic camera and LED module on the tip cap Reproduced with permissions, from [136]. Copyright 2020, IEEE. E) Integrated soft pneumatic strain gauges for strain measurement in relaxed, stretched, twisted, and bent states with filled blue-liquid channels for visualization Reproduced with permissions, from [118]. Copyright 2022, Springer Nature. F) Organohydrogel combined with triboelectric nanogenerators (TENGs) as strain sensors, demonstrating the single-electrode working mechanism Reproduced with permissions, from [133]. Copyright 2023, American Chemical Society. G) A soft and stretchable sensor skin with embedded ToF distance sensor, IMU, and resistive pressure sensors Reproduced with permissions, from [146]. Copyright 2020, IEEE. H) Comprehensive design of the soft manipulator, featuring ultrasonic sensors for proximity sensing and TENG sensors for shape and tactile sensing Reproduced with permissions, from [75]. Copyright 2023, American Chemical Society. I) Schematic of a soft robot with embedded optical proximity sensors for distance measurement in beating heart surgery Adapted with permissions, from [143]. Copyright 2016, IEEE.

comprehensive schematic of sensor technologies used for motion sensing. Similarly, sensors that measure load, pressure, and tactile changes, which are primarily responsive to applied forces, are classified as **force sensors**. Figure 3 shows visual representations of techniques used in force sensing. Additionally, a detailed numerical overview of the most commonly utilized sensing technologies for each quantity and specific characteristics such as sensing range, sensitivity, resolution, accuracy, and precision for each technology are provided in Table 1 for motion sensing and Table 2 for force sensing. Our goal is to highlight both widely used commercial sensors and cutting-edge sensors developed in research laboratories. The following discussion examines various sensing techniques, explaining how they measure physical quantities and why certain methods are preferred for specific types of measurements.

2.1 | Motion Sensors

In this subsection, we focus on shape sensors, strain sensors, and distance sensors, each with distinct characteristics. These sensors are defined and discussed in the following paragraphs.

Shape sensing involves measuring changes in an object's shape, displacement, bending angle, or curvature relative to a reference state, typically in response to external forces or environmental conditions. In different studies, the term 'shape sensing' also encompasses other geometric measurements such as displacement [81], deformation [82], deflection [83], curvature (defined as 1/R, where R is the radius of curvature) [84–86], configuration [8, 87, 88], and position [89]. Shape sensing technologies are primarily dominated by optical sensors [90] including cameras [91–100], optical fiber sensors [101], magnetic sensors [93], and piezoelectric sensors [102]. Alternative shape sensing technologies include resistive [97], piezoresistive [103], triboelectric and ultrasonic sensors [75].

Optical fiber sensors are distinguished by their lightweight nature, resistance to electromagnetic interference, and stretchability, making them ideal for integration into soft bodies [23]. Their compact design and exceptional sensitivity to deformations further enhance their value. These characteristics make them particularly effective for measuring a wide range of bending angles $0-180°$, curvatures 0–0.2 mm^{-1}, and displacements 0–160 mm [40, 43, 89, 92]. For instance, optical fiber embedded

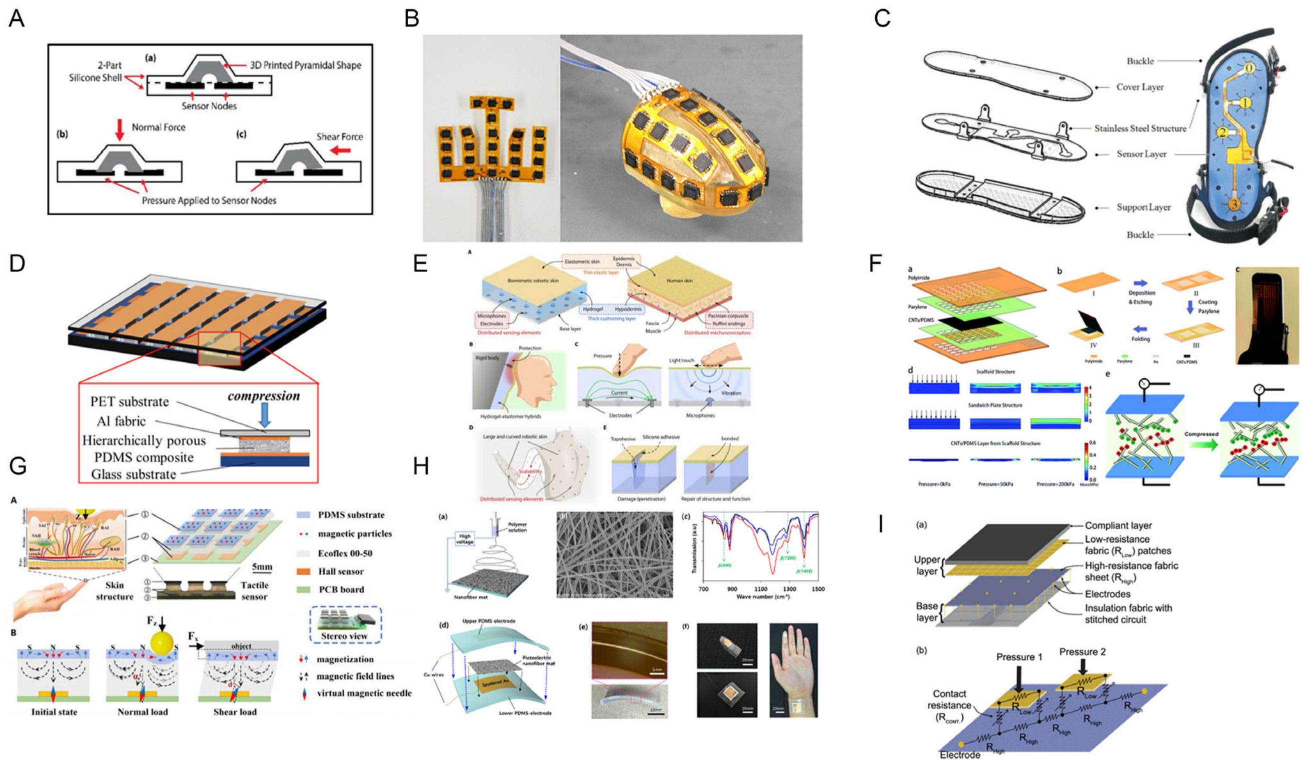

FIGURE 3 | Examples of various sensors used for load measurement in soft robots. A) A piezoresistive soft silicone sensor designed for force measurement in underwater applications Reproduced with permissions, from [202]. Copyright 2023, IEEE.; B) Flexible fingertip skin equipped with distributed magnets for force detection Reproduced with permissions, from [161]. Copyright 2017, IEEE.; C) Integrated soft capacitive sensor system for gait phase analysis and ground reaction force measurement Reproduced with permissions, from [164]. Copyright 2020, IEEE.; D) Fabrication process of a flexible capacitive pressure sensor with porous polydimethylsiloxane (PDMS)-based Reproduced with permissions, from [203]. Copyright 2021, Elsevier.; E) Biomimetic multilayer structure based on hydrogel-elastomer hybrids and human skin for piezoresistive pressure sensing Reproduced with permissions, from [204]. Copyright 2022, AAAS.; F) A flexible capacitive tactile sensor made up of a carbon nanotube (CNT)/polydimethylsiloxane (PDMS) layer, parylene films, and two polyimide (PI) films with specific electrode patterns Reproduced with permissions, from [192]. Copyright 2009, RSC Pub.; G) Schematic of the skin structure and soft magnetic tactile sensor, along with its working principle Reproduced with permissions, from [183]. Copyright 2021, AAAS.; H) Structure of a 3D flexible piezoelectric sensor designed for tactile sensing in wearable devices, specifically for fingertip and wrist applications Reproduced with permissions, from [187]. Copyright 2017, IOP Publishing.; I) Design of a piezoresistive tactile sensor and its sensing mechanism Reproduced with permissions, from [185]. Copyright 2021, IOP Publishing.

in a soft gripper can measure the deflection angle of a curved surface by relating the bending angle to the light intensity using an infrared LED, a phototransistor, and a plastic fiber [92, 95]. The shape of the deformed object can be reconstructed by linking multiple optical sensors together [52]. Another common approach in reconstructing the complete shape of a soft robot is capturing the positions of markers placed on it [82, 104, 105]. However, conventional optical sensors like cameras still face challenges such as high power consumption, complex data formats, and the need for high bandwidth for shape perception [75]. Additionally, their integration into tight spaces within soft systems can be impossible [82]. A combination of ultrasonic and triboelectric sensors with easy integration is proposed in [75] for gathering multimodal sensory data and remote object positioning. The ultrasonic sensor recognizes object shapes and distances by emitting and receiving ultrasonic waves. Meanwhile, triboelectric sensors have demonstrated promising capabilities in shape sensing for soft robots with high accuracy [106, 107]. These sensors are also easy to integrate, deliver high output, and are cost-effective [75]. Magnetic sensors are the other popular choice for detecting deformation in soft robotics by measuring variations in local magnetic fields caused by embedded magnets in elastomers [108]. The lack of wire connections for the permanent magnet in the elastomers contributes to a longer lifespan for these sensors [52]. These sensors can measure bending angles up to 360° and elongations up to 6.6 mm [46, 93, 109]. Additionally, high-resolution magnetic sensors developed in laboratories such as the ones introduced in [110, 111] are capable of measuring bending angles from 0 to 120° and displacements from 0 to 10 mm. Innovative self-powered piezoelectric sensors, such as piezoelectric nanogenerators (PENGs) fabricated in laboratories, generate voltage in response to changes in the shape of soft bodies. These sensors can detect bending or twisting angles ranging from 0 to 180° [91, 96, 102]. Additionally, they are capable of measuring displacements from 0 to 20 mm [91, 112] and bending curvatures between 0 and 0.16 mm^{-1}.

Strain sensing involves measuring the deformation or displacement of a material or structure as a change in length relative to the original length. This measurement is typically expressed as a dimensionless ratio or percentage. Strain-sensing technology includes a variety of sensors, such as piezoresistive [113], optical fiber [114], capacitive [115], triboelectric [116], and inductive sensors [117], which are available in both commercial and non-commercial forms.

TABLE 1 | Summary of functionalities of sensors in movement detection, and main technologies with key characteristics used in soft robots.

Sensor functions	Sensing techniques	Characteristics	Advantages and disadvantages
Shape Sensing	Optical fiber sensors [40, 43, 66, 89, 92, 95]	• Bending angle: $0-180°$ • Displacement: 0 – 160 mm • Bending curvature: 0 – 0.2 mm^{-1} • Sensitivity: 0.005 – 3.49 dβ/mm • Resolution: / • Accuracy: $2.1 \pm 2°$ • Precision: $0-0.05°$	• Advantages: High sensitivity and precision, lightweight, stretchable, long-distance communication with minimal signal loss, immune to the electromagnetic field, multifunctional sensors with no need to additional communication channel • Disadvantages: Require more extensive wiring
	Magnetic sensors [93, 109–111]	• Bending angle: $0-360°$ • Displacement: 0 – 10 mm • Bending curvature: / • Sensitivity: 0.0002 V/degree • Resolution: $0.5-0.8°$ and 0.0008 mm • Accuracy: 0.22 – 9.3 mm • Precision: 1.9 – 13.6%	• Advantages: Widest bending angle sensing range among available technologies, high resolution in displacement readings, requires no wiring, immune to hysteresis, simple design • Disadvantages: Low sensitivity in bending angle detection, Susceptible to electromagnetic field
	Piezoelectric sensors [91, 96, 102, 112]	• Bending angle: $0-180°$ • Displacement: 0 – 20 mm • Bending curvature: 0 – 0.16 mm^{-1} • Sensitivity: 0.12 – 0.16 V/mm and 0.016 V/degree • Resolution: / • Accuracy: / • Precision: /	• Advantages: High sensitivity, self-powered, no need for an external power source, stretchable • Disadvantages: Low sensitivity in bending angle measurement
Strain Sensing	Optical fiber sensors [134, 135, 137, 138]	• Sensing range: 0 – 250% • Sensitivity: 0.77 – 7.32 V/strain • Resolution: 0.000085% • Accuracy: 2.17 – 82.3% • Precision: 1.7 μ∈	• Advantages: Suitable for very high-resolution applications, immune to the electromagnetic field, multifunctional sensor long-distance communication with minimal signal loss • Disadvantages: Lowest detection range compared to other technologies
	Resistive and Piezoresistive sensors [118–126]	• Sensing range: 0 – 400% • Sensitivity: 0.946 $\Delta R/R_0/strain$ • Resolution: 0.05 – 0.07% • Accuracy: 3.99 – 4.4% • Precision: /	• Advantages: Broad measurement range compared to optical fiber sensors, cost-effective, simple design, lightweight • Disadvantages: Prone to hysteresis
	Triboelectric sensors [130–133]	• Sensing range: 0 – 500% • Sensitivity: 0.77 – 1 $\Delta R/R_0/strain$ • Resolution: / • Accuracy: / • Precision: /	• Advantages: Widest detection range, highly sensitive, self-powered, stretchable, low cost • Disadvantages: /
Distance and Proximity Sensing	Infrared time of flight sensors [80–151]	• Sensing range: 30 mm – 4 m • Sensitivity: 0.28 – 0.36 Lux/count • Resolution: 1 mm • Accuracy: 0 – 10 mm • Precision: 1 mm	• Advantages: Considerable sensing range, notable resolution and precision • Disadvantages: Low accuracy
	Ultrasonic proximity sensors [75, 141]	• Sensing range: 0 – 250 mm • Sensitivity: / • Resolution: 1 mm • Accuracy: 0 – 4 mm • Precision: /	• Advantages: Low power consumption, less data complexity, low cost • Disadvantages: /

(Continues)

Sensor functions	Sensing techniques	Characteristics	Advantages and disadvantages
	Optical proximity sensors [143]	• Sensing range: 0 – 25 mm • Sensitivity: / • Resolution: 0.05 mm • Accuracy: / • Precision: 0.013 mm	• Advantages: High precision and resolution • Disadvantages: Limited measurement range

Lab-designed resistive and piezoresistive sensors are extensively used in soft robotics due to their ability to measure strain by detecting changes in electrical resistance. A notable advancement is the development of a highly stretchable pneumatic strain gauge made of silicone elastomer with filled blue-liquid channels, described in [118]. This innovative sensor, which can measure strains up to 300%, is particularly suited for integration into the soft bodies of robotic systems. Moreover, resistive sensors are capable of enduring strains up to 400% of their original length [118–126]. These sensors are not only cost-effective but also simple to manufacture, facilitating the production of devices in a range of sizes tailored to various applications. Inductive sensors are also sensitive to larger strains, as the coil bends or stretches, the change in its length results in a variation in inductance [52]. This technique has been effectively employed in soft robots, yielding excellent strain readouts with ranges of up to 100% [117, 127]. An advancement of resistive sensors is the use of an array of micro-crumpled piezoresistive strain sensors with a corresponding model such that long-term mechancial robustness was achieved [128]. Capacitive sensors are highly responsive to strain, as they detect changes in the distance between their electrodes, leading to variations in capacitance [52, 53]. A stretchable capacitive sensor tendon introduced in [129] for strain measurement offers exceptional strain readouts of up to 600%. Similar to shape sensing, in strain sensing, high-output triboelectric nanogenerator (TENG) sensors [130–133] and optical fiber sensors [134–138] also can detect strains up to 500% and 250%, respectively. An innovative sensing technique uses a Soft Magneto-Mechano-Chromic (SoMMeC) structure comprising a magnetic actuator and a synthetic photonic film, enabling strain to be visually displayed through color changes across the entire visual spectrum [139].

Distance sensing measures the space between a sensor and an object without physical contact, making it crucial for accurately determining distances in numerous applications. In contrast, proximity sensing focuses on detecting the presence of nearby objects without providing precise distance measurements. In soft robotics, distance sensing is primarily achieved using infrared time-of-flight (IR ToF) sensors [140]. For proximity detection, a variety of sensors are employed, including ultrasonic [141], optical [142], optical fiber [143], and capacitive sensors [144]. These sensors are designed to detect the presence of nearby objects and are widely utilized in soft robotic systems. Most of these sensors are commercially available, providing practical solutions for both distance and proximity sensing in diverse applications.

Commercial ToF sensors, such as Sparkfun VL53L1X, are acclaimed for their precision and reliability in measuring distances [145]. The research described in [146] further extends this technology by integrating a ToF distance sensor into a multifunctional sensor skin in a soft gripper that also includes a resistive pressure sensor, an Inertial Measurement Unit (IMU), and a processor for signal processing and data transmission. This ToF chip is crucial for detecting distances up to 118 mm and is used to estimate the size, location, height, and presence of objects. ToF sensors are capable of detecting distances ranging from 30 mm to 4 m [80, 146, 147]. Acoustic sensors are another option, capable of measuring distances up to 1 m, even in underwater environments [148]. These sensors detect the distance by measuring the ToF of sound waves as they are emitted and reflected [149]. Many technologies still struggle to provide long-range measurements for proximity sensing in soft robotics. For example, a lab-designed capacitive proximity sensor can only detect objects within a range of 0–24 mm [150, 151]. However, some technologies, like commercial ultrasonic sensors, as reviewed in [141], can measure greater distances, identifying objects from 0 to 250 mm away. These sensors emit and receive ultrasonic waves, making them highly effective for distance measurement and obstacle detection [75].

Figure 2 showcases a variety of motion sensors previously discussed. This figure highlights implementations of shape sensing through magnetic and optical sensors, strain sensing using piezoelectric and strain sensors, and distance sensing through optical sensors. Table 1 organizes the presented information by sensor function, sensing techniques, characteristics, as well as advantages and disadvantages.

For motion sensing applications, there are various sensing technologies available with advantages and disadvantages to each. In terms of shape sensing, optical fiber sensors may be advantages if the application requires high precision and lightweight design without being worried about the extensive wiring required. In contrast, magnetic and piezoelectric sensors are advantageous in situations where precision is key and space is limited, as such surgical applications may be more relevant. For strain sensing, triboelectric sensors are advantageous for highly sensitive ranges, while resistive and piezoresistive sensors may be advantageous for strain sensing applications when cost and manufacturability are major considerations. In contrast, optical fibers may be more advantageous if the signal is required to travel longer distances. Finally for distance sensing, ultrasonic proximity sensors are advantageous for cost-sensitive systems, while infrared ToF sensors are ideal for systems where larger range is necessary,

TABLE 2 | Summary of functionalities of sensors in load measurements, and main technologies with key characteristics used in soft robots.

Sensor functions	Sensing Techniques	Characteristics	Advantages and Disadvantages
Force Sensing	Resistive sensors [155, 158–202]	• Sensing range: 0–20 N • Sensitivity: 0.1–0.37 N^{-1} • Resolution: / • Accuracy: 2.5 N • Precision: 0.54–1.46 N	• Advantages: Cost-effective, simple design, lightweight, immune to electromagnetic fields • Disadvantages: Low precision, susceptible to hysteresis
	Magnetic sensors [151, 159, 160]	• Sensing range: 0–8 N • Sensitivity: / • Resolution: 0.005 N • Accuracy: 0.04–0.3 N • Precision: /	• Advantages: Suitable for high-resolution applications, requires no wiring, immune to hysteresis, plain design • Disadvantages: Limited sensing range, prone to electromagnetic field
	Capacitive sensors [164, 205]	• Sensing range: 0–500 N • Sensitivity: / • Resolution: 0.5 N • Accuracy: 10.57 ± 1.72 N • Precision: /	• Advantages: Large measurement range compared to other technologies, low hysteresis, low cost • Disadvantages: Low accuracy
Pressure Sensing	Resistive and Piezoresistive sensors [170, 175, 176]	• Sensing range: 0–120 KPa • Sensitivity: 0.045 V/KPa • Resolution: 20 Pa–100 KPa • Accuracy: ±0.01– ±0.15 KPa • Precision: /	• Advantages: Highly accurate, immune to electromagnetic fields, Cost-effective, lightweight, simple design • Disadvantages: Prone to hysteresis
	Capacitive sensors [171–174]	• Sensing range: 0–300 KPa • Sensitivity: 0.0007–0.005 KPa^{-1} • Resolution: / • Accuracy: / • Precision: /	• Advantages: Broad sensing range, low hysteresis, low cost • Disadvantages: Low sensitivity, more susceptible to electromagnetic fields than resistive sensors
Tactile Sensing	Capacitive sensors [144, 192, 193, 196]	• Sensing range: 0.001–2550 KPa and 0–0.15 N • Sensitivity: 0.002–0.25 KPa^{-1} • Resolution: 0.01 mN • Accuracy: / • Precision: /	• Advantages: Wide detection range in pressure sensing, high resolution, low hysteresis, low cost • Disadvantages: /
	Magnetic sensors [182–184]	• Sensing range: 0–20 N and 0–4 mm • Sensitivity: / • Resolution: 0.01 N • Accuracy: 0.15 – 0.83 N • Precision: /	• Advantages: Broad force measurement range, high resolution in force readings • Disadvantages: Susceptible to electromagnetic interference
Tactile Sensing	Piezoelectric sensors [38, 186–188, 190, 195]	• Sensing range: 0 – 10 N, 0 – 1700 KPa, 0 – 15 μm and −20° – 80°C • Sensitivity: 0.165 V/N, 0 – 0.09 V/KPa, 0.06 – 0.126 V/μm, and 0.11 $V/°C$ • Resolution: 0.01 N, 5.2 – 10 μm • Accuracy: 0.01 μm, 0.01 N • Precision: 0.05 mm	• Advantages: High accuracy in force and displacement • Disadvantages: Low sensitivity and resolution
	Piezoresistive sensors [178, 185]	• Sensing range: 0 – 6 N • Sensitivity: 1 N^{-1} • Resolution: / • Accuracy: 0.1728 N • Precision: /	• Advantages: More sensitive compared to capacitive and magnetic sensors • Disadvantages: Low detection range

and optical proximity sensors may be advantageous for high-precision systems.

2.2 | Force Sensors

This subsection examines load sensors, pressure sensors, and tactile sensors, each serving unique purposes. The details and functions of these sensors are elaborated in the following paragraphs.

Load sensing involves detecting the magnitude of forces exerted at specific points by the environment, and in some cases, determining their direction. This information is then converted into a measurable electrical signal. In load measurement for soft robots, resistive sensors [152], capacitive sensors [153], and magnetic sensors [52, 154] are among the most commonly used types.

Laboratory-designed resistive sensors are among the primary tools for load sensing, as they detect applied force on soft body surfaces through changes in resistance [23]. Examples such as those described in [155–158] are typically small and offer relatively limited load measurement ranges, up to 20 N. Magnetic sensors are also essential in measuring perpendicular and tangential forces to surfaces [52]. They operate by detecting changes in the magnetic field as the distance between the sensor and a magnet varies in response to the applied load. One innovative application is detailed in [159], where distributed magnets are embedded within a silicone rubber fingertip. This sensor skin translates magnetic field variations into measurable normal and shear forces, capable of detecting loads up to 6 N. Hall effect-based magnetic sensors, which are commonly used in such setups, generally provide a sensing range from 0 to 8 N [151, 159–161]. Any external force applied on the soft robot surface can also be detected by capacitive sensors, as a result of changes in capacitance [162]. For example, the authors in [163] present a capacitive sensor integrated into a soft actuator that both generates force and monitors capacitance changes, ensuring precise control and consistent output under varying loads. This fast-response sensor is well-suited for low-force applications, providing high-resolution measurements around 1.55 N. Among lab-designed systems, the most extensive load range is provided by a capacitive sensing system introduced by Han et al. [164], capable of measuring loads from 0 to 500 N. This range significantly surpasses that of commercial force strain gauges.

Pressure sensing involves measuring the magnitude of pressure or distributed force applied to its sensing surface, but it does not determine the exact location or direction of the applied pressure. Pressure sensing is commonly used within soft robotics to measure forces exerted by the robot as well as forces applied to it [165]. Common applications for pressure sensors include grasping robots [166], for measurements of applied pressure; swimming robots [167], for measurements on swimming speed; and even tactile sensing [165]. By using pressure sensors, safety complaint activities can be guaranteed through constant monitoring of grasping force. Common types of pressure sensors include capacitive [168], resistive [169], and piezoresistive [170] sensors.

Our research indicates that capacitive sensors fabricated in laboratories are the primary sensors used for pressure sensing, much like their applications in force sensing. They are particularly effective in hydrostatic pressure scenarios, where changes in pressure directly alter the distance between electrodes, resulting in variations in capacitance. A capacitive sensor introduced in [171] is capable of measuring these hydrostatic pressures up to 300 KPa, equivalent to a depth of 30 m. Another study in [172] introduces a capacitive pressure sensor composed of a porous elastomer sandwiched by two aluminum electrodes. This sensor is capable of measuring pressures ranging from 0 to 230 KPa, making it suitable for depths up to 23 m. For non-hydrostatic pressure measurements, capacitive sensors have been designed to detect pressures from 0 to 60 KPa, as demonstrated in [173, 174]. Piezoresistive sensors are also widely used for pressure sensing due to their ability to detect applied pressure by measuring changes in electrical resistance within the piezoresistive layer when stretched or compressed [52]. Compact piezoresistive barometers are commonly used in soft robotics for pressure sensing, with a measurement range of 0–120 KPa [175, 176].

Tactile sensing aims to replicate the biological sense of touch [67]. These advanced sensors measure various attributes including the magnitude and direction of force and pressure, as well as texture, temperature, vibration, and object slip, emphasizing high resolution [23]. They identify the surface type by monitoring a change in impedance as they contact surfaces [67]. Most tactile sensors are non-commercial and are specifically fabricated to achieve high resolution and sensitivity. Magnetic [52, 177], piezoelectric [178], piezoresistive [179], capacitive [144], and optical [180] techniques are among the most widely used sensors in tactile sensing for soft robotics [67].

Magnetic sensors are extensively common due to their ability to detect changes in magnetic field intensity caused by the displacement of a magnet when the sensor surface is touched. This feature makes them highly effective for applications in soft grippers, where they can detect slips, enhancing the safety and efficiency of robotic operations [52, 159, 181]. They can be integrated into electronic skins (e-skins) and multilayer sensor skins to measure multi-directional forces ranging from 0 to 20 N [182–184]. Piezoresistive sensors also gather tactile data through direct contact with external environments, making them suitable to measure various quantities detectable by the biological sense of touch [23]. A notable advancement in piezoresistive tactile sensing is the development of a layered textile-based skin with distributed electrodes, designed to enhance both resolution and sensitivity [185]. This innovative sensor is fabricated to estimate force and its localization. Piezoelectric materials can also be particularly effective in tactile sensing applications [52, 178, 186]. An example is a flexible skin developed in [187], which consists of a nanofiber mat serving as the piezoelectric active layer sandwiched between two PDMS electrodes. This configuration enables fast detection of tactile forces and skin deformations, converting these mechanical changes into electrical signals. These sensors are capable of detecting a range of forces from 0.1 to 10 N, with the ability to sense pressures and surface displacements up to 1.7 MPa and 4 mm in depth, respectively [38, 186, 188]. Piezoelectric materials are also widely used in applications such as health monitoring, minimally invasive surgery, and tissue hardness measurement [38, 188]. A well-known example is a tactile sensor that uses piezoelectric polymer transducers embedded within the sensor's rubber skin [189]. These transducers detect changes in stress as the sensor interacts with different surfaces. This capability allows the sensor to accurately capture and analyze details of surface textures, providing detailed information about the texture of different surfaces as the sensor moves over them. Multifunctional tactile sensors, as described in [190], are designed for easy autopositioning and intelligent sensory perception in soft systems. These sensors integrate triboelectric, piezoelectric, and pyroelectric properties within a soft skin, enabling them to effectively measure both pressure and temperature autonomously. They are capable of detecting pressures within a range of 0–50 KPa and temperatures from $-20°$ to 80°C.

Capacitive sensors are another widely used technology for tactile sensing in soft robots. These sensors can also be very lightweight and stretchable, as demonstrated in [191], where a capacitive robotic skin was developed using conductive elastomers separated by a dielectric layer. When the skin is stretched, the overlapping area and the distance between the elastomer plates change, leading to alterations in capacitance. Researchers have widely utilized these sensors for pressure sensing, capable of detecting pressures up to 2550 KPa [192–196]. Capacitive sensors developed by Liu et al. [195] are also designed to detect multidirectional forces. These sensors can measure forces in the x, y, and z directions within ranges of 0–0.15 N, 0–0.15 N, and 0–0.1 N, respectively. These nonlinear sensors can also measure displacements with a high resolution and accuracy.

Among commercially available tactile sensors, optical or camera-based sensors, such as those described in [197, 198], are particularly effective at capturing high-resolution tactile data in artificial skins, making them suitable for mass production. These multimodal sensors can measure lower forces ranging from 0 to 1 N and displacements from 0 to 10 mm. Other advancements in soft tactile sensors include integrating three-axis accelerometers within flexible polymeric frameworks. These sensors can detect and analyze sliding movements, accurately determining the direction, velocity, and location of movement across large surfaces [199]. Additionally, highly sensitive barometric microelectromechanical system (MEMS) tactile sensors represent a cutting-edge approach currently being developed to improve object slip detection [200, 201].

Figure 3 showcases a variety of force sensors discussed previously. This figure highlights implementations of load sensing using piezoresistive and capacitive sensors, pressure sensing using capacitive and piezoresistive sensors, and tactile sensing using capacitive and magnetic sensors. Table 2 organizes the presented information by sensor functionality, sensing techniques, sensor characteristics, and associated advantages and disadvantages.

As shown in Table 2, sensors have varying advantages and disadvantages. Resistive sensors tend to be cost-effective, lightweight, and immune to electromagnetic fields, making them suitable for mass-production applications. However, if the application requires high precision such as biomedical applications resistive sensors may not be ideal. Magnetic sensors have the advantage of high-resolutions and immunity to hysteresis, making them suitable for precision-focused applications, unless electromagnetic interference or large sensing ranges are of concern. Capacitive sensors are great sensors for applications requiring larger measurement ranges, low hysteresis, and low cost. As such capacitive sensors are also suitable for mass-production applications.

3 | Controllers in Soft Robotics

For control specialists, the opportunities offered in the field of soft robotics are paired with significant challenges. Each of these stem from the inherent complexity, which is present in systems throughout the field. In particular, the combination of compliant construction and underactuated dynamics, which allow soft robots to safely interact with diverse environments, also necessitate a divergence from traditional robotic control strategies. Nevertheless, research in the field has allowed for the deployment of soft systems in a wide array of applications [205, 206], ranging from biomimetic locomotion [44, 45], to medical assistance [207], and object manipulation [208]. This broad applicability poses further challenge, as a diversity in robot design leads to a need for a variety of models to capture system dynamics [3, 209]. Even so, the high potential of soft robotics and its wealth of use cases have spurred on continued research into the topic and numerous studies and surveys have explored control strategies for soft robots [29, 50, 56]. Most of these works classify

controllers based on their underlying architecture, commonly distinguishing between model-based, model-free, and hybrid approaches.

Model-based controls rely on mathematical representations of the soft robot's dynamics to predict and regulate its behavior. Though the field encapsulates robots of widely differing geometries [210, 211], there are many examples of continuum models as both absolute and relative coordinates reduction can be applied, allowing for computational efficiency [212]. Several popular models include the Cosserat rod model [213, 214], the Kirchhoff model [215], the Euler–Bernoulli beam theory [216], piecewise constant curvature (PCC) models [29], and the Euler–Lagrange framework [217]; however the field is not limited to these examples [3, 29, 218]. While model-based approaches may enable precise control, they often require extensive computational resources and detailed system information [219]. Thus, model-free approaches have been considered as an alternative. Such approaches leverage adaptive and data-driven techniques such as neural networks [46, 220, 221] and reinforcement learning [51, 222, 223] to learn control policies directly from sensor inputs and actuation data. Many new model-free control methods have emerged, including recurrent neural networks, long short-term memory models, deep convolution neural networks, and deep reinforcement learning [46, 220–222]. The inclusion of new model-free approaches remains an area of continuous research such that more models are being applied to the control of soft robotics [224, 225]. These methods offer flexibility and adaptability, particularly when dealing with unknown or highly nonlinear dynamics, but they often require large amounts of training data and may lack interpretability due to their black-box nature [223]. Finally, hybrid controllers combine elements of both Model-based and Model-free approaches to exploit their respective advantages. These controllers typically use a mathematical model to provide structural insights while incorporating data-driven components to enhance adaptability and robustness [23, 50, 226].

Offering new perspective, this review adopts a functional classification of control strategies, organizing them based on the specific task they are designed to perform. Specifically, we focus on two primary categories: motion control and force control. A fundamental perspective on robotic functions is that while a robot can both move and apply forces, the primary objective of a given control strategy is typically centered on one of these aspects—either achieving precise movement in space or exerting controlled forces to interact with its environment [227]. Within **motion control**, this review is particularly interested in hierarchical control structures combining motion planning and trajectory tracking. For the field of soft robotics, this structure is primarily seen in continuum robots and can be further categorized into pose control, segment control, and tip control. Pose control governs the entire robot to achieve a specific orientation or position [228]. Segment control focuses on controlling specific sections of the soft robot [229], while tip control regulates only the movement of the robot's tip [46]. Additional work exists beyond this categorization, including controllers designed to manage deformation-based motion, such as swinging [230], extension [231], and compression [232]; however, less focus will be placed on these more specialized examples. **Force controllers** are those, which are designed to regulate how a soft robot interacts with its environment by applying and responding to forces. This includes tasks such as grasping [233], object manipulation [234], and adaptive interaction with surfaces or external forces [235]. In these cases, compliance control plays a crucial role in enabling the robot to adjust its stiffness or deformation in response to external contact, ensuring safe and adaptable physical interaction [236]. In this review, some controllers for locomotion are also considered as force controllers, as regulation of environmental forces is crucial to this task [237]. By focusing on these functional categories, this review provides a foundation for selecting appropriate control architectures and sensor configurations tailored to various soft robotics applications.

The remainder of this section focuses on these two functional groups—motion tracking control and force control—providing a detailed exploration of their respective strategies, applications, and the key considerations for selecting the appropriate control approach based on the task requirements and available sensors.

3.1 | Motion Control

Within soft robotics, motion control refers to the regulation of a systems pose over time. Often, the highly deformable structures seen throughout the field present challenges in achieving precise motion control, but such precision not always be necessary. For example, in the case of controlling the motion of a soft robotic fish [238], the exact angle of the robots tail is less important than controlling the frequency of the motion. However, in the case of soft continuum robots, more emphasis may be placed on exact pose reached by the system. Further, such systems are commonly attached to a fixed base leading to a constrained setting for implementing more precise motion control strategies. Different strategies in motion control have been developed with differing levels of complexity depending on the needs of the application. Tip pose control [239, 240] is one such development, where the end effector is guided to a desired location. This approach can be extended in complexity to multi-segment control [241], which involves regulating the position of multiple key points along the body. An even more complex objective is full pose control [242], which has emerged as a compelling yet challenging objective, as it requires regulation of the entire structure's configuration, which is complicated by the underactuated and highly flexible nature of soft robots. These increasing levels of control granularity offer varying trade-offs in terms of computational complexity, resolution, and applicability depending on the target application.

Focusing on positional control of only the distal end of a rod-like soft robot, tip control reduces the dimensionality of the problem while still enabling meaningful task execution. A notable example uses feedback from a camera on the tip of an expanding soft robot to steer the system to a visual goal while achieving real time obstacle avoidance over a planar surface [239]. Another approach integrates visual servoing with a model-free control algorithm to align the tip with a desired image or orientation, enhancing accuracy in unstructured environments [46]. Additionally, tip control has been implemented in a cable-driven soft robot designed for surgical applications, where a piecewise constant curvature model enables real-time motion regulation [243]. Across these examples, visual shape and distance-based sensors are essential for providing feedback and maintaining control precision.

Segment control expands on the principles of tip control by regulating multiple intermediate points along the robot's body. Each segment is treated as a controllable node, allowing for more detailed shape manipulation and improved adaptability to complex tasks or environments. In one implementation, a cable-driven system is modeled as a series of springs and joints, allowing for efficient forward kinematics computation. Torque is applied to body-embedded cables based on feedback from distance sensors, enabling a closed-loop control scheme [229]. Another example involves a pneumatically actuated soft robot with multiple chambers controlled via visual servoing in conjunction with a PCC model, enabling accurate deformation and positioning [231]. Moreover, segment control has been achieved using robots constructed from dielectric elastomer actuators, where the system behaves like self-adjusting springs. In this case, an energy-shaping control scheme enables the linearized model to account for the robot's nonlinearities [244]. While PCC models are common in segment control, they are not always sufficient to capture the full range of soft robot deformation. To address this limitation, piecewise universal joint models have been proposed [245]. These models relax the constant curvature constraint, offering improved fidelity in capturing the robot's shape and resulting in more accurate and robust control strategies [246]. As with tip control, segment-level implementations typically rely on visual shape and distance sensors for real-time feedback.

Full pose control represents a more comprehensive objective, aiming to regulate the entire shape or configuration of the soft robot. Due to the system's underactuated and nonlinear characteristics, full pose control remains a complex and active area of research. It is generally considered an extension of multi-segment control, with additional challenges related to system observability, actuation redundancy, and computational demands. One approach implements artificial muscles, with individual actuators governed by input currents to guide the robot's structure to target configurations [228]. Another method utilizes visual servoing to achieve compliant obstacle avoidance in dynamic environments, benefiting from real-time feedback to produce less conservative, more adaptive behavior [247]. Additionally, observer-based control systems have been developed to incorporate finite element models to enable real-time tracking and control of complex soft robot morphologies [242]. These advancements in full pose control are pushing the boundaries of what is achievable in soft robotics, particularly in tasks requiring high degrees of dexterity, environmental interaction, or adaptability.

Beyond tethered soft continuum robots, motion controllers can also be implemented for locomoting soft robots, which may follow some path. These tracking controllers typically implement vision-based sensors for distance and shape sensing in order to establish a closed loop control of the system [248, 249]. Tracking control can be achieved in a variety of manners, with examples existing for each of model-based control [250], model-free control [251], and hybrid control [252], over a variety of types of locomotion, such as crawling [253], walking [254], and swimming [255]. A recent advancement in tracking control for soft robotics takes the form of dynamic tracking controllers, which reduce the order of finite element models to speed up computational times, convergence, and robustness of the controller [256]. In order to drive locomotion of specific soft robots, a force controller on the inner loop of the system can be designed to interact with the environment and drive the system.

3.2 | Force Control

Broadly, force controllers are designed to regulate the interaction between the robot and its environment to accomplish tasks such as self-propulsion or object manipulation [252]. Critical aspects of force controller functionality include determining when force should be applied—often informed by sensor feedback—and specifying the magnitude of the force required [235]. Due to the variability in soft robot design, these controllers are typically customized for specific systems using either detailed model-based approaches, generalized model-free approaches, or hybrid approaches [223]. Force controllers are also integral to various forms of soft robotic locomotion, including slithering, swimming, and walking. In these systems, controllers must be tailored to generate precise inputs that enable effective motion, often in conjunction with motion controllers [252].

Force controllers are crucial for object interaction tasks such as grasping and manipulation [257]. Soft robotic hands, owing to their compliant and anthropomorphic characteristics, can replicate human-like grasping when equipped with tactile and pressure sensors. Such capabilities have opened applications for soft systems in industries such as construction, where robots perform repetitive handling tasks [258]. Additional advanced implementations combine strain and tactile sensors with machine learning models, such as long short-term memory (LSTM) networks, allowing soft robots to identify and grasp objects with appropriate force [259]. Further, the inherent compliance of soft materials makes them suitable for safe human–robot interaction. For example, integrating optical fiber-based tactile sensing enables the development of compliant force controllers that prevent over-gripping [260]. In rehabilitation contexts, soft robotic exoskeletons with force sensors and neural networks assist in restoring hand function by regulating finger force output [261]. Manipulation tasks often involve not only grasping but also releasing or repositioning objects. Force controllers facilitate object placement, throwing, or transport by interpreting data from shape sensors [234]. In pushing tasks, tactile sensor input is used to modulate contact force, enabling precise load application [262].

To demonstrate the effectiveness of this approach through closed-loop accuracy and stability, a case study of force control can be examined. The experimental setup consists of an anthropomorphic soft finger with embedded soft strain sensors, as originally presented by Thuruthel et al. [263]. This study highlights the development of a closed-loop model-free controller that provides robust and accurate state estimation for a passive, underactuated anthropomorphic finger with embedded strain sensors. Control is implemented through a model-free controller based on a proportional control scheme, where the estimated force is subtracted from the desired force to produce an error signal. This error signal is then combined with the end-effector position and sent to the UR5 robot, which then moves the anthropomorphic finger causing for new strain data to be collected. This closed-loop configuration is further depicted in Figure 4. Within this experimental setup the long short-term memory

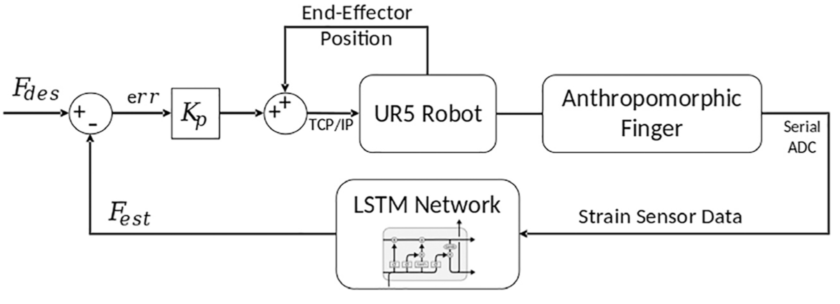

FIGURE 4 | Control architecture for closed-loop force control with the long short-term memory model Reproduced with permissions, from [263]. Copyright 2022, Mary Ann Liebert, Inc.

model is selected as temporal disturbances such as hysteresis and drift are present within the sensor.

The study then conducts three sets of experimental tests to validate the control structure. The first test investigates the impact of the proportional gain on the performance; the second test measures the steady-state error of the system; and the third examines the frequency response of the system. The first experiment demonstrates that higher gains resulting in faster convergence but more oscillations and instability. This experiment also showcases that the overall stability of the controller was dependent on the accuracy of the state estimator, parameters of the PID controller, delays within the system, and the desired force profile. The second experiment evaluates the steady state performance of the system, revealing a mismatch between the actual and predicted data points, with an averaged error of 0.17 ± 0.14 N. The third experiment shows that the prediction accuracy of the system is not affected by the frequency of motion, which indicates that the model had generalized the system very well. As demonstrated by this case study, a closed-loop controller has been successfully developed for a model-free system with embedded soft strain sensors. This system also addresses common sources of sensor error such as drift and hysteresis. As such this system highlights the interplay between soft robotic controllers and sensors in a fashion that achieves closed-loop stability and accuracy.

Within force control, locomotion control methods should also be considered, as locomotion methods require application of forces on the environment. Slithering is among the fundamental modes of locomotion within soft robotics, which relies on force regulation to achieve inner loop control for path following tasks [237]. As such, force controllers have been derived to enable several distinct slithering mechanisms. Peristaltic motion, reminiscent of an inchworm, uses compression control in combination with potentiometer-based shape feedback to achieve multi-directional and efficient movement [264, 265]. Rectilinear motion, akin to snake-like oscillations, employs force controllers guided by a combination of reinforcement learning and central pattern generators, with camera-based feedback for shape and distance sensing [251]. Another common strategy is two-anchor crawling, inspired by caterpillars, which involves segmental actuation guided by pressure sensor feedback to coordinate motion based on environmental contact forces [266, 267].

Walking is another form of motion which relies on force regulation. However unlike slithering, walking involves phases where the robot's body is elevated above the ground. Numerous studies have investigated gait strategies, noting that increasing the number of limbs can enhance stability at the expense of control complexity [268]. For instance, octopus-inspired robots leverage multiple limbs, with each limb governed by a force controller that manages stride length and ensures balance [269]. Quadrupedal soft robots utilize a combination of limb-swinging and stance phases, enabled by pressure and flow sensors, to execute a variety of gaits including crawling, walking, and trotting [254, 270, 271]. Bipedal soft robots have also been demonstrated. One such example models each leg as a massless spring-damper system, with force controllers orchestrating motion based on shape and distance data from vision sensors [230]. Additionally, some bipedal systems integrate walking and swimming capabilities. In these cases, force controllers stabilize the robot's gait using virtual hinges modeled as torsional springs, in conjunction with pressure-based feedback [272].

Finally, swimming is another prevalent locomotion mode in soft robotics, with design inspirations drawn from a range of aquatic organisms including octopuses, fish, and manta rays. In octopus-like swimmers, force controllers coordinate tentacle movements—expanding and then rapidly closing—to create propulsion, with guidance from pressure sensors [272]. For fish-inspired robots, controllers regulate the amplitude and frequency of fin oscillations, leveraging strain sensor data to enable closed-loop swimming control [238]. Manta ray-inspired designs incorporate deformable dielectric elastomers for shape sensing, allowing force controllers to regulate fin pitching and achieve undulatory swimming patterns [273–275].

(For a more comprehensive overview of soft robot locomotion, refer to retrospectives such as [208, 237].)

4 | Challenges and Future Directions in Soft Robotics

The field of soft robotics has experienced rapid growth in recent years, driven by advancements in materials, fabrication techniques, sensors, and control strategies. Despite this progress, several key challenges remain, and numerous promising research directions are emerging that could shape the next generation of soft robotic systems. While the field is broad and still evolving, we highlight a few of these directions here, as we believe they are particularly relevant and aligned with the focus of this review.

4.1 | Material Innovation, Sensor Fusion, and Embedded Intelligence

A key area for future advancement in soft robotics is the development of improved sensor technologies. Soft robotic systems stand to benefit greatly from sensor fusion, where data from diverse sensing modalities—such as stretch sensors, capacitive sensors, and inertial measurement units (IMUs)—are combined to enhance environmental perception and feedback control. However, integrating these sensors within soft bodies presents several persistent challenges. Fabricating miniature sensors that are seamlessly embedded in soft substrates requires materials that are not only flexible and durable but also biocompatible with their surroundings [276].

Despite significant progress, such as the use of conductive polymers and ionic-liquid-based sensors [54], further innovations are needed to create sensors that can detect a wide range of physical stimuli without compromising the robot's mobility. Ideally, these sensors should be lightweight, self-healing, and energy-efficient, utilizing compact power sources to maintain functionality in harsh and unstructured environments [277]. However, the inclusion of such advanced sensing technologies often demands more sophisticated electronics, wiring, and power management solutions [54].

Emerging technologies like triboelectric and piezoelectric nanogenerators offer promising pathways toward self-powered sensing in soft robots. These systems harvest energy from mechanical deformation and are highly sensitive to small voltages and currents, making them well-suited for integration into deformable platforms [65]. At the same time, soft robotic sensors are not immune to the durability and performance issues faced by their rigid counterparts. For example, extending sensor lifespan across various operating environments remains a common hurdle. Moreover, traditional sensing modalities such as LiDAR, RADAR, and infrared, which rely on signal reflections, are often ill-suited for underwater or highly deformable contexts due to interference from hydrodynamic effects and structural compliance [52, 278, 279].

To realize robust, intelligent, and fully integrated soft robotic systems, future efforts must extend beyond isolated advancements in materials or sensing technologies. Instead, a co-design approach—one that simultaneously advances materials science, sensor fusion, embedded computation, and low-power electronics—will be critical. Achieving this vision will require sustained interdisciplinary collaboration across fields such as physics, electrical and mechanical engineering, materials science, and biomedical engineering [276]. Such integration will pave the way for soft robots that are more autonomous, perceptive, and adaptable than ever before.

In this context, one of the central challenges in soft robotics is the development of multifunctional materials that can simultaneously support actuation, sensing, and self-healing. Future research should prioritize materials that not only provide mechanical compliance and resilience but also embed sensing and computational functions at the material level. This concept of ”material computation” holds the potential to dramatically enhance the autonomy and responsiveness of soft robots operating in complex, unstructured environments.

4.2 | Toward Adaptive and Intelligent Control of Soft Robotic Systems

Modeling and control of soft robotic systems remain among the most significant challenges in the field due to their inherent nonlinearities, high DoF, and complex interactions with uncertain environments. While integrating real-time sensor feedback into control frameworks has shown promise, the field is still in its early stages and ripe for innovation.

Current control strategies often focus on simplified scenarios, such as tip-position control using distributed actuation. However, more nuanced problems like shape control of Cosserat rod models with localized actuators remain largely underexplored. Dynamic control, including trajectory tracking for soft arms interacting with moving targets in three-dimensional space, is another key area that requires further development [280].

Model-free approaches, including deep reinforcement learning and other data-driven methods, offer flexibility but face several open questions. These include how to effectively train models under complex, time-varying conditions, how to manage error accumulation, and how to ensure efficient sim-to-real transfer in real-world environments [3, 23, 51, 233]. Moreover, these methods are computationally intensive and highly dependent on the quality of training data, which can significantly impact control performance [281].

To address these challenges, hybrid control strategies that blend classical control methods with learning-based approaches—such as physics-informed neural networks—are gaining traction. These frameworks offer a way to incorporate domain knowledge while retaining adaptability to unmodeled dynamics. Ultimately, progress in soft robot control will require unified efforts across model-based, model-free, and hybrid approaches. A co-design philosophy that tightly integrates modeling, control, actuation, and sensing will be key to advancing toward more intelligent, robust, and autonomous soft robotic systems.

At the actuation level, relatively few studies have explored how low-level actuator controllers impact overall system stability, responsiveness, and control bandwidth [50]. One promising yet underutilized concept in this context is morphological computation—the idea that a robot's physical structure can offload computational effort by shaping its interaction with the environment [50, 282]. This mechanism can serve as a form of zero-lag feedback, enhancing real-time responsiveness without requiring explicit sensing or control. However, its full potential has yet to be realized in controller design. Future research could exploit these intrinsic mechanical properties not only to improve precision and robustness, but also to enable truly autonomous operation in unstructured environments. Achieving this level of autonomy will require systems that can adapt to new tasks, self-calibrate, and dynamically reconfigure their behavior based on sensory input. Realizing this vision calls for the co-design of morphology, sensing, and control in a unified framework. Advances in reinforcement learning, evolutionary algorithms, and embodied intelligence are expected to play critical roles in enabling such adaptable and intelligent soft robotic systems.

Finally, future advancements must remain closely tied to application domains. From biomedical devices and wearable robotics to marine exploration and search-and-rescue missions, real-world deployment demands not only functional performance but also safety, transparency, and ease of human–robot interaction. Trust and interpretability will be central to these goals, necessitating interdisciplinary collaboration across engineering, cognitive science, and human-centered design. For commercial adoption of soft robotics, regulation and standards must be developed for all domains of use. Additionally, the reproducibility of academic results must be improved, and the manufacturing techniques optimized [283]. As soft robotics is a broad and evolving field, sensing and control techniques are often evaluated separately, partially due to the lack of standardized development. This is an area that the field will develop as innovation stabilizes and the best use case for each advancement becomes obvious. In the biomedical domain, the clinical transition of soft robotics has allowed for some initial testing; however, the biocompatibility of these devices should be further investigated [284, 285]. Although there are some soft robotics devices that have reached the commercial market, their overall presence remains limited [207].

5 | Conclusion

This survey provided an in-depth exploration of state-of-the-art soft robotics, with a focus on sensors and their significance in controlling soft systems. Key characteristics of sensors were explored, and a function-based classification was introduced to deepen the understanding of their roles in soft robot systems. Additionally, the review outlined the contributions of various sensors to control design and system functionality. The discussion of closed-loop control approaches, including model-based, model-free, and hybrid controllers, emphasized the crucial role of real-time sensor feedback in achieving effective control. Notable challenges in sensor integration, modeling, and control in soft robotics were identified, with the latest solutions and potential research gaps presented for future investigations.

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Conflicts of Interest

The authors declare no conflicts of interest.

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