

Review

Soft Robotics: Enabling Technologies, Applications, and Future Perspectives

Yibo Wang ¹, Mengwei Wu ^{1,*}, Bintaou Zou ², Yimeng Du ¹, Hengxu Du ^{1,*} and Pengfei Chen ^{3,*}

¹ Marine Engineering College, Dalian Maritime University, Dalian 116026, China; wangyibo1@dmlu.edu.cn (Y.W.); dym314159@dmlu.edu.cn (Y.D.)

² Dalian Administration of Customs Dalian 116001, China

³ Department of Materials Science and Engineering, University of Wisconsin–Madison, Madison, WI 53706, USA

* Correspondence: wumengwei@dmlu.edu.cn (M.W.); duhengxu@foxmail.com (H.D.); pchen365@wisc.edu (P.C.)

Abstract

Soft robots built from compliant materials and deformable structures are increasingly used in medical intervention, wearable assistance, delicate manipulation, and environmental exploration, where conventional rigid robots are limited by high mechanical impedance and poor morphological adaptability. However, their transition from laboratory prototypes to deployable systems remains constrained by coupled bottlenecks in materials, actuation, sensing, modeling, control, energy supply, and manufacturing. This review summarizes recent advances in soft robotics through an evaluative framework covering actuation and materials, modeling and simulation, control strategies, multimodal sensing, and representative applications. Instead of treating these topics as independent descriptions, we compare the underlying mechanisms, measurable performance indicators, strengths, limitations, and application boundaries. Three conclusions emerge. First, no single actuation strategy can simultaneously maximize output force, response speed, energy efficiency, durability, miniaturization, and untethered operation. Second, high-fidelity continuum models improve physical accuracy but remain difficult to use for real-time control, whereas reduced-order and data-driven models improve efficiency at the cost of generalization, interpretability, or contact fidelity. Third, practical soft robots will depend on system-level integration of embedded sensing, physics-informed learning, robust control, reliable materials, and scalable fabrication. Future progress should therefore prioritize standardized benchmarks, lifecycle reliability, energy-autonomous operation, and task-specific comparisons with rigid robotic systems.

Keywords: soft robots; intelligent flexible materials; biomimetic actuation; multimodal perception

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1. Introduction

Achieving safe interaction and highly adaptive operation in complex, unstructured, and dynamically changing environments has become an important direction for the development of intelligent robots. Relying mainly on discrete rigid links, high-rigidity actuators, and precise control algorithms, rigid robots have high positioning accuracy and repetitive operation capabilities in structured scenarios. However, when facing unstruc-

tured environments such as soft tissues, narrow spaces, fragile targets, and complex terrains, rigid robots often exhibit problems such as insufficient contact adaptability, high collision risk, and limited operational safety due to their high mechanical impedance. For example, in minimally invasive medical scenarios, rigid instruments may cause damage to fragile tissues [1]; in extreme-environment detection, rigid structures have difficulty passing through tortuous and narrow spaces [2]; in fine grasping and agricultural harvesting tasks, traditional end effectors are also prone to causing target damage due to a lack of morphological adaptation capabilities [3]. These limitations have driven the continuous exploration of new flexible robot systems.

Soft robots typically use flexible materials such as elastomers and hydrogels as their structural basis, and achieve continuous deformation and environmental adaptation through the large deformation capacity and low modulus characteristics of the material itself. Unlike rigid systems that rely on sensor feedback and control algorithms to achieve “active compliance”, soft robots can provide high passive compliance at the material level, thus showing significant advantages in contact interaction, shape adaptation and safe operation. Generally speaking, the elastic modulus of such materials is much lower than that of traditional engineering structural materials, often as low as megapascals or even lower [4]. This integrated design concept of materials and structure makes soft robots show broad prospects in applications such as biomimetic motion, flexible grasping and human-machine collaboration.

In recent years, soft robots have made significant progress in multiple application areas. In marine environments, flexible grippers can be used for non-destructive sampling of fragile organisms [5]. In the medical field, magnetically controlled catheters, flexible microdevices, and targeted delivery platforms provide new pathways for minimally invasive interventions [6,7]. In rehabilitation assistance scenarios, wearable flexible devices can provide more natural movement support and assistance to the human body [8]. These studies show that soft robots have unique advantages in improving environmental adaptability, enhancing interaction safety, and expanding the boundaries of robot operations. However, most existing systems are still in the prototype verification or scenario demonstration stage, and there is still a significant gap between them and long-term stable and autonomous operation in complex environments.

The factors restricting the further development of soft robots are mainly reflected in multiple aspects such as materials, modeling, control and power supply. First, soft materials are prone to fatigue, aging, creep and tearing under long-term cyclic loads, which affects the life and reliability of the system [9]. Second, soft robots usually have characteristics such as high nonlinearity, strong coupling, time-varying parameters and infinite degrees of freedom, which pose significant challenges to their dynamic modeling and state prediction [10]. In addition, due to the complex structural deformation, sparse distribution of sensor information and significant external disturbances, traditional control methods have difficulty simultaneously taking into account real-time performance, accuracy and robustness, which limits the stable closed-loop operation of the system in complex environments. Finally, many soft systems still rely on external air pumps, hydraulic devices or wired power supply, which not only restricts the system integration, but also hinders its development towards being lightweight, long-lasting and cableless [11].

From the perspective of biological system evolution experience, natural soft structures such as elephant trunks, octopus arms, and fish fins have shown excellent performance in terms of high-compliance movement, environmental adaptation, and complex operation. In contrast, engineered soft robots still have significant shortcomings in terms of energy efficiency, structural durability, perception ability, and autonomous collaboration. The fundamental reason is that a highly collaborative system architecture has not yet

been formed between material behavior, driving mode, perception mechanism, and control strategy. With the development of technologies such as smart materials, embedded sensing, data-driven modeling, and machine learning control, soft robots are evolving from single flexible devices to integrated systems of materials, structure, perception, and control [12]. Therefore, how to improve system accuracy, robustness, and autonomy while maintaining high compliance has become an important research problem in this field.

Recent review articles have provided valuable summaries of specific branches of soft robotics, including hydrogel and responsive materials [4], wearable and implantable soft robots [8], soft-robot modeling [13], learning-based control [14], artificial intelligence-assisted design [12], sensing in soft robotics [15], sensorimotor soft materials [16], and additive manufacturing [17]. These reviews clarify important progress within individual topics, but the literature still lacks a compact technology-chain perspective that links materials and actuation, modeling, control, sensing, and applications under a shared set of performance concerns. To address this gap, the present review emphasizes the coupling among enabling materials, actuation mechanisms, physical and data-driven models, feedback control, multimodal sensing, and representative application scenarios. To ensure that this review is evaluative rather than merely descriptive, each section compares representative studies and robotic systems using explicit criteria wherever possible. Rather than only listing recent advances, it highlights the strengths, limitations, and trade-offs that determine whether soft robotic systems can move from laboratory prototypes toward robust, autonomous, and deployable platforms.

To make the development timeline explicit, this review summarizes the evolution of soft robotics as four overlapping stages. First, the field established material compliance and pressure- or field-driven actuation as alternatives to rigid-link mechanisms, with fluidic, electric, thermal/photothermal, magnetic, and environment-responsive systems forming the basic actuation/material toolbox [18–28]. Second, modeling and simulation progressed from high-fidelity continuum descriptions toward reduced-order, geometric, and data-assisted models that can support design iteration and real-time prediction, as reflected in recent modeling-focused reviews [13]. Third, control and autonomy evolved from geometric and model-based controllers toward learning-based, sim-to-real, and physics–data fusion strategies [14]. Fourth, sensing and application development increasingly emphasized embedded multimodal perception, soft sensorimotor materials, additive manufacturing, wearable/implantable systems, environmental exploration, and application-specific deployment [1–8,11,12,15–17]. This development trajectory indicates that the core challenge has shifted from proving that soft structures can deform and moved toward building reliable, perceptive, controllable, and deployable soft robotic systems.

To make the review evaluative rather than purely descriptive, we formulated module-specific evaluation criteria for the five parts of the review: actuation and materials, modeling and simulation, control strategies, sensing technologies, and applications. Before each major section, a concise lead-in sentence introduces the corresponding criteria, so that the related studies and robotic systems are discussed under a shared analytical framework rather than presented as isolated descriptive summaries.

This positioning defines the unique value of the review and provides a concise framework for understanding the development of soft robotics toward practical intelligent systems, as summarized in Figure 1.

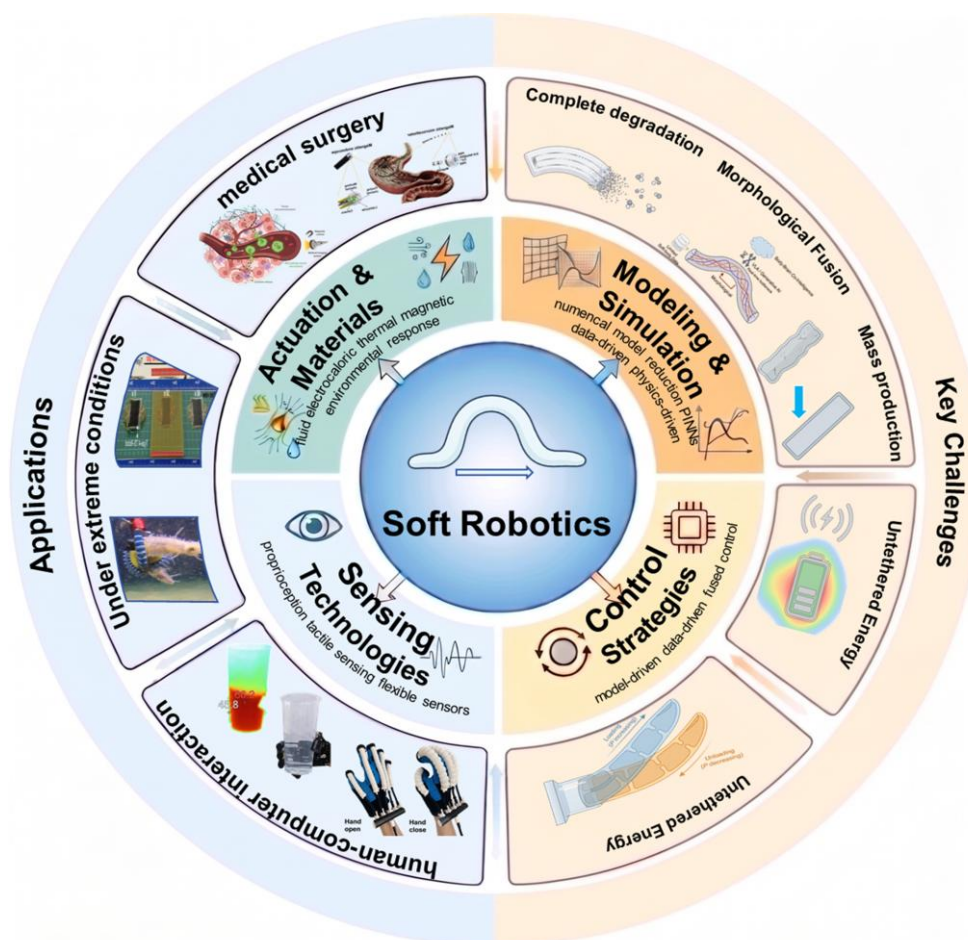


Figure 1. Systematic overview of soft robotics.

2. Driving Mechanism and Material System

The performance limits of soft robots largely depend on their actuation mechanisms and material systems. Unlike rigid robots that rely on high-stiffness transmission chains for precise motion, soft robots typically achieve higher compliance and stronger environmental adaptability by inducing continuous deformation through pressure fields, field-induced responses, or environmental stimuli within flexible materials. As shown in Figure 2, based on their actuation mechanisms, existing soft robots mainly include fluid-driven, electric-driven, thermal and photothermal-driven, magnetic-driven, and environmentally responsive driven types. Different actuation methods have their own characteristics in terms of output force, response speed, controllability, integration difficulty, and potential for cableless operation, and also correspond to different application scenarios and engineering constraints. A comparative summary of these actuation mechanisms and material systems is provided in Table 1.

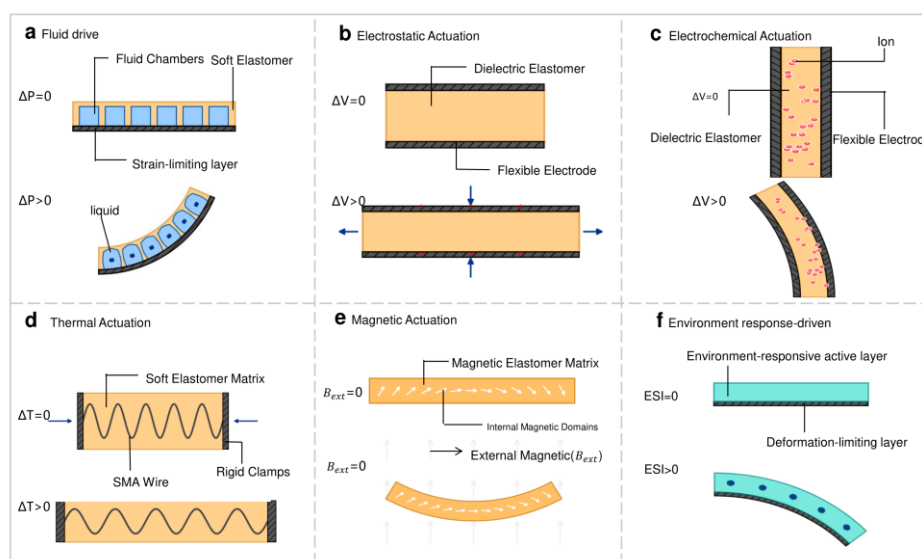


Figure 2. Working principles of common soft-robot actuation methods: (a) Fluid actuation; (b) electrostatic actuation; (c) electrochemical actuation; (d) thermal actuation; (e) magnetic actuation, where the arrow denotes the direction of the applied external magnetic field B_{ext} ; (f) environmental response actuation.

Table 1. Concise comparison of major actuation mechanisms and material systems for soft robots.

Actuation Mechanism	Typical Materials/Components	Key Advantages	Main Limitations	Representative Applications/Refs.
Fluid actuation	Elastomer chambers; pneumatic/hydraulic media; fiber or fabric constraints	Mature technology; high output force; programmable bending, torsion, or extension	Requires pumps/valves; pneumatic compressibility lowers efficiency; fatigue, rupture, and control difficulties remain	Soft grippers, rehabilitation gloves, high-load continuum actuation [9,10,18,19]
Electric actuation	DEAs, HASELs, IPMCs, flexible electrodes, ionic/electrolyte layers	Direct electrical drive; fast electrostatic response; low-voltage IPMC bending; easy electronic integration	High-voltage insulation, film rupture/leakage, ion-diffusion delay, dehydration, and limited cycle life	Microbots, underwater/in vivo manipulation, compact electronically controlled actuators [20,21]
Thermal/photothermal actuation	SMAs, LCEs, SMPs, photothermal polymer composites	Cableless heat/light actuation; high recovery stress; large deformation or stroke; compact and low-noise	Thermal inertia, slow cooling, hysteresis, heat accumulation, limited light penetration, and fatigue	Miniature actuators, morphing/origami structures, near-surface biomedical devices [22,23]
Magnetic actuation	Magnetoactive elastomers; ferromagnetic particles; programmable magnetic domains	Remote and untethered actuation; miniaturizable; low-frequency fields can penetrate tissues	Field-gradient decay, stiffness–torque trade-off, bulky coil systems, and sensing interference	Magnetic catheters, vascular navigation, drug delivery, narrow-space exploration [6,20,24,25]
Environmentally responsive actuation	poly(N-isopropylacrylamide) (PNIPAM)/active gels; humidity-, pH-, or chemically responsive polymers; bilayers; 4D-printed structures	Uses ambient stimuli; no onboard pumps or cables; suitable for autonomous/off-grid operation	Slow diffusion response, low output/stability, poor precise control, delamination, and printing-resolution limits	Environmental monitoring, humidity/chemical grippers, self-regulating adaptive structures [26,27]

Accordingly, actuation mechanisms are compared in terms of output capability, response speed, control difficulty, energy or tethering requirement, durability, and application suitability.

2.1. Fluid Drive

Fluid drive is one of the most mature and widely used drive methods in soft robots. Its basic principle is to convert internal fluid pressure into controllable mechanical deformation (Figure 2a). Since pure elastic bodies often produce isotropic expansion under internal pressure, it is difficult to form directional output. Therefore, it is usually necessary to introduce high modulus fibers, fabrics or other constraint layers on the outer layer of the flexible cavity to break the structural symmetry and guide the deformation direction [18]. Through this structural design, the originally non-directional fluid pressure can be converted into deterministic motions such as bending, torsion or linear expansion [16,28]. This type of drive has the advantages of large output force and good pressure holding performance, but it also exposes a series of bottlenecks when it is applied to complex environments. Under high pressure load, hyperelastic materials are prone to local bulging or even rupture failure [9]; large deformation characteristics significantly increase the difficulty of high-precision closed-loop control and dynamic prediction [10]; at the same time, stress concentration, fatigue and interface peeling are also prone to occur at the interface between soft and hard materials [28]. In addition, the compressibility of the gas medium further reduces the energy conversion efficiency and makes the system highly dependent on external pumps and valves, thus limiting its lightweight and cableless development [29].

Fluid-driven actuation can be further divided into positive-pressure pneumatic, vacuum-driven pneumatic, hydraulic, and pneumatic–hydraulic hybrid routes. Positive-pressure pneumatic actuators use compressed gas to inflate chambers and are lightweight and deformation-rich, but gas compressibility, leakage, pumps, and overpressure failure limit precision and autonomy. Vacuum-driven actuators use negative pressure to collapse designed cavities or folds, improving fail-safe contact but requiring controlled buckling and reliable sealing. Hydraulic systems use nearly incompressible liquids to improve force transmission and positioning stability, especially in underwater or high-load scenarios, but introduce leakage, weight, and sealing challenges. Pneumatic–hydraulic hybrid systems combine gas compliance with liquid force transmission, trading simplicity for improved output stability and tunable damping.

Current work emphasizes structural programming and manufacturability. Fabric lattice artificial muscles use chamber topology and fabric constraints to improve contraction and force-to-weight ratio at lower pressure [30,31]. Three-dimensional knitting integrates actuation with the flexible body, reducing adhesive-interface peeling and improving puncture resistance, although multiaxial buckling can remain. Textile engineering improves robustness but not energy autonomy. Miniaturized electroosmotic pumps and dielectric-fluid management may reduce bulky pneumatic hardware [19,32], yet power density and maturity remain insufficient for high-load, long-endurance deployment.

2.2. Electric Drive

Electric drives convert electrical input directly into mechanical work [20]. They include electrostatic systems, represented by DEAs [33] and HASELs [34], and electrochemical systems, represented by IPMCs [35] (Figure 2b,c). Electrostatic drives provide fast response; DEAs can exceed 100 Hz [36], and HASELs improve force through hydraulic amplification [34]. Electrochemical drives bend below 5 V, supporting underwater micromanipulation and interventional use, but are limited by ion diffusion. Practical barriers remain: electrostatic systems need kilovolt insulation, HASELs risk rupture and leakage [37], prestretched DEA frames reduce compliance [38], and electrochemical systems suffer slow response, dehydration, and limited cycle life [39]. Additive manufacturing [17,40], biodegradable polymers [41], compact high-voltage modules, and SENS architectures [11,21] are being explored for integration and autonomy.

Beyond DEAs, HASELs, and IPMCs, emerging electrically driven soft actuators include conductive-polymer, hydrogel, ionogel, electrochemical, and electrothermal/Joule-heating systems. Ionic and electrochemical actuators offer low-voltage operation and compatibility with wet or biointegrated environments, but their bandwidth and force output are constrained by ion transport, electrolyte retention, back-relaxation, and electrode stability. Electrothermal actuators convert current into heat through conductive fillers, heaters, or liquid-metal traces to activate SMA, SMP, LCE, or bilayer structures. They avoid kilovolt-level fields and are easy to integrate with flexible circuits, but suffer from thermal inertia, cooling delay, heat accumulation, and efficiency loss. Thus, electric actuation involves a trade-off among voltage level, force output, bandwidth, integration, and long-term stability.

2.3. Thermal and Photothermal Actuation

Unlike electric drives, which face risks of high-voltage insulation or liquid leakage, thermal and photothermal drives (Figure 2d) directly induce material deformation through temperature field changes, providing a cableless driving path [22]. Representative smart materials for this type of system include shape memory alloys (SMAs), liquid crystal elastomers (LCEs), and shape memory polymers (SMPs), which achieve thermal recovery by relying on solid-state phase transitions, molecular chain orientation transitions, and glass transitions, respectively. Overall, SMA has high recovery stress, but the achievable uniaxial strain is relatively limited, usually around 8% [42]; LCE and SMP can achieve larger deformation amplitudes, are suitable for flexible deformation and large stroke drives, and can achieve ultra-large deformation ranges of 50% or even more than 100% [43]. Since there is no need to configure micro pumps or high-voltage electronic modules, thermal drives have advantages in system miniaturization and low-noise covert operation, but usually at the cost of reduced response bandwidth and energy efficiency.

The main bottleneck of thermal drive lies in thermal inertia. The heating process can be achieved quickly through transient current or light, while the cooling process relies on passive heat conduction. The asymmetry between the two rates can easily lead to heat accumulation, response hysteresis and bandwidth reduction [44]. In addition, the limited penetration depth of near-infrared light in biological tissues also restricts the application of photothermal drive in deep medical scenarios [22]. To alleviate these problems, researchers have introduced highly thermally conductive fillers such as liquid-metal nanoparticles into polymer matrices to improve the efficiency of heat conduction and photothermal conversion [45]. On the other hand, they have used nonlinear geometric designs such as bistable buckled shells and origami structures to temporarily store slowly input thermal energy as elastic potential energy and release it through a sudden jump at the critical point to achieve rapid transient motion [46]. At the same time, some actuators can also form self-excited oscillations under constant heat source by relying on thermo-mechanical feedback loops [23]. However, while such strategies improve dynamic performance, they will also further aggravate material fatigue and lifespan degradation.

For thermally driven actuators, performance should be evaluated not only by deformation amplitude but also by heating route, heating time, cooling mode, thermal efficiency, hysteresis, and cycle fatigue. Joule heating is easy to control electronically but can cause heat accumulation, whereas photothermal triggering enables remote and spatially selective actuation but depends on optical absorption, penetration depth, and heat dissipation. Passive cooling is often the rate-limiting step, so rapid actuation generally requires thin structures, conductive fillers, active cooling, or bistable mechanisms that convert slow thermal charging into fast mechanical release.

2.4. Magnetic Drive

Unlike thermal drives, which are limited by heat conduction and the resulting hysteresis, magnetic drives utilize passive magnetic fields to achieve remote non-contact manipulation, which is one of the important ways to achieve cableless soft robots. As shown in Figure 2e, its basic principle is to embed micro/nano-scale ferromagnetic particles into an elastic matrix, and use the interaction between the external magnetic field and the internal magnetic moment to directly convert the magnetic field energy into torque or deformation [24]. Low-frequency magnetic fields have less attenuation in biological tissues and non-magnetic barriers, giving magnetic soft robots a unique advantage in scenarios such as deep blood vessel navigation and targeted manipulation [6]. At the same time, since no power supply or complex transmission structure is required, this type of system is also easier to miniaturize. However, the magnetic field gradient force decays rapidly with spatial distance, which significantly limits its driving efficiency in long-distance and deep environments.

Magnetic actuation can be implemented using either permanent magnets or electromagnetic coil systems. Permanent magnets provide strong static fields without continuous electrical power and are suitable for compact, short-range, and low-power manipulation, but their field direction and gradient are usually changed by mechanical motion, limiting programmability and closed-loop bandwidth. Electromagnetic coils can generate programmable fields and gradients for dynamic trajectory control, multi-axis steering, and image-guided navigation, but they require bulky hardware, high current, thermal management, and careful treatment of sensing interference. Therefore, permanent magnets favor simple and portable actuation, whereas electromagnetic systems favor programmable but hardware-intensive control.

To obtain sufficient driving torque, it is usually necessary to increase the content of magnetic particles, but this will significantly increase the stiffness of the matrix and weaken the intrinsic compliance and large deformation capacity of the material [47]. In addition, traditional mold casting can only magnetize the material in a single direction [48], and complex motion usually still relies on a large-volume, high-energy-consuming three-dimensional electromagnetic coil array [49]. At the same time, traditional magnetic control systems generally lack sensing capabilities and are prone to failure due to collisions under conditions without visual feedback [20]. In order to alleviate the “stiffness-torque” paradox and improve control capabilities, researchers have begun to use voxel-level direct-write 3D printing and thermally assisted reprogramming technology to realize the programming and reconstruction of local magnetization directions [50,51]. In addition, magnetic putty based on dynamic cross-linked networks provides a new idea for material self-healing and extreme deformation [25]; however, such ultra-compliant fluid materials often face serious shortcomings such as extremely low mechanical bearing capacity and poor long-term morphological stability. Overall, magnetic drive still needs to find a new balance between driving field decay, material magnetic energy product and sensing integration.

Addressing the perception blind spots caused by open-loop control and obtaining reliable interactive feedback under strong alternating magnetic field interference has become an essential step for magnetically controlled soft robots to develop towards closed-loop applications. Since traditional silicon-based electronic sensors are prone to severe signal drift in strong magnetic fields, developing non-electromagnetically dependent, interference-resistant flexible sensing mechanisms (related progress will be discussed in detail in Section 5) has become a crucial prerequisite for perfecting this system. Ultimately, to truly unleash the application potential of magnetic actuation, future efforts still need to find new physical breakthroughs in overcoming the spatial attenuation of the driving field and increasing the magnetic energy product of soft materials.

2.5. Environment-Responsive Actuation

Environment-responsive drives convert ambient humidity, pH, chemical potential, or temperature changes into deformation through active gels such as PNIPAM or stimulus-responsive polymers (Figure 2f) [26]. They can operate without batteries, cables, or pumps, but output and stability depend strongly on the environment. Homogeneous swelling often produces isotropic, low-torque deformation [26], whereas asymmetric structures generate directional motion at the cost of response times from minutes to hours [52]. Multi-material 4D printing programs anisotropic fibers or bilayers for humidity-driven bending and twisting [27], and self-excited mechanisms can generate rhythmic motion [23,53]. Remaining limits include delamination, printing resolution, weak tunability, and the autonomy–controllability balance.

Long-term reliability is a key limitation of environment-responsive materials. Hydrogels and responsive polymers may suffer dehydration, swelling fatigue, hysteresis, microcracking, ion or solvent leaching, and stiffness drift after repeated stimulus cycles. Bilayer and 4D-printed structures also face interfacial delamination, residual stress, printing defects, and batch-to-batch variation. For biodegradable or transient systems, degradation is useful only when the functional service window is maintained before failure. Therefore, these actuators should be evaluated using retained deformation, response recovery, cycle stability, storage stability, and degradation pathway rather than initial stimulus response alone.

Section 2 shows that actuation choice balances output, controllability, integration, and autonomy. Fluidic systems deliver large deformation and force but need pumps, valves, sealing, or tubing. Electric and electrochemical systems suit electronic integration, yet face high-voltage, ion-diffusion, dehydration, or cycle-life limits. Thermal and photothermal routes allow compact or remote triggering, but cooling constrains bandwidth. Magnetic actuation enables remote manipulation, whereas field decay and particle-induced stiffness limit performance. Environment-responsive systems reduce power demand but sacrifice speed, force, and precision. Actuator selection should follow the task and acceptable compromises among force, speed, safety, lifetime, and integration.

Representative values in Section 2 illustrate mechanism-specific rather than universal performance advantages. DEAs can exceed 100 Hz, while IPMC-type electrochemical drives operate below 5 V but are limited by ion diffusion. SMAs provide high recovery stress at about 8% strain, whereas LCE/SMP systems can reach 50% or even >100% deformation but are constrained by thermal inertia and cooling. Environment-responsive systems may avoid onboard power, yet their response can last from minutes to hours.

3. Modeling and Simulation Technology

Soft robots are characterized by large deformation, strong nonlinearity, and multi-field coupling, making their state evolution difficult to describe directly using traditional rigid-robot models. Therefore, modeling and simulation are not only the foundation for structural design and performance evaluation, but also a key link connecting materials, actuation, and control. Existing research has mainly developed three approaches to address this issue: high-fidelity numerical simulation based on continuum mechanics, analytical dimensionality reduction and parameterization models for real-time control, and hybrid modeling methods combining physical priors and data learning (as shown in Figure 3).

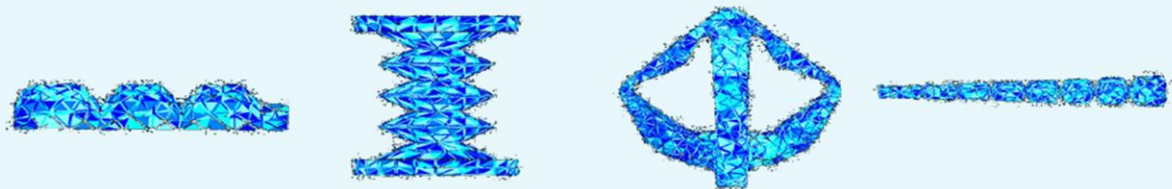
Accordingly, modeling methods are evaluated in terms of physical fidelity, prediction error, computational cost, real-time capability, parameter dependence, and experimental validation. A benchmark-oriented comparison of these modeling and simulation methods is provided in Table 2.

Table 2. Benchmark-oriented comparison of modeling and simulation methods for soft robots.

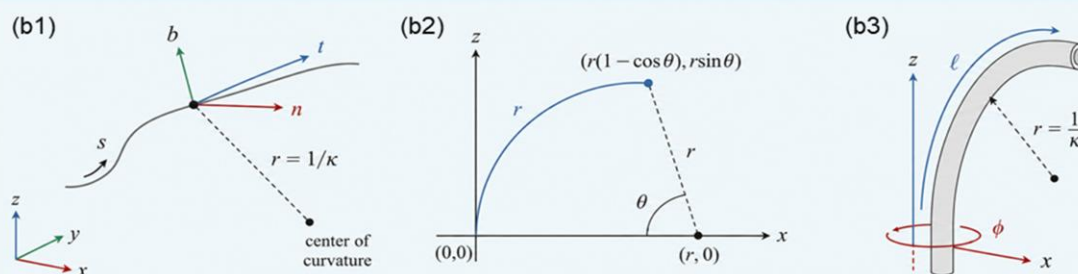
Method Category	Quantitative Metrics	Evidence in This Review	Main Trade-Off
Continuum numerical models	Prediction error; mesh/DOF; runtime; contact robustness; validation error.	High fidelity; cost usually case-dependent or NR.	Accurate for deformation/contact; costly and parameter-sensitive.
Reduced-order/geometric models	End-effector/shape error; update rate; runtime; identification error.	Often real-time feasible; exact timing frequently NR.	Efficient and interpretable; weaker under contact, loads, and non-uniform deformation.
Data-driven models	Prediction error; data size; inference time; generalization/out-of-distribution (OOD) error.	Fast after training; generalization varies by dataset.	Flexible for nonlinearities; limited by data coverage and interpretability.
Physics-informed/residual models	Residual error; sim-to-real reduction; training time; online rate; validation error.	Compensate sim-to-real error when residual data exist; reductions are study-specific.	Balance physics and data; depend on prior model, sensors, and validation.

Note: NR means not reported or not safely extractable; values are not ranked unless task, scale, hardware, contact condition, and error metric match.

a 3D Volume Mesh Discretization for Finite Element Method (FEM)



b Geometric Parameterization using Arc Parameters and Frenet-Serret Frames



c Residual Physics Pipeline for Sim-to-Real Gap Compensation

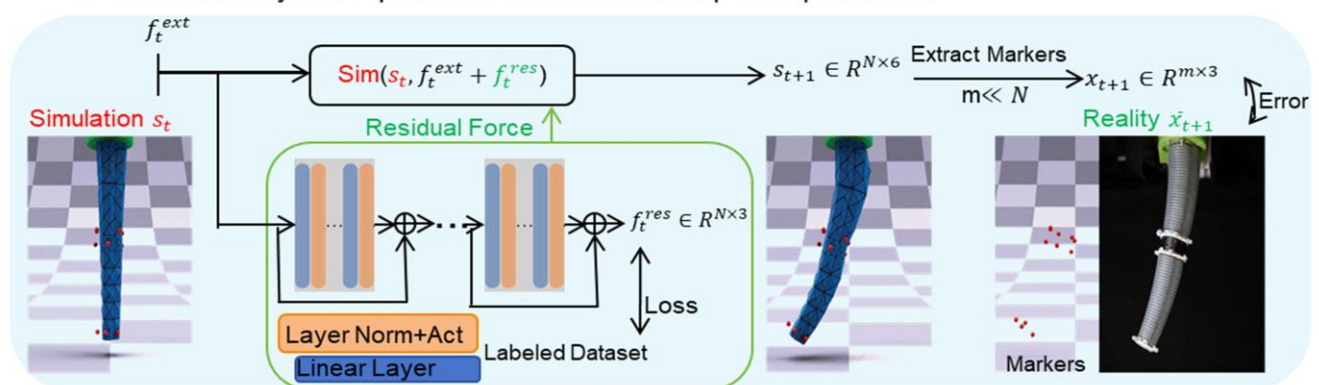


Figure 3. (a) Numerical simulation based on continuum mechanics; (b) dimensionality reduction and geometric parameterization of analytical model; (c) hybrid data-driven modeling pipeline. . In

panel (b), the internal subpanels (b1 – b3) show the Frenet – Serret frame, planar constant-curvature arc geometry, and three-dimensional constant-curvature arc parameterization, respectively. Panel (a) adapted from Coevoet et al. [54], reproduced with permission from Taylor & Francis. Panel (b) created by the authors. Panel (c) adapted from Gao et al. [55], licensed under CC BY 4.0.

3.1. Continuum-Mechanics-Based Numerical Methods

Soft robots have high degrees of freedom and strong material nonlinearity, making continuum numerical simulation powerful but costly. Finite element and material point methods combine hyperelastic constitutive models with spatial discretization to solve large-deformation mechanics [56–58] (Figure 3a). Contact handling remains critical; incremental potential contact improves robustness for self-collision and non-penetrating contact [59,60]. However, full-mesh simulation is computationally intensive, parameter dependent, and sensitive to fatigue or temperature drift. Differentiable simulators such as DiffPD, ChainQueen, and DiffAqua support morphology-control co-optimization [61–64], but non-smooth contact, long-sequence gradients, and memory load remain limiting. Domain randomization can improve robustness, yet may yield conservative policies [65].

3.2. Model Dimensionality Reduction and Parameterization

To avoid the computational bottleneck of full-mesh simulation, researchers have further developed model dimensionality reduction and parameterization methods, the core of which is to map the infinite degrees of freedom of the continuum into a finite-dimensional state space. For slender soft systems, the Cosserat rod theory is one of the commonly used basic models. It abstracts the three-dimensional elastic body into a one-dimensional space curve with a local frame, which can describe the main deformation modes such as bending, torsion, tension and shear [13,66,67] (Figure 3b). Based on this, the piecewise constant strain (PCS) and piecewise constant curvature (PCC) models are widely used because of their simple form and ease of solving inverse kinematics [68,69]; however, these methods usually rely on idealized geometric assumptions and are prone to significant deviations under self-weight, external load or collision [70]. To improve the ability to describe non-uniform deformation, researchers have proposed variable curvature models and lumped-parameter models. The former fits the curvature distribution through splines or polynomials, while the latter equates the continuum to a mass-spring-damping network [71,72]. However, these methods either introduce more undetermined parameters or sacrifice continuous stress information, making it difficult to simultaneously achieve both accuracy and real-time performance. In recent years, hybrid architectures combining parametric models and lightweight learning modules have gradually gained attention, namely, using PCC or PCS as low-dimensional physical priors and then compensating online for unmodeled curvature deviations, frictional drag, and external disturbances [73,74]. This approach balances interpretability and computational efficiency to some extent, but its stability and generalization ability are still limited by data distribution.

3.3. Data-Driven Modeling

When physical priors are insufficient or difficult to obtain explicitly, research has shifted further towards a pure data-driven modeling paradigm. Early methods often used feedforward neural networks to construct end-to-end mappings (Figure 3c) [75]. With further development, neural networks were used to capture the local-to-global deformation propagation laws in soft structures [76,77], while Transformer enhanced the dynamic prediction ability of long-sequence sensor data with the help of a self-attention mechanism [78]. However, such models are essentially still black-box agents, and their performance

is highly dependent on training data. When faced with distributed deformation or abnormal friction, they are prone to making predictions that do not conform to physical common sense. To alleviate the dimensionality curse brought about by high-dimensional observation, autoencoders and their variational forms were used to construct low-dimensional latent spaces [79]; however, the physical meaning of latent variables is limited, and reconstruction errors affect the stability of state estimation. In view of the highly nonlinear characteristics of soft systems, Koopman operator theory provides another path, namely, mapping nonlinear dynamics to high-dimensional linear systems through observation functions, thereby directly employing linear control methods [80]. Deep Koopman further learns the observation dictionary through neural networks and introduces spectral constraints to enhance stability [81,82]. Meanwhile, physics-informed neural networks (PINNs) use partial differential equations as soft-constraint embedding loss functions to reduce reliance on labeled data and improve physical consistency [83,84]. However, these methods typically suffer from high training costs, difficulty in balancing loss weights, and insufficient convergence under large deformations and time-varying boundaries. Overall, data-driven methods improve modeling flexibility, but further improvements are needed in interpretability, stability, and out-of-distribution generalization.

A further limitation of data-driven modeling is the lack of standardized soft-robot datasets. Training data are often collected from specific robot geometries, actuator pressures, camera views, embedded sensors, or contact conditions, making cross-study comparison difficult. Labeling full-body deformation, contact force, material state, and environmental disturbance is expensive and often requires motion capture, marker tracking, finite element simulation, or manual annotation. Differences in sampling rate, calibration, normalization, and train–test split can also change reported prediction accuracy. Future datasets should therefore report robot morphology, actuator input, sensor layout, environmental condition, labeling method, and evaluation metric in a standardized format.

Section 3 frames modeling as a balance among accuracy, efficiency, and interpretability. Continuum numerical methods capture deformation, contact, and stress, but are costly and parameter-sensitive. Reduced-order and geometric models support real-time control, yet lose accuracy under load, contact, or non-uniform deformation. Data-driven models capture unmodeled nonlinearities, but depend on training coverage and may fail outside sampled conditions. Physics-informed and residual-learning models preserve physical structure while correcting errors. Their usefulness still depends on prior-model quality, sensor observability, contact validation, and compatibility with the intended control architecture.

4. Control Strategy

Soft robots are characterized by strong nonlinearity, strong coupling, and high degrees of freedom, making their control a core challenge that consistently limits their practical applications. Existing research has broadly established three technical paths to address this issue: classical model control based on geometric mapping and dynamic equations; intelligent control relying on machine learning; and fusion control combining physical priors with data-driven approaches. Each method has its own advantages in terms of modeling accuracy, real-time performance, robustness, and generalization ability, and is tailored to different levels of task complexity and application scenarios. A concise comparison of these control strategies is provided in Table 3.

Table 3. Concise comparison of major control strategies for soft robots.

Control Strategy	Core Idea	Key Advantages	Main Limitations	Suitable Scenarios/Refs.
Classical model-based control	Uses geometric mapping, PCC/PCS, Cosserat rod theory, or dynamic equations	High interpretability; efficient for structured tasks; accurate when parameters and contacts are known	Sensitive to hysteresis, loads, contact, and parameter drift; dynamic models can be computationally costly	Free-space tracking, known-contact manipulation, transparent mechanical analysis [13,70,85,86]
Machine learning-based intelligent control	Learns surrogate dynamics, MPC policies, or RL policies from data/simulation	Captures nonlinear deformation and manufacturing variations; fast inference after training; adaptable to high-dimensional sensing	Requires representative data; limited interpretability and out-of-distribution generalization; sim-to-real gap remains	Data-rich manipulation, locomotion learning, adaptive control, high-dimensional sensing-control tasks [14,87]
Physics–data fusion control	Combines physical priors with learned residuals, online identification, or physics-guided RL	Balances accuracy, robustness, real-time performance, and interpretability; reduces unmodeled-error effects	Depends on prior-model quality, loss-weight design, excitation trajectory, and online identification stability	Contact-rich manipulation, dynamic environments, sim-to-real deployment, interpretable adaptive control [55,86,88,89]

Accordingly, control strategies are compared in terms of tracking accuracy, convergence behavior, robustness, data requirement, interpretability, and real-time feasibility.

4.1. Classical Model-Based Control

Classical mechanical control mainly includes two categories: kinematic control and dynamic control. The former focuses on the geometric mapping between the control input and the end pose, while the latter further introduces physical factors such as force, inertia, elasticity and contact to improve the control accuracy of soft robots in complex tasks. In free space without external obstacles, kinematic control is widely used because of its high computational efficiency and simple model structure [85]. This type of method usually describes the mapping between the control input and the end pose through geometric relationships, and can complete trajectory tracking well under ideal conditions; for microrobots in the air-jumping or flying stage, pure kinematic calculation can also provide sufficient positioning accuracy [90]. However, since soft robots have the characteristics of a continuum, the system theoretically has infinite degrees of freedom, and the inverse kinematic problem often exhibits multiple solutions and strong nonlinearity, making it difficult to uniquely deduce the driving input from the target pose [91]. At the same time, kinematic control does not explicitly consider mechanical equilibrium. When the system is subjected to external loads or comes into contact with the environment, the viscoelastic hysteresis of the material and external resistance will cause the actual deformation to deviate from the geometric prediction, forming an obvious “virtual–real gap” [70]. To alleviate this problem, researchers have introduced Cosserat rod theory and variable curvature spline models to replace the simple constant curvature assumption, thereby more accurately describing the non-uniform deformation of flexible structures under stress [66]. At the same time, morphological computation

and data-driven implicit mapping methods have also been used to reduce the singularity problem in analytical differentiation [31,92]. However, when the task involves contact force adjustment, external load compensation, or confined space operations, pure geometric mapping still has difficulty meeting the requirements.

Kinematic control aims to convert control inputs into configurations and end poses in the working area through geometric mapping (Figure 4). The core of this method is to ignore the inertia of the system, the nonlinear elasticity of the material, and the external contact forces, and only focus on the evolution of kinematic variables such as position and velocity [93]. At the basic modeling level, the piecewise constant curvature (PCC) model is widely used; this model assumes that the continuous deformation of the soft actuator can be discretized into several segments of circular arcs with constant curvature, thereby simplifying the forward kinematics problem to the solution of algebraic trigonometric equations [69].

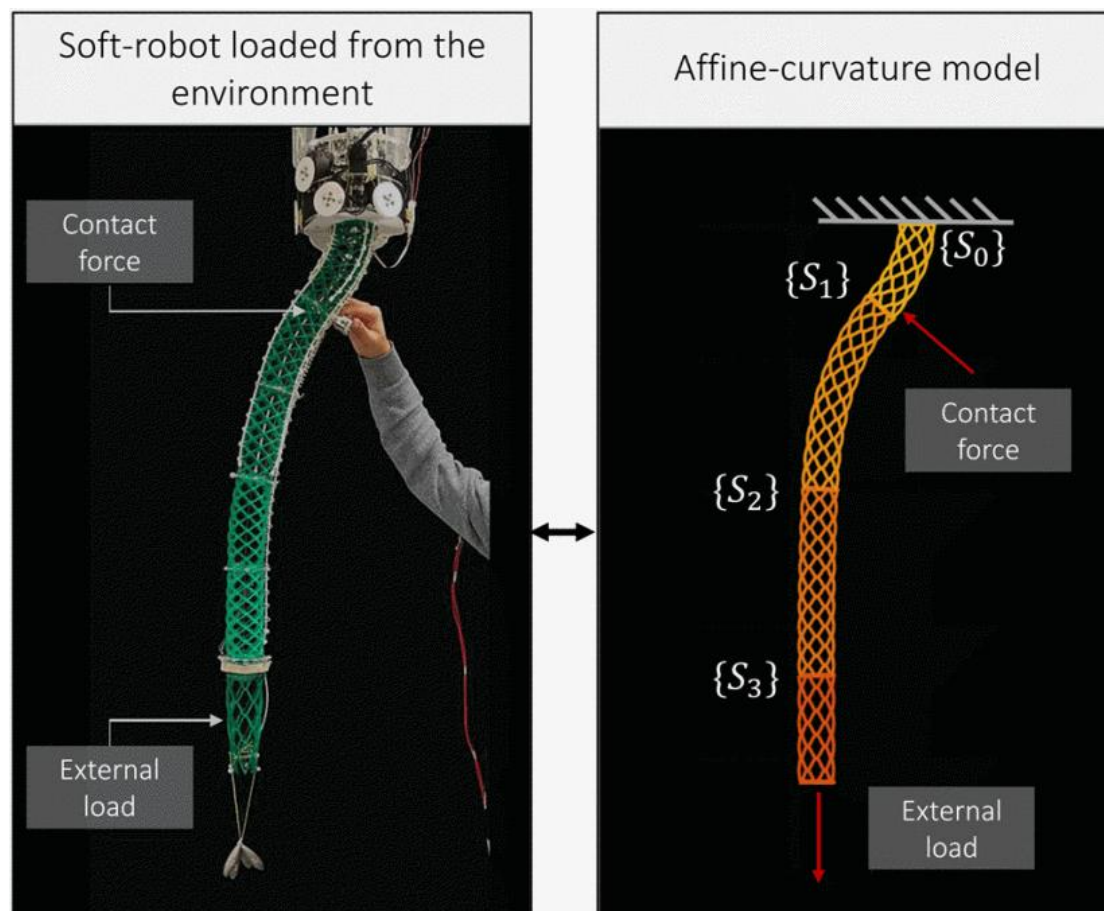


Figure 4. Comparison of kinematic control based on piecewise constant curvature and dynamic control based on Cosserat rod theory. Adapted from Stella et al. [94], reproduced with permission from IEEE.

In contrast, dynamic control further incorporates factors such as system inertia, material elastic potential energy, gravity, and external contact forces [13], which can more completely describe the motion behavior of soft robots in real environments. Its modeling methods mainly include enhanced rigid body models, Lagrangian dynamics, and continuum dynamic models based on Cosserat rod theory [67,95,96]. These methods can compensate for nonlinear deformation caused by physical contact and time-varying external loads, thereby improving the accuracy of trajectory tracking and force control. For example, based on operational space control, soft robotic arms can perform high-dynamic tasks such as writing

and dynamic throwing [75]; microrobots can use dynamic models containing magnetic energy and elastic strain energy to accurately control their flight trajectories in the air [97]; multilayer magnetic control soft robots can achieve continuous tumbling and precise targeted attachment through interlayer magnetic interaction modeling [98]. However, the cost of dynamic models is high computational complexity and sensitivity to material parameters. The hyperelastic and viscoelastic characteristics of soft materials make the solution of partial differential equations time-consuming, making it difficult to achieve low-latency real-time solutions on limited airborne hardware [99]. At the same time, parameters such as local stiffness and damping are prone to drift with temperature or fatigue, and fixed-parameter controllers are prone to significant tracking errors when parameters are mismatched [88]. To address these issues, researchers have further proposed a hybrid control method that combines PINNs with Lagrange or Hamiltonian dynamics. This method compensates for unmodeled errors by identifying stiffness and damping parameters online [88,100] and reduces real-time control costs by using lumped-parameter models [86]. However, this type of online identification is dependent on the excitation trajectory, and closed-loop instability may still occur under high-frequency dynamic contact.

Adaptive control and sliding-mode control provide useful complements to purely geometric or fixed-parameter controllers. Adaptive control can update uncertain stiffness, damping, or input–output mapping parameters online, improving robustness against material aging, payload variation, and fabrication differences. Sliding-mode control is attractive for uncertain nonlinear systems because it can suppress bounded disturbances and modeling errors, although chattering, actuator bandwidth limits, and pressure or voltage saturation must be considered in soft robots. Recent studies provide more specific support for these controllers in continuum and soft-robot systems. Wang et al. compared sliding-mode, Lyapunov-redesign, and adaptive controllers for a soft continuum manipulator for minimally invasive surgery, emphasizing model uncertainty and nonlinearities as central control challenges [101]. Lu et al. developed an adaptive online-learning method for robust 3-D shape servoing of continuum and soft robots in unstructured environments, showing the importance of proprioceptive feedback and online adaptation under variable robot conditions [102]. Kazemipour et al. proposed an adaptive dynamic sliding-mode controller for soft continuum manipulators, combining Euler–Lagrange dynamics with robustness against parameter uncertainty and external disturbances [103]. These studies indicate that adaptive and sliding-mode controllers remain important when learning data are limited or when robustness must be supported by explicit stability analysis, although their performance still depends on excitation quality, stability-proof assumptions, actuator saturation, and disturbance bounds.

4.2. Machine Learning and Intelligent Control

Learning-based MPC replaces difficult analytical dynamics with learned surrogate models. Motor babbling or simulation data predict state evolution, and MPC optimizes inputs over a finite horizon [87,104]. This captures hysteresis, non-uniform deformation, and manufacturing variation better than many analytical models and has been used in soft-origami reverse design [87]. It also supports sim-to-real control (Figure 5). Real-world RL avoids modeling but has low sample efficiency, risks material fatigue during exploration, and complicates reward acquisition in high-dimensional soft states. Naive sim-to-real transfer trains in ideal simulation but often fails because soft systems have many degrees of freedom, nonlinear materials, and hysteresis. Domain randomization improves robustness by perturbing mass, stiffness, and friction during training [105]. Adaptive domain randomization estimates simulator-parameter distributions from limited real interaction, improving target-system adaptation while retaining robustness.

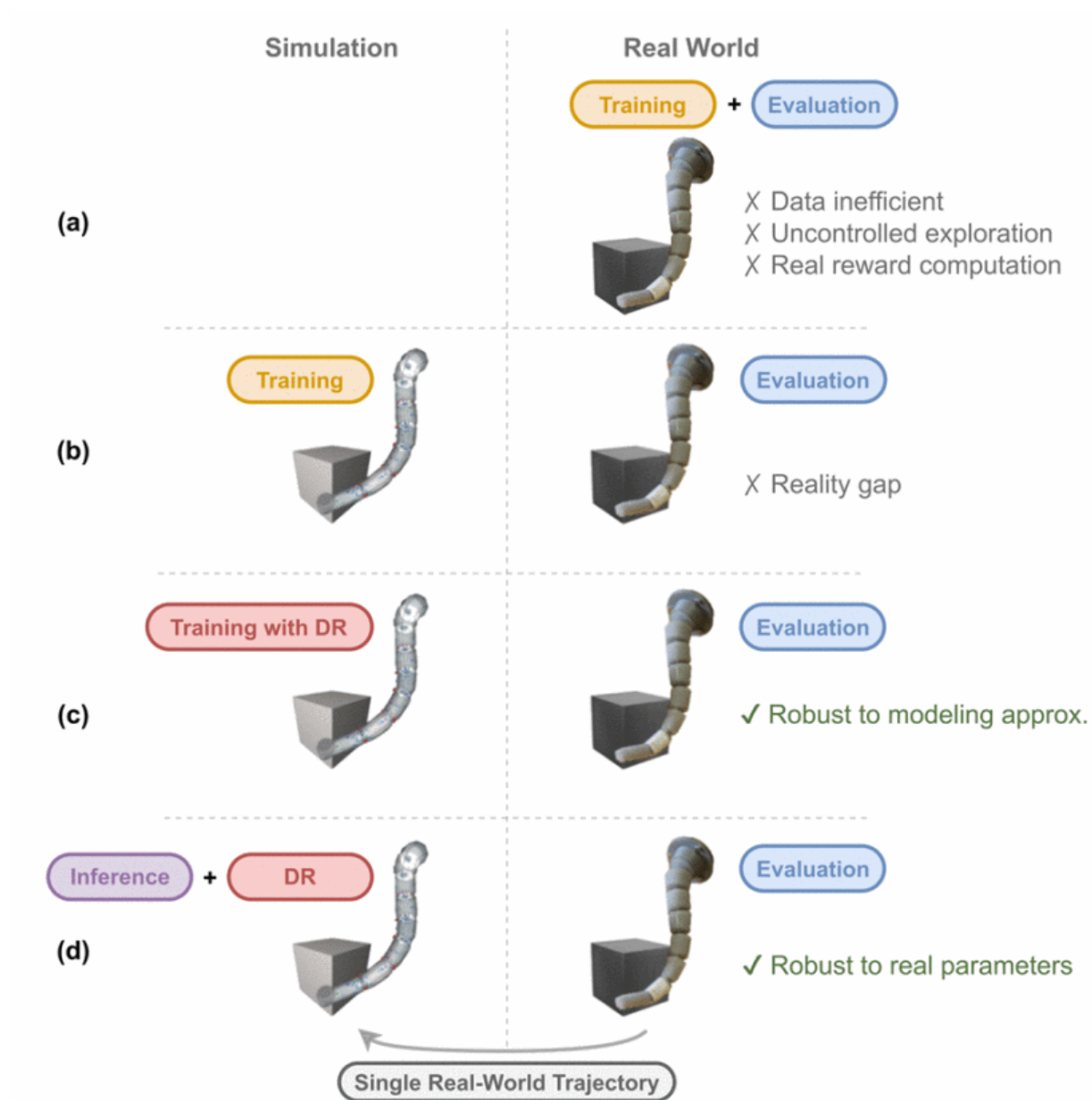


Figure 5. Paradigms in RL-based robot learning: (a) Training directly on the real world; (b) naive sim-to-real transfer suffers from the reality gap; (c) training with domain randomization increases robustness to modeling approximations and errors; (d) distributions over simulator dynamics parameters may be automatically inferred from real-world data for use with DR. Panel (a) represents direct real-world training, which avoids model mismatch but requires extensive physical interaction and may cause material fatigue during uncontrolled exploration. Panel (b) represents naive sim-to-real transfer, in which a policy trained using a nominal simulator may lose performance because of the reality gap. Panel (c) introduces domain randomization (DR), whereby material, contact, and dynamic parameters are varied during simulation training to improve robustness to modeling uncertainty. Panel (d) further uses limited real-world observations to infer a more representative distribution of simulator parameters. Together, the four panels illustrate the progressive reduction in real-world training cost and improvement of sim-to-real robustness. Adapted from Tiboni et al. [105], reproduced with permission from IEEE.

Representative studies provide more explicit quantitative evidence for learning-based soft-robot control. In neural network-model-based MPC, Hyatt et al. reported that a DNN-MPC controller for a six-degree-of-freedom pneumatic soft robot achieved a total average steady-state error of 0.040 rad without integral control and 0.018 rad with integral control,

with average 10–90% rise times of 2.94 s and 2.63 s, respectively; these values were lower than those of the corresponding first-principles MPC controllers, whose average steady-state errors were 0.0816 rad and 0.051 rad and whose average rise times were 7.46 s and 5.74 s [100]. Domain-randomization-based RL also provides quantitative evidence of transfer efficiency: Tiboni et al. showed that training with a simplified MultiGait model reduced training time by 7.9×, from about 55 days to 7 days for 500 k timesteps, while preserving transfer performance on the more accurate model [105]. In robust learning-based control, Han et al. showed that the DeSKO controller used only 1/25 of the data required by SAC in simulation and resisted external disturbances of up to five times the maximum control input without failure; in real-world SoPrA tracking, DeSKO achieved average tracking errors of 1.28, 1.30, and 1.33 cm for the S-, R-, and L-shaped trajectories, respectively, and ran at a closed-loop rate of 100 Hz with a 30-step prediction horizon [106]. For model-free reinforcement learning, general RL control frameworks have been widely used in robotic control [107], and Satheeshbabu et al. trained a DDPG policy for 100,000 episodes and reported a 98% success rate in simulation, with path-tracking errors of 0.83 ± 0.30 cm for a horizontal line, 0.71 ± 0.21 cm for a circle, and 0.93 ± 0.57 cm for Viviani's curve; after feedback transfer to the prototype, the closed-loop errors under no load were 1.01 ± 0.49 cm, 1.21 ± 0.61 cm, and 1.32 ± 0.97 cm for the three curves, respectively [108]. In the residual-physics learning strategy discussed below, the average beam trajectory error was reduced from 1.32 mm to 0.52 mm, and the pneumatic soft-arm error was reduced by 21.1%, with a lower simulation-cost increase than traditional system identification [55]. These values show that learning-based and physics-data fusion controllers can improve tracking accuracy, convergence behavior, and sim-to-real robustness, but the reported numerical performance remains task-specific because robot morphology, actuator type, trajectory scale, sensing configuration, and hardware platform differ across studies.

However, learning-based control still faces dual limitations in generalization ability and computational cost in practical deployment. High-precision surrogate models usually rely on a large number of labeled samples and are essentially statistical fits to the training distribution. Therefore, when material parameters decay due to fatigue or environmental boundaries change, the prediction accuracy often drops significantly, resulting in a “virtual–real gap”. At the same time, neural network inference places high demands on the computing power of edge controllers, limiting their real-time application. To alleviate these problems, researchers have constructed lightweight reduced-order surrogate models through feature extraction to reduce the overhead of online MPC optimization [12]. On the other hand, Koopman-operator-based modeling has been introduced to map nonlinear dynamics to a high-dimensional linear observation space and use mature linear control tools [81,82]. When high-quality controlled data is difficult to obtain or the task itself has strong trial-and-error attributes, reinforcement learning (RL) has become an important path. RL learns control strategies directly under the constraint of a reward function through trial and error between the agent and the environment [107], and has been verified in soft-continuum-arm trajectory-tracking tasks [108]. However, its sample efficiency is low, and real physical exploration can easily lead to fatigue or even fracture of flexible materials [9]. Therefore, current research mostly adopts the sim-to-real paradigm, and combines domain randomization, differentiable physics engines and morphological computation to narrow the gap between virtual and real, improve convergence speed and deployment security [10,14,30].

4.3. Physics–Data Fusion Control

Model-driven control is interpretable and provides stability boundaries, but loses accuracy under contact, hysteresis, and parameter drift. Data-driven control captures residuals and nonlinear disturbances but can generalize poorly and violate physical consistency. Physics–data fusion therefore uses analytical models to constrain dynamics and learning

modules to compensate unmodeled errors. Residual compensation learns fluid–structure interaction, friction, and fatigue effects for online correction, while physics-guided RL embeds energy, morphology, or lumped-parameter constraints into rewards [86,88,89,100]. This improves the balance among accuracy, robustness, and real-time performance, but remains sensitive to loss weights, prior-model bias, and online identification stability.

As shown in Figure 6, this pipeline corresponds to the residual compensation method in the fusion control strategy. In this process, an analytical simulator based on continuum mechanics first provides the physical priors for the large deformations of the soft robot. Then, the system uses a neural network to extract sparse motion markers from the real world to learn an external “residual force.” This residual force is specifically used to correct the error between the simulator’s predictions and the actual physical state, thereby compensating for unmodeled material hysteresis, anisotropy, or manufacturing tolerances. In practice, this process significantly narrows the “virtual–real gap” of the soft robot. Compared to traditional system identification methods, residual compensation offers significant improvements in both accuracy and robustness. For example, in the simulation-to-real-world transfer task of a passive flexible beam, this method reduces the average trajectory error by approximately 60.3% (from 1.32 mm to 0.52 mm) with a smaller variance; and in the task of a pneumatic soft arm (SoPrA) with complex fiber constraints, the error is further reduced by 21.1%. In addition, in terms of computational efficiency, traditional system identification often leads to ill-conditioned solutions of dynamic equations in pursuit of high accuracy, increasing the computational cost to 3.12 times the original. The residual compensation method, by introducing a lightweight network, achieves higher tracking accuracy with only 1.96 times the computational cost, and better balances the real-time performance and accuracy of high-degree-of-freedom systems [55].

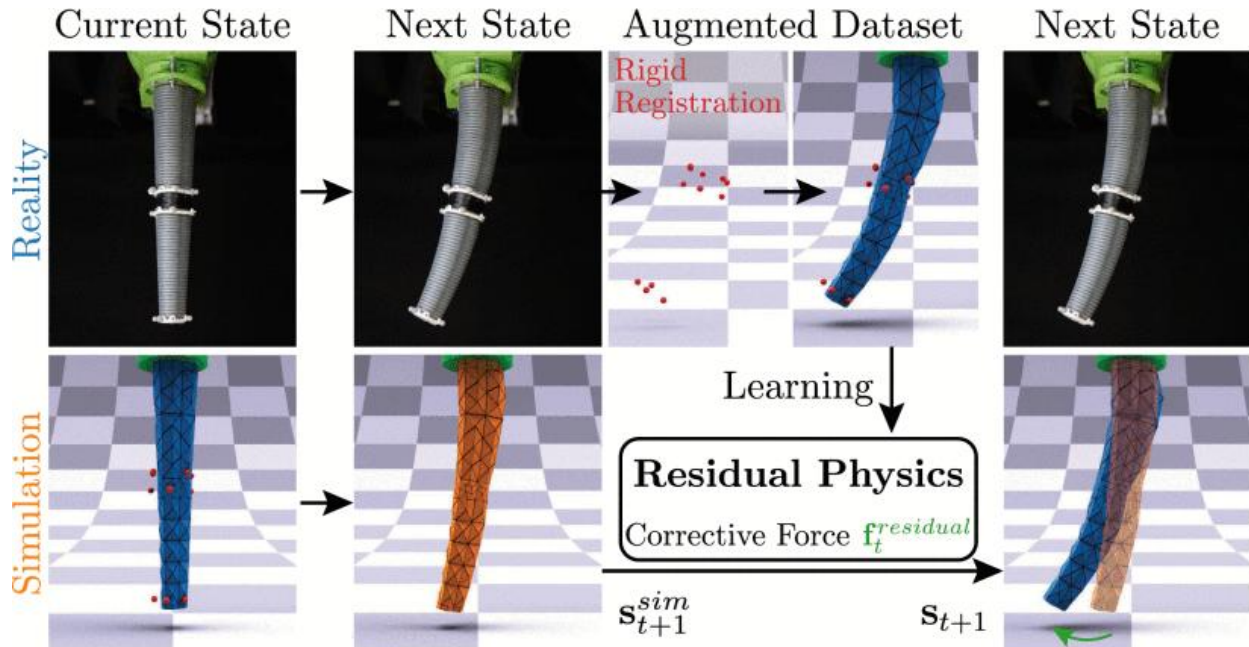


Figure 6. Overview of the residual-physics learning pipeline for high-degree-of-freedom soft robots. The baseline simulator predicts the next state of the soft robot using the current state, actuation input, material model, and boundary conditions. Sparse markers measured on the real robot are registered to the simulation coordinate frame and compared with the corresponding simulated markers. The residual network learns a corrective force applied to the simulated mesh to compensate for unmodeled effects, such as viscoelasticity, anisotropic reinforcement, friction, and manufacturing variations. The training loss measures the mismatch between corrected simulated markers

and real markers. The resulting model therefore combines physical simulation with data-driven residual compensation. Adapted from Gao et al. [55], licensed under CC BY 4.0.

Section 4 shows that control design balances accuracy, robustness, data demand, and real-time feasibility. Classical model-based control is efficient and interpretable when parameters and contacts are known, but fragile under hysteresis, load variation, and uncertainty. Learning-based control handles nonlinear dynamics and rich sensing, yet needs representative data and safe exploration. Physics–data fusion adds robustness through learned compensation, but depends on loss design, online identification, computation, and excitation quality. Controllers should be judged by tracking error, convergence, disturbance tolerance, latency, safety, and reproducibility.

5. Sensing Technology

Sensing technology is fundamental for soft-robots to achieve closed-loop control and safe interaction. Its core task is to convert continuous deformation, contact interactions, and environmental disturbances into measurable signals. Existing research has mainly focused on three paths to achieve this goal: first, research on soft perception mechanisms and interaction patterns oriented towards self-state reconstruction, focusing on how proprioception and tactile perception can collaboratively acquire robot posture, curvature, and external contact information; second, flexible electromechanical coupling sensing technologies, represented by resistive, piezoresistive, capacitive, and conductive liquid sensors, emphasizing high-compliance integration with the soft-robot body; and third, low-hysteresis high-frequency sensing technologies, represented by fiber optic and magnetic sensing, focusing on improving measurement accuracy, dynamic response, and adaptability to complex environments. Different sensing mechanisms have their own characteristics in terms of sensitivity, hysteresis characteristics, integration complexity, and anti-interference capabilities, and correspond to different soft-robot application scenarios.

Accordingly, sensing technologies are evaluated in terms of sensitivity, resolution, measurement range, response speed, hysteresis, drift, durability, and integration difficulty.

5.1. Soft Perception Mechanisms and Interaction Patterns

The effectiveness of closed-loop control depends heavily on high-fidelity observation of the robot's own state. Proprioception refers to the robot's ability to perceive its own spatial pose, kinematic state, and internal continuous deformation in real time, and is therefore the basis for three-dimensional morphological reconstruction, precise control, and safe operation [109]. Currently, proprioception is mainly acquired through two methods: external tracking and internal perception. The former usually relies on optical motion capture systems, which are suitable as real reference values in experiments, but are difficult to use directly for offline operation due to the influence of camera array size and line-of-sight occlusion; the latter achieves autonomous perception through embedded sensing, and has become the main direction of practical deployment. To achieve internal body perception, researchers have proposed a variety of sensing technologies that can be adapted to large strain scenarios, which can be summarized into four categories: electrical, optical, electromagnetic and structural integration. Resistive, piezoresistive and conductive liquid sensors use geometric changes or resistivity fluctuations to sense deformation [110]. Optical sensors are represented by fiber Bragg gratings (FBGs), which reconstruct curvature through spectral frequency shift. Electromagnetic sensors calculate the bending state through the relative displacement of permanent magnets and Hall elements. Structural integration sensors use 3D knitting to integrate conductive yarns with flexible bodies. In

general, these technologies all face a trade-off between intrinsic compliance and high signal fidelity. Resistive, conductive liquid and 3D knitting solutions match the soft body well, but are easily affected by viscoelastic hysteresis and zero-point drift. Although FBG and magnetic sensing have fast dynamic response and low hysteresis, the former relies on complex spectral demodulation equipment, while the latter is easily affected by external magnetic field interference and array crosstalk.

To address the above issues, research is being advanced in a coordinated manner across three levels: algorithms, materials, and structures. At the information processing level, recurrent neural networks (RNNs) can be used to compensate for the hysteresis error of piezoresistive materials [111]. At the hardware level, multi-material 3D printing helps to achieve integrated manufacturing of sensing and actuation and reduce impedance mismatch [112,113]. A more forward-looking approach is the stimulus-response electro-fluidic nervous system (SENS) [21], which attempts to achieve low-level feedback through fluid logic gates. However, proprioception alone is still insufficient to support complex interactions. The system also needs to further introduce tactile perception to obtain information such as force, pressure distribution, and texture during the robot's contact with the environment. Tactile perception (exteroception/tactile sensing) aims to analyze the physical interaction information between the robot and the external environment [114], which is the key to the transition of soft robots from passive compliance to active closed-loop operation. Traditional methods typically deploy distributed sensor arrays on the actuator surface to capture contact force and spatiotemporal distribution [115]. In recent years, "internal vision" has provided a new approach for high-resolution tactile perception, such as embedding a miniature camera inside a bubble gripper to reconstruct the contact state by observing the deformation of the inner surface [116]. However, such solutions introduce rigid components and increase the onboard computing burden. Meanwhile, capacitive sensors and tactile skin based on triboelectric nanogenerators (TENGs) have attracted attention due to their high sensitivity and self-powered nature [117,118], but still face problems such as humidity sensitivity, high output impedance, and difficulties in wiring high-resolution arrays [109]. Therefore, current tactile perception is developing towards multimodal fusion, automated structural design, and machine learning decoding, reducing mechanical interference through automated wiring, and using deep learning to directly decode interactive intentions from noisy signals [119,120].

5.2. Flexible Electromechanical Sensing Technologies

Flexible force-electric coupling sensing technology is the most widely used internal sensing scheme in soft robots. Its core is to convert deformations such as stretching, bending or compression into measurable electrical signals. According to different mechanisms, this type of method mainly includes resistive, piezoresistive, capacitive and conductive liquid sensors, which have their own characteristics in terms of sensitivity, hysteresis characteristics and integration methods. Resistive sensors (Figure 7a) and piezoresistive sensors (Figure 7b) sense deformation by the change in resistance of elastic conductive materials during stretching, bending or compression [121]. These sensors can usually be integrated with flexible bodies by combining multi-material 3D printing, conductive polymers or special conductive inks. They have the advantages of low cost and wide applicability and are often used for continuous arm posture reconstruction and gripper tactile recognition. However, their output usually has obvious nonlinearity and mechanical hysteresis, which limits the accuracy of high-frequency dynamic measurement. Therefore, it is often necessary to use methods such as recurrent neural networks (RNNs) for error compensation [122].

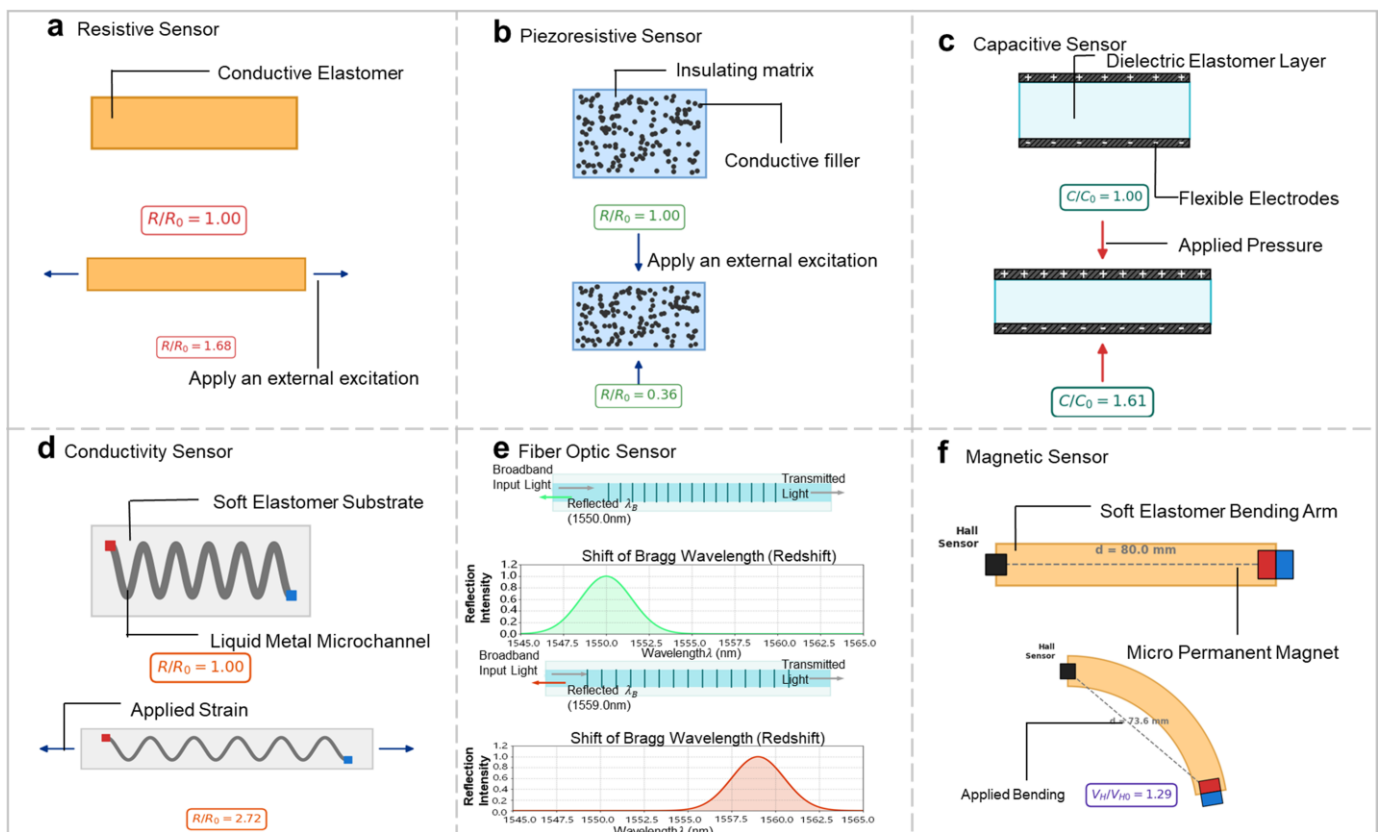


Figure 7. Working principles of common soft-robot sensing technologies. (a) Resistive sensor; (b) piezoresistive sensor, where R is the instantaneous resistance and R_0 is the initial or reference resistance, so R/R_0 denotes normalized resistance; (c) capacitive sensor, where C/C_0 denotes normalized capacitance relative to the reference capacitance C_0 ; (d) conductive liquid sensor, where the red and blue blocks indicate the two electrical terminals at both ends of the conductive liquid microchannel; (e) fiber optic sensor; (f) magnetic sensor. The measurand, deformation range, and calibration condition differ across panels, so sensitivity or resolution values should not be directly ranked without matched test conditions.

Capacitive sensors (Figure 7c) sense deformation by measuring changes in the distance between electrodes, effective area, or dielectric environment, and are often divided into two modes: self-capacitance and mutual capacitance [123]. Their structure is usually composed of a highly elastic dielectric layer and flexible electrodes, and they have the advantages of fast response, high sensitivity, and low hysteresis. They can be used for deformation measurement, contact recognition, and short-range non-contact sensing [124]. These sensors are often combined with finite element models or machine learning methods for tactile grip force prediction and wearable human–computer interaction; however, their ability to recognize insulators is weak, and they are easily affected by humidity, parasitic capacitance, and stray electric fields.

Conductive liquid sensors (Figure 7d) are based on Ohm's law and calculate strain by measuring the resistance fluctuations caused by changes in the geometric parameters of microchannels during stretching or compression [125]. These sensors are typically fabricated by prefabricating microchannels inside an elastomer and injecting liquid metal or ionic liquid [126]. Due to their good flexibility, large stretching range, and good impedance matching with the substrate, they are often used for large-scale posture sensing in continuous arms and flexible fingers. However, their limitations are also obvious, mainly including dynamic hysteresis caused by the elastic rebound, and the risk of encapsulation failure and liquid leakage under long-term cyclic loading.

5.3. Low-Hysteresis Optical–Magnetic High-Frequency Sensing Technology

Compared with flexible force and electrical sensing, optical and magnetic sensing technologies emphasize high-frequency response, low hysteresis and anti-interference capabilities, making them suitable for scenarios with higher measurement accuracy requirements. Fiber optic sensors and magnetic sensors utilize spectral shift and magnetic flux change to calculate deformation, respectively, and have unique advantages in minimally invasive guidance and high-precision attitude reconstruction. Fiber optic sensors (Figure 7e) utilize the optical wave interference effect to calculate deformation by monitoring the shift in the reflected spectral wavelength when the fiber is strained [15]. Micro- and nano-silicon-based optical fibers or high-strength hydrogel optical fibers are usually embedded in soft continuous arms in single or array form, enabling continuous curvature measurement with high spatial resolution, anti-electromagnetic interference and no mechanical hysteresis [127]. Therefore, this type of sensor is widely used in MRI-compatible minimally invasive soft robots to support high-precision attitude reconstruction and safe guidance in narrow cavities. However, its strong dependence on external spectral demodulation equipment limits its further expansion into fully automated, cableless systems.

Magnetic sensors (Figure 7f) are based on the Hall effect and calculate the deformation state of soft bodies by measuring the local magnetic flux change caused by the relative displacement of micro permanent magnets [128]. Typically, micro permanent magnets are paired with Hall elements on flexible printed circuit boards and embedded inside actuators to obtain compact, low-cost, and low-hysteresis high-frequency dynamic signals [128]. With its non-contact penetrating tracking capability, this technology is often used for tip positioning of catheters in minimally invasive surgery and can be combined with medical imaging to provide real-time spatial navigation for targeted micro- and nano-robots [129]. Its main limitation is that it is relatively sensitive to environmental magnetic fields and is susceptible to crosstalk between surrounding metal devices and arrays.

Representative sensing studies also provide quantitative evidence for the trade-offs among sensitivity, spatial resolution, response speed, durability, hysteresis, integration complexity, and cost in soft-robot sensing. For self-healing multimodal sensing, Dai et al. reported self-healing efficiencies of 98.4% and 98.9% for the insulating polymer and conductive hydrogel, fracture strains of 1028% and 4052%, hydrogel conductivity of $9.95 \times 10^{-2} \text{ S cm}^{-1}$ at 25 °C, adhesion strength up to 17.9 kPa, electrical recovery within 0.2 s, and a strain gauge factor of 1.86 in the 0–200% strain range [118]. For dual-mode capacitive tactile and proximity sensing, Qin et al. reported a proximity detection distance of up to 20 cm, a pressure range up to 200 kPa, sensitivities of 0.098 kPa^{-1} in the 0–12 kPa range and 0.004 kPa^{-1} in the 12–200 kPa range, a low detection limit of 10.2 Pa, a response time of 90 ms, a relaxation time of 180 ms, negligible hysteresis, and durability over 10,000 loading–unloading cycles [123]. For large-area capacitive tactile sensing, Pagoli et al. developed a $100 \text{ mm} \times 100 \text{ mm}$ soft capacitive pad with a 9×9 electrode matrix and 10 mm electrode spacing; the sensor could detect up to five simultaneous touch points, used low-cost silicone, conductive ink, and paper-based electrodes, and achieved force estimation in a soft gripper with approximately 2.5 N contact force after neural network calibration [124]. For fiber-integrated optical sensing, Leber et al. fabricated thermally drawn soft robotic fibers with outer diameters down to 700 μm , aspect ratios up to 10^3 , and embedded optical guides that enabled submillimeter distance resolution up to 18 mm [127]. For magnetic tactile sensing, Yan et al. used a sinusoidally magnetized flexible film with a thickness of about 0.5 mm to achieve self-decoupled normal/shear-force sensing, normal-force sensitivity of 0.01 kPa^{-1} up to 120 kPa, shear-force sensitivity of $0.1\text{--}0.27 \text{ kPa}^{-1}$, a response time of about 15 ms, and approximately 60-fold localization enhancement from a physical resolution of 6 mm to about 0.1 mm [128]. These examples indicate that capacitive sensors

are attractive for low-cost large-area integration, hydrogel-based sensors improve stretchability and damage tolerance, optical fibers offer compact distributed perception, and magnetic skins provide high-resolution force decoupling; however, the reported performance values remain difficult to rank directly because sensor geometry, loading mode, calibration method, readout electronics, soft-robot integration strategy, and testing conditions differ substantially across studies.

Section 5 shows that soft-robot sensing balances measurement quality with mechanical compatibility. Optical and visual methods provide spatial information but depend on lighting, calibration, line of sight, and occlusion. Embedded flexible sensors enable local feedback, yet can introduce stiffness mismatch, wiring complexity, hysteresis, drift, and durability concerns. Multimodal sensing improves observability, but increases calibration, synchronization, and system complexity. Deployable systems should be judged by integration difficulty, signal stability under repeated deformation, environmental robustness, cost, and control compatibility, not only sensitivity or resolution.

6. Cutting-Edge Application Areas and Key Challenges

6.1. Cutting-Edge Application Areas

Soft robots, with their intrinsic compliance, high deformability, and excellent environmental adaptability, are demonstrating unique advantages in various highly complex scenarios. Compared to traditional rigid robots, they are better suited for applications with limited space, fragile targets, complex contact processes, or highly uncertain task environments. Currently, cutting-edge applications of soft robots mainly focus on three areas: extreme-environment detection, medical surgical intervention, and human–computer interaction and smart wearables (Figure 8).

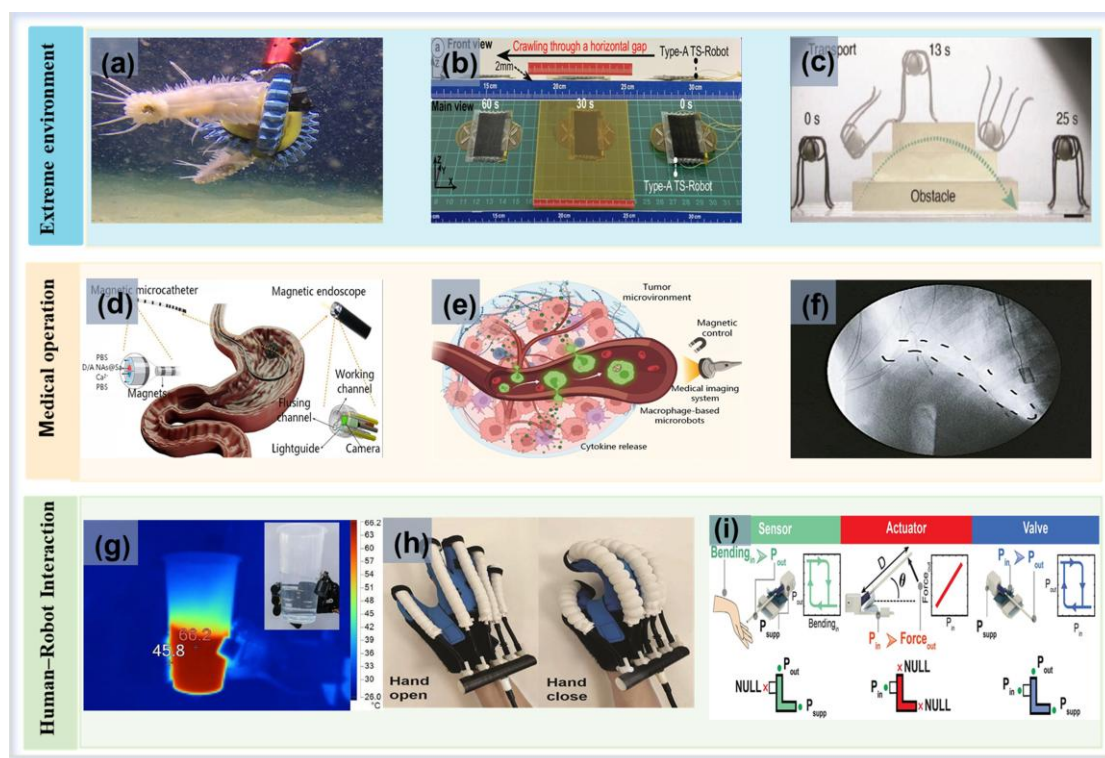


Figure 8. Representative soft robotic systems for environmental exploration, medical intervention, and human–robot interaction. (a–c) Environmental and extreme-environment applications: (a) A glove-controlled, hydraulically actuated soft robotic manipulator for compliant and delicate deep-sea biological sampling; (b) an ultra-thin dielectric-elastomer soft robot capable of crawling, climbing, swimming, and multimodal locomotion in narrow spaces; and (c) a magnetoelastic miniature

soft robot capable of controlled jumping and amphibious locomotion. **(d–f)** Medical applications: **(d)** A magnetically guided continuum soft robot for minimally invasive navigation and site-specific therapeutic delivery; **(e)** macrophage-based microrobots integrating magnetic steering, medical imaging, and antitumor functions; and **(f)** implantable pneumatic artificial muscles that augment diaphragm motion for respiratory assistance. **(g–i)** Human–robot interaction, wearable assistance, and embodied soft systems: **(g)** A conformable multimodal sensor capable of detecting deformation, temperature, and contact-related signals; **(h)** a knitted pneumatic rehabilitation glove combining textile comfort with wearable motion assistance; and **(i)** multifunctional fluidic units integrating sensing, valving, and actuation to generate electronic-free responsive robotic behaviors. Together, these examples demonstrate how compliance, actuation, sensing, and control are integrated according to the specific requirements of environmental exploration, biological intervention, and physical human–robot interaction. Panel **(a)** adapted from Phillips et al. [130], licensed under CC BY 4.0. Panel **(b)** adapted from Wang et al. [24], licensed under CC BY 4.0. Panel **(c)** adapted from Wang et al. [90], licensed under CC BY. Panel **(d)** reproduced from Wang et al. [6], licensed under CC BY-NC-ND 4.0. Panel **(e)** adapted from Dogan et al. [49], licensed under CC BY 4.0. Panel **(f)** adapted from Hu et al. [131], licensed under CC BY 4.0. Panel **(g)** adapted from Dai et al. [118], reproduced with permission from Wiley-VCH GmbH. Panel **(h)** adapted from Yang et al. [132], reproduced with permission from Wiley-VCH GmbH. Panel **(i)** adapted from Mousa et al. [133], licensed under CC BY 4.0.

Accordingly, representative applications are assessed according to task success, safety, damage risk, payload or force demand, endurance, autonomy, and deployment maturity.

Compared with rigid robots, soft robots are most advantageous when contact safety, shape adaptability, and damage reduction are more important than absolute positioning accuracy, payload, or high-speed operation. In medical intervention and wearable assistance, compliance can reduce tissue or user discomfort, but sterilization, durability, force control, and regulatory validation remain demanding. In delicate grasping and environmental sampling, soft structures reduce damage to fragile targets, but payload, repeatability, and long-term endurance may be lower than rigid systems. Therefore, the application value of soft robots should be evaluated against task-specific rigid-robot baselines rather than assumed from compliance alone.

6.1.1. Extreme-Environment Detection

In extreme unstructured environments, the compliance and cross-medium maneuverability of soft robots provide new pathways for exploration missions [134]. As shown in Figure 8a, in deep-sea scenarios, biomimetic soft sampling grippers can achieve non-destructive capture of fragile marine organisms using a passive pressure compensation mechanism [5]. As shown in Figure 8b, flattened soft systems can output large torques in near-millimeter-level confined gaps [135] and achieve multimodal movements such as crawling and swimming in narrow spaces, thereby completing complex exploration missions that cross solid–liquid boundaries [24]. In addition, amphibious robots based on magnetoelastic coupling mechanisms can also overcome the limitations of water surface tension and perform controlled cross-medium movements (Figure 8c) [90]. However, the long-term deployment of such systems in real extreme scenarios is still limited by factors such as material fatigue, strong friction and wear, and external power supply constraints. In particular, untethered operation and high-load continuous maneuvering still face significant challenges.

6.1.2. Medical Surgical Intervention

In in vivo intervention and rehabilitation medicine, the compliance and biocompatibility of soft robots are reshaping the way traditional instruments are used. Compared with rigid instruments, flexible micro- and nano-robots are more suitable for performing targeted delivery and local intervention tasks in narrow, tortuous and fragile in vivo environments [136]. For example, magnetically controlled continuum soft robots can achieve precise drug delivery to lesion areas under medical imaging guidance (Figure 8d) [6]; for example (Figure 8e), microrobots based on living macrophages can achieve in situ tracking and closed-loop navigation with the help of magnetic particles and multimodal imaging [49]. In terms of organ assistance, implantable soft ventilators can contract synchronously with the host diaphragm, thereby assisting in the reconstruction of respiratory function (Figure 8f) [131]. Although such systems have significant clinical potential, their engineering translation is still constrained by factors such as in vivo navigation accuracy, biological barrier penetration ability and long-term implant material fatigue life, and also needs to meet strict clinical safety and regulatory requirements.

6.1.3. Human–Robot Interaction and Smart Wearables

In the field of human–computer interaction and smart wearables, soft robots provide an ideal platform for safe, comfortable and continuous physical interaction. Their passive compliance allows them to conform more naturally to the human body contour and play a role in motion assistance, rehabilitation training and wearable sensing. For example (Figure 8g), researchers embedded triboelectric nanogenerators into soft structures to build a self-driven sensing network that does not require external power supply. This network can convert small deformations of the human body into electrical signals for posture monitoring and digital twin feedback [118]. For example (Figure 8h), 3D knitting technology was used to integrate pneumatic actuators and sensor arrays, enabling the system to fit the human body seamlessly like clothing [137]. Combined with machine learning decoding algorithms, flexible sensing signals can be used to reconstruct hand and upper limb movement trajectories with high fidelity. In addition, some studies have further utilized flexible fluid logic valves to build electronic-free physical circuits to achieve low-level motion decision-making based on environmental stimuli (Figure 8i) [133]. However, such systems still face problems such as humidity sensitivity, signal crosstalk and an insufficient dynamic response rate in actual deployment. The robustness of these systems in complex human–computer interaction scenarios still needs to be improved.

6.2. Key Challenges and Future Outlook

While soft robots have demonstrated broad application potential in fields such as extreme detection, medical intervention, and human–computer interaction, their further practical deployment still faces multiple constraints at the material, system, and manufacturing levels. Overall, future research will focus primarily on three aspects: fully degradable soft robots, deep coupling of intelligence, perception, and control, and large-scale mass production.

Future progress should focus on technologies that close the gap between soft compliance and system reliability. Promising directions include durable multifunctional materials, miniaturized untethered power and actuation units, embedded multimodal sensing, physics-informed learning, adaptive and robust control, and scalable additive or textile manufacturing. The main bottlenecks remain fatigue, energy autonomy, benchmark standardization, closed-loop sensing under large deformation, sim-to-real transfer, manufacturability, and long-term validation in realistic tasks. These directions are consistent with the evaluation framework of this review and emphasize deployability rather than isolated material or actuator performance.

6.2.1. Fully Degradable Soft Robots

While current soft robots have achieved partial biocompatibility or biodegradability in their body materials, their actuators, sensors, and control circuits often still rely on non-degradable electronic components, leading to problems such as electronic waste and implant residues. As shown in Figure 9a, with the development of transient electronics and bio-based materials, soft robots are evolving from partial degradability to system-wide degradability [138,139]. For example, flexible sensors and electrodes constructed based on fungal mycelium, gelatin, and degradable metals have provided a new material basis for transient soft robots. Such systems can achieve non-toxic degradation through hydrolysis, enzymatic hydrolysis, or environmental metabolism after completing their tasks, making them suitable for scenarios such as minimally invasive medical treatment and environmental monitoring [140,141]. However, fully degradable soft robots still need to strike a balance between service stability and controllable degradation, especially requiring breakthroughs in the manufacturing challenges of on-demand degradation mechanisms and multi-material transient integration [142].

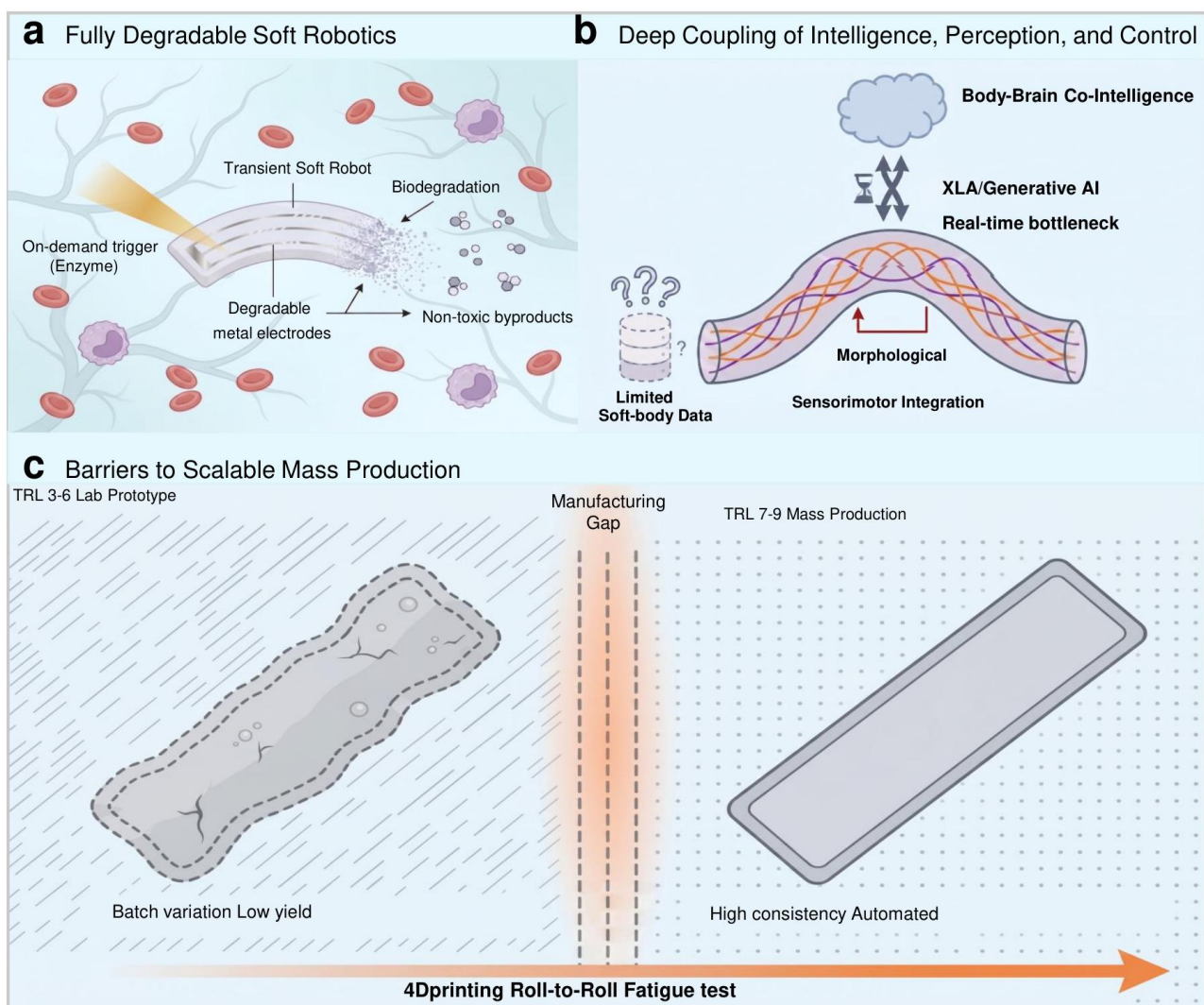


Figure 9. Key challenges and future prospects in the field of soft robotics. (a) Fully degradable soft robots require a balance between operational stability and controllable degradation, so that the system can maintain mechanical integrity, sensing reliability, and actuation performance during service while degrading safely after completing its task. (b) Deep coupling of intelligence, perception, and control requires embedded sensing, physics-informed learning, morphology-aware control,

and low-latency onboard decision-making to improve autonomy in uncertain environments. (c) Large-scale manufacturing remains limited by material variability, manual fabrication, production yield, interface reliability, and the lack of standardized fatigue and durability testing. These three directions collectively describe the transition of soft robots from laboratory prototypes toward reliable, autonomous, scalable, and deployable robotic systems.

6.2.2. Deep Coupling of Intelligence, Sensing, and Control

The application of soft robots in complex environments is limited by the difficulty in coordinating perception, control, and form. Traditional “perception, planning, and execution” architectures often struggle to balance real-time performance and robustness when facing high-degree-of-freedom, highly nonlinear systems. In recent years, morphological computation and sensor-driven integration have provided new solutions to this problem. By integrating multimodal sensor networks with flexible actuation materials at the microscopic level [112,143], soft robots can leverage their physical adaptability to absorb some environmental disturbances and process information, thereby reducing the load on the central control system (Figure 9b). Furthermore, reinforcement learning based on surrogate modeling and simulation-to-reality transfer methods [106,108], as well as the introduction of visual, language, and action models [144], have enabled soft robots to possess stronger embodied reasoning and autonomous decision-making capabilities. In the future, the key to this direction remains the acquisition of high-quality interactive data, real-time cross-modal synchronization, and low-latency coupling between large models and soft physical systems.

6.2.3. Barriers to Mass Production

Despite rapid progress in soft robotics at the laboratory level, its industrialization remains constrained by a significant manufacturing gap (Figure 9c). Currently, relatively simple and fault-tolerant industrial flexible grasping systems have reached a high level of maturity, while highly integrated medical soft catheters and bionic robots are still mostly in the prototype or early clinical validation stage. The key reason for this difference lies in the systemic gap between laboratory prototypes and industrial mass production in terms of manufacturing processes, material consistency, and quality testing systems. Currently used manual casting, sacrificial molds, and low-speed 3D printing processes are insufficient to meet the consistency and stability requirements of mass production. In the future, promoting multi-material integrated 4D printing, roll-to-roll flexible electronics manufacturing, and the construction of standardized fatigue life testing systems will be important directions for breaking through the bottleneck of large-scale manufacturing [27,145,146].

Section 6 shows that soft-robot value is not defined by compliance alone. In medical and wearable systems, deployment also requires sterilizability, reliability, force control, and regulatory compatibility. In exploration and manipulation, soft structures protect fragile targets and adapt to terrain, yet payload, endurance, autonomy, and harsh-environment resistance remain limiting. Human–robot interaction benefits from soft contact and embodied sensing, but still needs reproducible manufacturing and durability. Application advantages must be justified against deployment requirements and supported by reliable actuation, sensing, control, energy supply, and manufacturable design.

7. Conclusions

Soft robots, as a novel robotic system integrating flexible materials, intelligent actuation, state perception, and autonomous control, are providing new technological pathways for tasks such as detection, medical intervention, and human–robot interaction in complex unstructured environments. This paper systematically reviews the major re-

search progress in this field, focusing on materials and actuation, modeling and simulation, control strategies, sensing technologies, and cutting-edge applications of soft robots. Overall, soft robots have gradually moved from the development stage of single flexible actuators to a system integration stage that integrates materials, structure, perception, and control, demonstrating significant advantages in extreme-environment adaptability, safe interaction capabilities, and task flexibility. However, there is still a significant gap between soft robots and truly robust, autonomous, and large-scale applications. At the material level, soft systems still face fatigue, creep, and failure issues under long-term cyclic loading. At the modeling level, the high degrees of freedom and strong nonlinearity of continuums pose challenges to accurate description and real-time solution. At the control level, complex contact, parameter drift, and the virtual–real gap restrict high-precision closed-loop operation. At the perception level, how to achieve high-fidelity, multimodal, and low-hysteresis state acquisition while maintaining intrinsic compliance remains a key issue that urgently needs to be addressed. Meanwhile, issues such as complete degradation, deep coupling of intelligent perception and control, and large-scale manufacturing also determine whether soft robots can move from laboratory prototypes to engineering systems and practical applications.

In the future, the focus of soft-robot development will no longer be limited to improving the performance of single modules, but will place greater emphasis on the collaborative design and system coupling between materials, actuation, perception, modeling, and control. On the one hand, it is necessary to further develop programmable materials, low-power actuation, and highly integrated sensing technologies to improve the environmental adaptability and long-term reliability of systems; on the other hand, the integration of physical models and data-driven methods should be strengthened to promote the improvement of the intelligence, autonomy, and interpretable control capabilities of soft robots. With the continuous integration of interdisciplinary technologies, soft robots are expected to play a wider role in fields such as deep-sea exploration, precision medicine, wearable interaction, and biomimetic intelligent systems, and gradually form a next-generation robot paradigm for real and complex environments.

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