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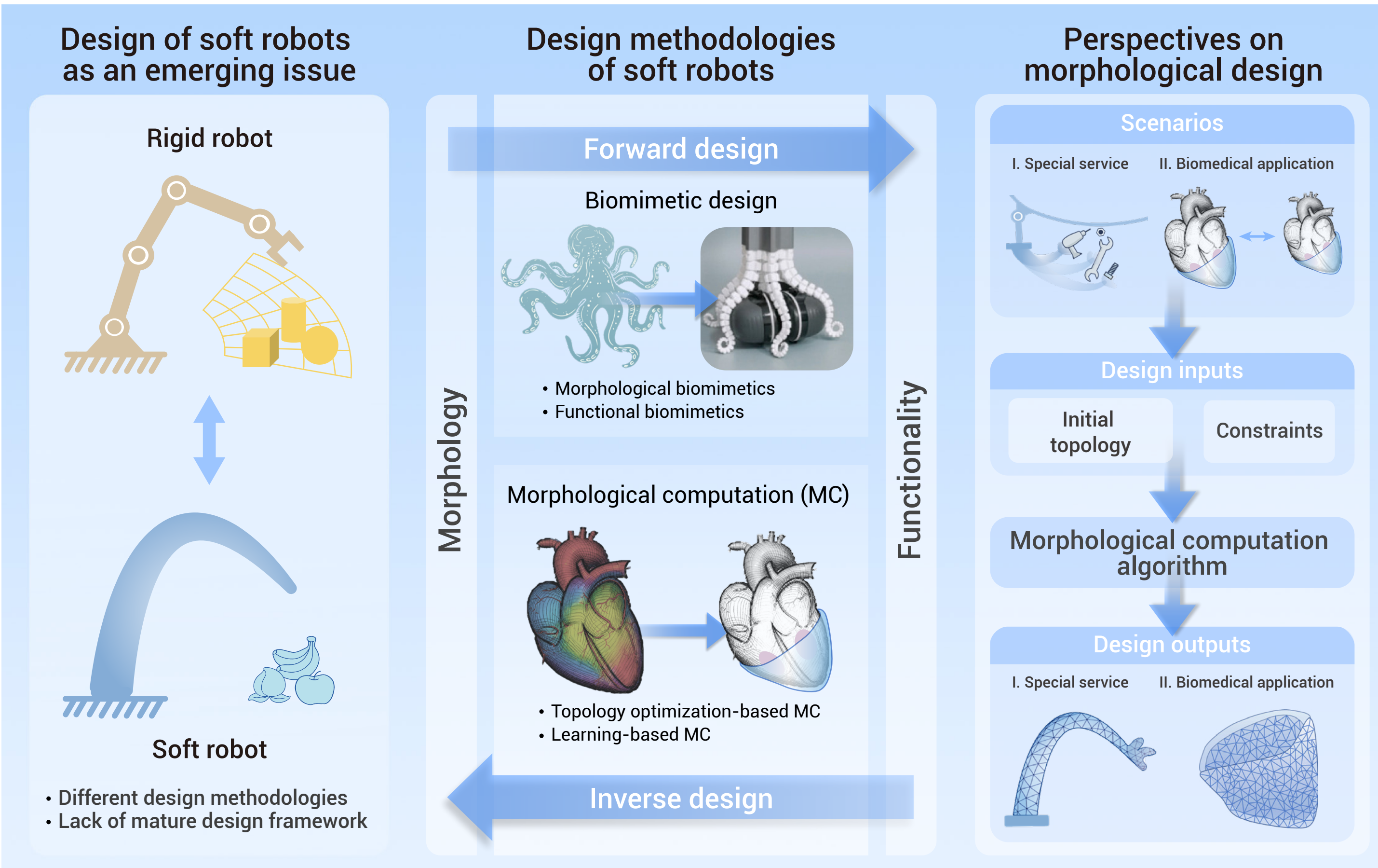
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Soft robot design is challenging as the materials, actuation and control patterns differ from rigid robots.
- Methodologies including forward biomimetic methods and inverse morphological computations are reviewed.
- Challenges and perspectives on morphological design of soft robots for new application scenarios are given.

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Morphological design methodologies of soft robots

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Over the past decade, robots have gradually extended from rigid robots to soft robots regarding the morphology. Because of their good environmental adaptability, dexterous flexibility, and functional characteristics, soft robots have shown good potentials in application scenarios such as special services and biomedical applications. Traditional design methodologies for rigid robots, which typically proceed from functional requirements to mechanism and joints and then to sensing and actuations, are difficult to apply directly to soft robots because of the different materials, morphologies, actuations and control patterns. In contrast, the morphological design of soft robots must consider the properties of soft materials, the continuum-level infinite degrees of freedom, actuation and control patterns, which make the morphological design of soft robots a new and challenging issue. Although studies on soft robots have been frequently reported in recent years, a mature framework of the design methods has not yet been given. Therefore, this survey aims to construct a systematic framework of morphological design methodologies of soft robots. In this survey, existing morphological design methods are divided into two categories, forward design using biomimetic methods and inverse design using morphological computation, and each category is introduced respectively with subcategories. The survey also analyzes the challenges of design of soft robots for new applications. As a perspective, a framework of morphological computation of soft robots for multi-object manipulation or time-varying object interaction is given to provides a reference for design of soft robots with growing applications in special services or biomedical scenarios.

INTRODUCTION

Since the emergence of robots in the 1950s, the field has advanced rapidly, driven by scientific progress and the rising demand for automation and intelligence. Since initially developed as rigid industrial robots for manufacturing, robots have expanded to services, healthcare, and scientific exploration, continuously broadening the functional boundaries. Within this extension, soft robots have emerged as a distinct paradigm. Compared to traditional rigid robots, soft robots have shown three key advantages—environmental adaptability, dexterous flexibility, and functional characteristics,[1] which enable them to perform better in special services and biomedical applications, such as conforming to complex curved surfaces, maneuvering through confined and tortuous environments,[2] or safely interacting with biological tissues. These capabilities grant soft robots' unique competitiveness across scenarios in unstructured environments.

The morphological design pipeline for rigid robots generally follows a mature paradigm: beginning with application scenarios including workspace and payload, proceeding to kinematic analysis based on mechanism with discrete degrees of freedom, and ultimately leading to the development of decoupled actuators and mechanism control (Figure 1). These methodologies have been extensively validated through decades of modeling, simulation, and practical implementation. By contrast, because of differences in materials, morphologies, actuations and control patterns, the morphological design paradigms of rigid robots are difficult to directly apply to soft robots. In this context, morphological design plays a fundamental role in shaping the functionality and performance of soft robots.[3] The morphological design of soft robots is typically application-driven, with subsequent choices of materials, morphologies, actuations and control. However, the morphological design of soft robots is complicated by material nonlinearity, continuum-level infinite degrees of freedom, and control patterns, making morphological design a new and challenging issue.

In recent years, although research and reviews on materials, actuation, control and applications of soft robots have been frequently reported,[4-15] a mature framework of morphological design methodologies for soft robots has not yet been given. Chen et al.[7] provided an in-depth discussion of robotic design optimization in terms of architecture, modeling, implementation, and future trends, with particular emphasis on optimization. Pinskier et al.[16] proposed a valuable taxonomy of design approaches—ranging from bioinspired to computer-generated methods—organized according to levels of automation, thereby highlighting the role of automation in shaping design strategies. In practice, realizing target functionalities often calls for methodologies explicitly tailored to application-driven requirements. In contrast to these prior surveys, the present survey focuses explicitly on morphological design methodologies from the perspective of application-driven requirements. Building upon existing approaches, we examine the state of the art, identify open challenges, and discuss opportunities for advancing morphological computation. Through this survey, we aim to summarize and survey existing methods, then establish the logic and framework of morphological design methodologies on this basis, and eventually provide a reference for morphological design requirements.

The remainder of this paper is organized as follows. The second section introduces the overall design framework. The third section reviews the forward design using biomimetic methods including morphological biomimetics and functional biomimetics. The fourth section reviews the inverse design using morphological computation including topology optimization and learning-based methods. The fifth section outlines existing challenges and perspectives, and the sixth section concludes the survey.

OVERVIEW OF MORPHOLOGICAL DESIGN METHODOLOGIES

The design methodologies for soft robots can be broadly categorized into forward design and inverse design. Forward design begins with a known morphology and explores its potential functions, whereas inverse design starts from a desired function and seeks the morphology required to achieve it. The conceptual distinction between these two paradigms is illustrated in Figure 2,[17] which provides the foundation for subsequent discussions. Building upon this conceptual basis, Figure 3 presents the overall framework of design approaches considered in this survey, offering a schematic guide to the analyses that follow. To complement this framework, Table 1 summarizes representative studies across both categories, serving as a point of reference for the more detailed examination in the subsequent sections.

Forward methodology

Forward design can be interpreted as an approach in which morphology is examined to explore potential functionality. This approach is most frequently realized through biomimetic design, where designers draw inspiration from the biological appearance and functionality of creatures. These natural models serve as valuable references for robotic design.

In this process, the initial morphological parameters are used as input, and the output is robotic performance, while robotic performance—mechanical and kinematic properties—constitutes the output. The workflow typically proceeds in three stages: (i) proposing an initial morphology inspired by biological systems, (ii) evaluating its properties through theoretical analysis or simulation, and (iii) experimentally verifying whether the morphology satisfies functional requirements. If the morphology can perform the intended movement and operation, then the design process is complete. Otherwise, further modifications of soft robots are required. There are many representative examples of specific biomimetic methods in the morphological design of soft robots. Further details will be discussed in the third section of "Forward

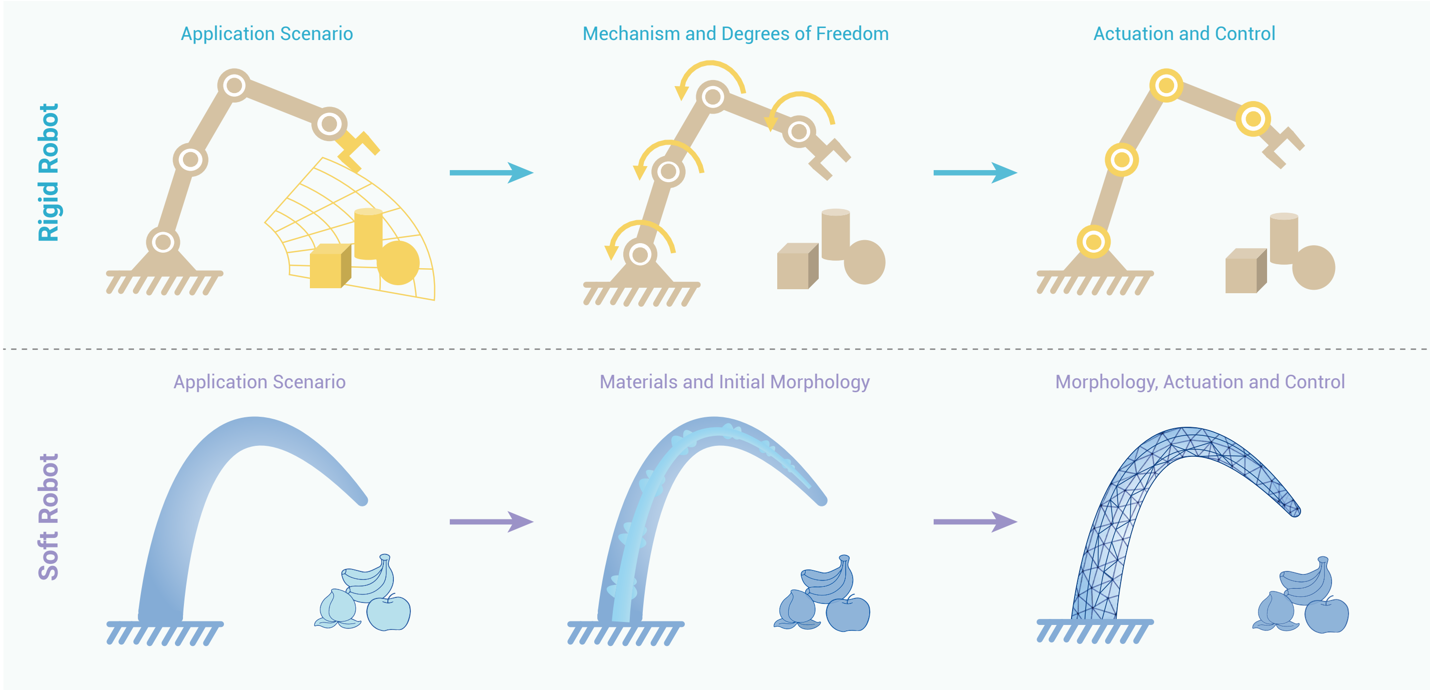

Figure 1. Comparison of design fundamentals of rigid robot and soft robot.

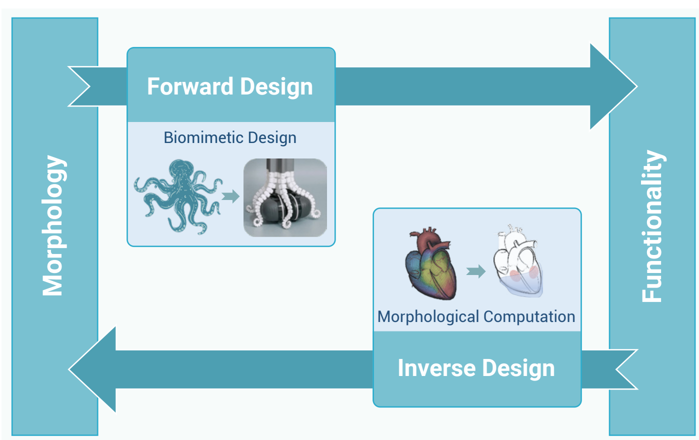

Figure 2. Conceptual illustration of forward design and inverse design of soft robots.

Design: Biomimetic Methods".

Inverse methodology

In contrast to forward design, inverse design aims to determine a robot's morphology from a specified functionality. However, finding a direct analytical solution for this "function-to-form" problem is highly challenging due to the complexities of modeling soft bodies and the substantial computational cost involved.

To address this challenge, modern approaches reformulate the inverse design problem into tractable tasks for mathematical optimization or data-driven models. This paradigm is primarily realized through two powerful methodologies: topology optimization approaches and learning-based approaches. Topology optimization frames morphological design as a material distribution problem, whereas learning-based design treats it as an interpolation task within a data-driven model. Together, these computational strategies represent the state of the art in inverse design for soft robotics. The process begins with both the initial morphological parameters and target functionality as inputs. Morphological parameters are typically derived from an initial guess or inferred from training data, while the optimized morphology is obtained by minimizing the discrepancy between predicted and desired performance. There are many representative examples of specific topology optimization and learning-based methods in the morphological design of soft robots. More details are provided in the fourth section of "Inverse Design: Morphological Computation".

FORWARD DESIGN: BIOMIMETIC METHODS

In nature, diverse organisms have evolved characteristic morphologies and functions to adapt to different physical environments. Designing soft robots that replicate these environment-specific traits is termed biomimetic design. The final morphology is typically refined through theoretical analysis, simulation, and experimental validation, often requiring multiple iterations.[18] In this section, we survey biomimetic design from two perspectives: design driven by biological morphologies, which includes underwater morphological design, ground morphological design, and aerial morphological design; and design driven by biological functions, which includes grasping and manipulation, locomotion and gaits, and circulation and muscular actuation.

Morphological biomimetics

In this category, morphological biomimetic design is distinguished according to the physical media with which organisms interact, as the surrounding medium shapes the structural features required for survival and locomotion. By abstracting these environment-dependent morphologies, researchers have developed soft robots capable of operating in underwater, ground, and aerial settings. Selected cases of morphological biomimicry across underwater, ground, and aerial contexts are illustrated in Figure 4.

Underwater morphological design. In the underwater domain, soft robots can be broadly divided into exploration and monitoring, operation and resource acquisition, and interaction and assistance. Exploration and monitoring robots are typically inspired by efficient swimmers such as fish, jellyfish, or scallops, and aim to achieve stable locomotion, endurance, and sensing in complex environments. Li et al.[19] developed a self-powered, snailfish-inspired soft robot that successfully operated at 10,900 m in the Mariana Trench, demonstrating the feasibility of untethered systems under extreme pressures (Figure 4A). Katzschmann et al.[20] reported an acoustically controlled robotic fish capable of free swimming and ecological exploration, enabling minimally invasive observation of marine life (Figure 4B). Similarly, Robertson et al.[30] introduced RoboScallop, a bivalve-inspired robot that propels itself by rapid shell opening and closing, offering an alternative locomotion strategy for ecological monitoring.

Operation and resource soft robots often draw inspiration from cephalopod tentacles to enable flexible grasping and gentle manipulation for underwater

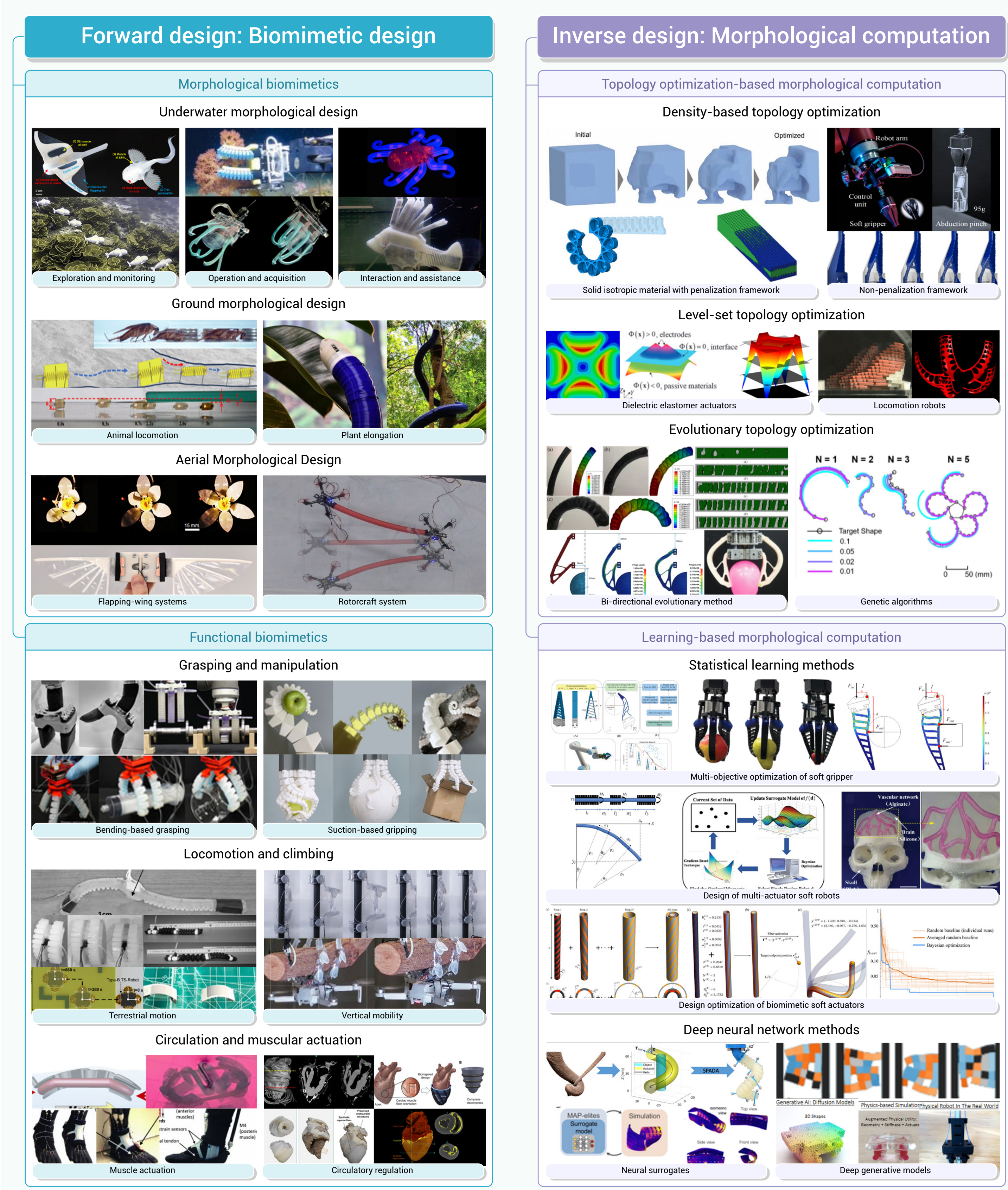

Figure 3. Overall framework of design methodologies of soft robots.

tasks. Driven by the need for minimally invasive interaction with fragile marine organisms, researchers have developed soft grippers for non-destructive sampling. Galloway et al.[21] demonstrated the first application of soft grippers in deep-reef environments, successfully collecting delicate corals without damage (Figure 4C), while Burgess et al.[22] developed nanofiber-reinforced ultragentle actuators capable of manipulating gelatinous species such as jellyfish with minimal contact pressure (Figure 4D). These studies highlight the advantages of soft grippers in ecologically responsible sampling

Table 1. Summary of existing morphological design methodologies of soft robots.

Methodologies			Applications	References	
Categories	Subcategories				
Biomimetic Design	Morphological Biomimetics	Underwater Morphological Design	Soft robot in the mariana trench	2021, Nature	19
			Acoustically controlled soft robotic fish	2018, Sci. Robot.	20
			Bivalve inspired swimming robot	2019, IEEE Robot. Autom. Lett.	30
			Grippers for biological sampling on deep reefs	2016, Soft Robot.	21
			Ultragentle manipulation of marine organisms	2019, Sci. Robot.	22
			Octopus-inspired autonomous robot	2016, Nature	23
			Energy-dense circulatory systems for soft robots	2019, Nature	24
		Ground Morphological Design	Active-morphing insect robots	2025, Nat. Commun.	25
			Plant-inspired growth-like climbing robot	2024, Sci. Robot.	26
		Aerial Morphological Design	Butterfly robot with MXene artificial muscles	2019, Sci. Robot.	27
			Soft actuators for flapping flight	2022, Sci. Robot.	28
			Soft-deformable multirotor robot	2025, ICRA	29
	Functional Biomimetics	Grasping and Manipulation	Elephant trunk manipulator	2006, ICRA	43
			Logarithmic spiral-shaped robots	2025, Device	17
			Fabric-based soft fixture	2019, Sci. Robot.	31
			Fast-response, stiffness-tunable soft actuator	2019, Adv. Funct. Mater.	32
			Soft robots with hierarchical suction intelligence	2025, Sci. Robot.	33
		Locomotion and Climbing	Caterpillar-inspired multimodal soft locomotion	2012, BioRob	44
			Inchworm-like pneumatic robot	2018, Soft Robot.	34
			A 3D-printed soft robot	2019, Soft Robot.	35
			Soft robots for exploration of narrow spaces	2024, Nat. Commun.	36
			Light-driven amphibious mini soft robot	2024, Adv. Intell. Syst.	37
			Soft robots with various movements	2024, Sci. Robot.	38
		Circulation and Muscular Actuation	Skeletal muscle–based swimmer	2021, Sci. Robot.	39
			Pneumatic artificial muscles for wearables	2014, Bioinspir. Biomim.	40
			Soft robotic sleeve supports heart function	2017, Sci. Transl. Med.	41
			An organosynthetic dynamic heart model	2020, Sci. Robot.	42
Morphological Computation	Topology Optimization-based Morphological Computation	Density-based Topology Optimization	Topology optimization for locomotive soft robots	2024, Sci. Adv.	59
			Thermal–sintering modelling of filament fusion	2020, Mater. Des.	74
			Voxel-based digital material design	2021, Mater. Des.	75
			Topology-optimized multimaterial pinch gripper	2025, IEEE-ASME TMECH	60
			Topology-optimized cable-driven soft gripper	2020, Struct. Multidiscip. Optim.	47
			Pressure-driven soft actuators	2020, Struct. Multidiscip. Optim.	46
			Nonlinear topology optimization for soft robots	2020, RoboSoft	61
			Multimaterial bioprinted actuators optimization	2020, Int. J. Bioprinting	48
		Level-set Topology Optimization	Multimaterial compliant structures	2009, Proceedings of GECCO	76
			Freeform soft robots for forward locomotion	2012, IEEE Trans. Robot.	62
			Bioprinting for soft actuator design	2019, Smart Mater. Struct.	78
			Automatic design of elastomer actuators	2019, IEEE Trans. Robot.	63
			Graded lattice topology optimization	2018, Mater. Des.	65
			Electrodes in dielectric elastomer actuators	2023, Soft Robot.	64
			Design of ferromagnetic soft active structures	2020, ICRA	49
Morphological Computation	Topology Optimization-based Morphological Computation	Evolutionary Topology Optimization	Soft pneumatic bending actuators	2019, IEEE-ASME TMECH	66
			Dielectric elastomer soft actuators	2021, Proc. Natl. Acad. Sci.	79
			Motor-driven compliant gripper design	2018, Soft Robot.	53
			Optimized pneumatic soft finger	2020, IEEE Robot. Autom. Mag.	80
			Design of bellow soft pneumatic actuators	2023, RoboSoft	67
	Learning-based Morphological Computation	Statistical Learning Methods	Multi-objective optimization of soft gripper	2024, Soft Robot.	96
			Bi-level design of multi-actuator soft catheters	2021, IEEE TMRB	97
			Bayesian optimization of fiber-based actuators	2023, Com. Meth. Appl. Mech.	98
		Deep Neural Network Methods	Design of soft pneumatic actuators	2024, Robot. Rep.	99
			Data-driven design of magnetic soft materials	2025, Nat. Commun.	100
			MorphVAE for conditioned body generation	2024, Proc. AAAI	101
			Diffusebot for morphology–control co-design	2023, NeurIPS	102

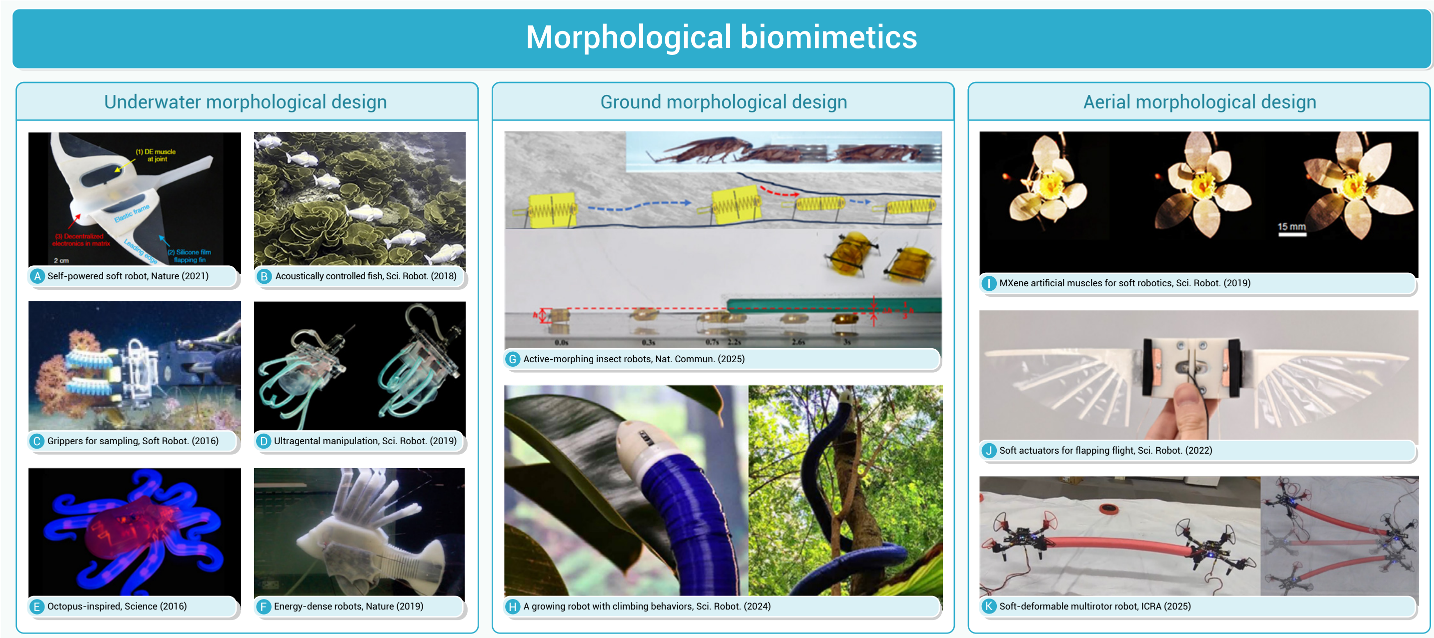

Figure 4. Morphological biomimetics for soft robot design (A) Soft robot in the mariana trench.[19] (B) Acoustically controlled soft robotic fish.[20] (C) Grippers for biological sampling on deep reefs.[21] (D) Ultragentle manipulation of fragile marine organisms.[22] (E) Octopus-inspired autonomous robot.[23] (F) Energy-dense circulatory systems for soft robots.[24] (G) Active-morphing insect robots.[25] (H) A growing soft robot with climbing behaviors.[26] (I) MXene artificial muscles for soft robot.[27] (J) Soft actuators for flapping flight.[28] (K) Soft-deformable multirotor robot.[29]

and biodiversity assessment.

Interaction and assistance soft robots, by contrast, emphasize autonomy and operational endurance through integrated architectures and bio-inspired energy strategies. Wehner et al.[23] developed a fully soft, octopus-inspired autonomous robot integrating actuation, embedded microfluidic logic, and catalytic fuel decomposition for untethered locomotion (Figure 4E). Extending this approach, Aubin et al.[24] introduced a synthetic vascular system combining hydraulic force transmission, actuation, and energy storage, enabling continuous operation for up to 36 hours (Figure 4F). Collectively, these advances illustrate how multifunctional and bio-inspired designs enhance the autonomy and endurance of soft robots, supporting safe and sustained deployment in aquatic environments.

Ground morphological design. Although not exhaustive, ground soft robots can be conveniently discussed in two broad categories: animal locomotion and plant elongation. In the first category, Che et al.[25] developed a cockroach soft robot capable of rapid running and body flattening to pass through sub-millimeter gaps, demonstrating high agility in confined ground environments (Figure 4G). In the second category, Dottore et al.[26] reported a plant robot that employed a growth-like elongation strategy to change its shape and climbing behavior, thereby achieving autonomous movement in unstructured terrains through tropism and adaptive extension (Figure 4H). These studies highlight animal locomotion and plant elongation as two complementary paradigms for terrestrial soft robot design.

Aerial morphological design. For convenience, aerial soft bio-bionic robots may be loosely grouped into flapping-wing systems and rotorcraft systems. Umrao et al.[27] developed "dancing butterflies" powered by ionically cross-linked MXene artificial muscles, achieving millisecond-level responses at low voltage (Figure 4I). Similarly, Jonathan et al.[28] created liquid-amplified zipping actuators for micro air vehicles, inspired by the firefly Photinus, enabling lightweight and high-frequency flapping flight (Figure 4J). These studies highlight the potential of flapping-wing mechanisms for achieving agile and responsive aerial motion. In the second category, Itahara et al.[29] presented a multirotor aerial robot, in which multiple rotors are interconnected by passive flexible elements to allow in-flight deformation (Figure 4K). By incorporating soft structural components and modeling them with the piecewise constant strain approach, the system achieved both stable flight and dynamic bending, overcoming limitations of conventional rigid multirotor platforms. This work demonstrates how rotorcraft systems can leverage structural flexibility to enhance adaptability and expand functional capabilities in aerial soft robots.

Functional biomimetics

Functional biomimicry shifts the design focus from external form to underlying principles of action, seeking to reproduce the essential capabilities of biological systems. Even when the robot's outward appearance differs greatly from that of natural organisms, these designs capture the mechanisms that enable unique movements and functions. Selected examples of functional biomimetics in grasping and manipulation, locomotion and climbing, and circulation and muscular actuation are illustrated in Figure 5.

Grasping and manipulation. Although simplified, grasping and manipulation in soft robots can be conveniently described into two categories: bending-based grasping and suction-based gripping. In the first category, bending-based grasping, researchers have drawn inspiration from the continuum deformations of elephant trunks, octopus arms, and even human fingers to achieve compliant gripping. Walker et al.[43] developed a multi-section manipulator by analyzing the geometric deformation of an elephant's trunk, later demonstrating complex grasping tasks on a mobile platform with the system, while the more recent SpiRobs system[17] imitated logarithmic spiral morphologies observed in appendages such as octopus' arms and elephant trunks, allowing scalable and low-cost fabrication with adaptive grasping of objects of various sizes (Figure 5A). Extending this line, Fei et al.[31] proposed a fabric-based soft fixture with tunable stiffness driven by positive pressure, composed of two planar fingers and a cylindrical wrist. In the second category, suction-based gripping, efforts have focused on discrete gripping units with stiffness modulation and adhesive capabilities (Figure 5B). Zhang et al.[32] introduced fast-response, stiffness-tunable actuators fabricated through hybrid multi-material 3D printing, enabling adaptive and robust gripping of objects (Figure 5C). In parallel, Rossiter et al.[33] integrated fluidic circuits with suction cups to mimic the hierarchical neuromuscular control of octopus suckers, thereby combining grasping with tactile sensing and enhancing multifunctionality in soft robotic grippers (Figure 5D).

Locomotion and climbing. Locomotion and climbing adaptation in soft robots are introduced here through two broad aspects: terrestrial and vertical mobility. In the first category, terrestrial mobility, researchers have developed diverse gaits inspired by caterpillars and inchworms to enable adaptive ground movement. Trimmer et al.[44] presented a caterpillar-inspired robot with six distinct gaits, demonstrating the potential of gait diversity for environmental adaptability. Wu et al.[34] designed a pneumatic soft robot inspired by inchworm crawling, consisting of dual-column actuators, feet, and sensors to enable forward movement and turning through differential actuation timing

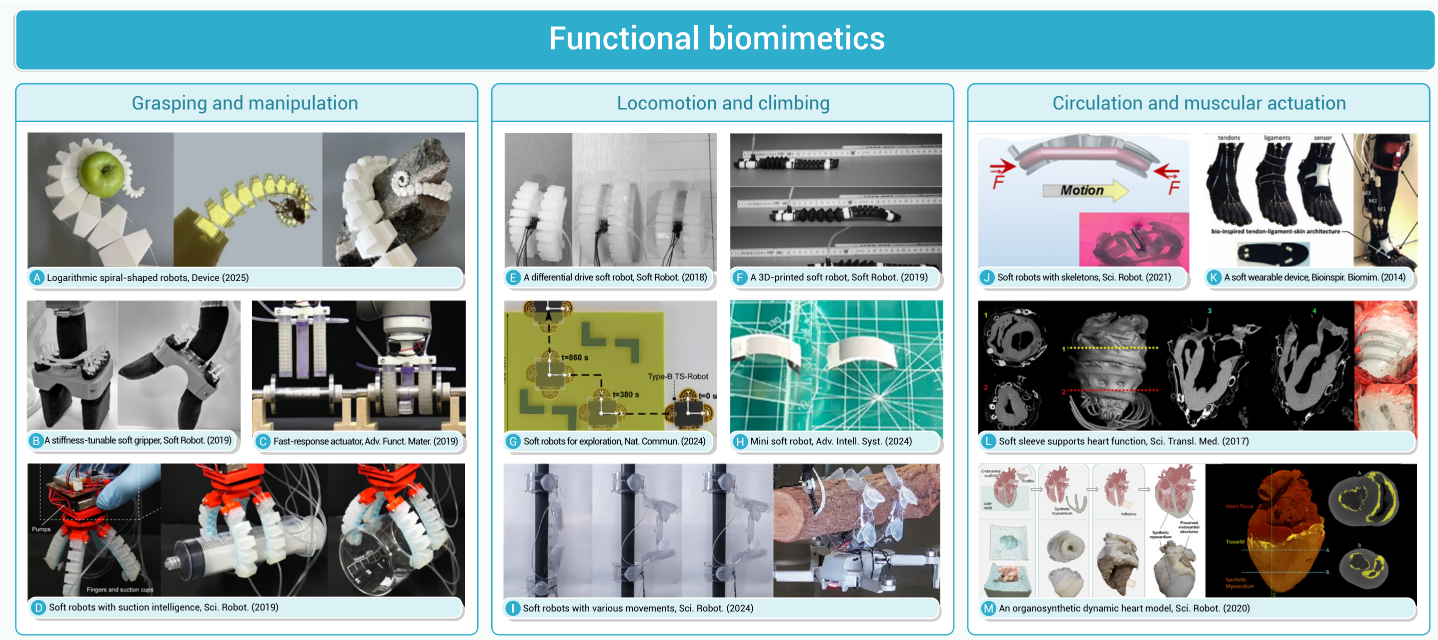

Figure 5. Functional biomimetics for soft robot design (A) Logarithmic spiral-shaped robots.[17] (B) A stiffness-tunable soft gripper.[31] (C) Fast-response, stiffness-tunable soft actuator.[32] (D) Soft robots with hierarchical suction intelligence.[33] (E) A differential drive soft robot.[34] (F) A 3D-printed soft robot.[35] (G) Soft robots for exploration of narrow spaces.[36] (H) Light-driven amphibious mini soft robot.[37] (I) Soft robots with various movements.[38] (J) Soft robots with self-stimulating skeletons.[39] (K) A bio-inspired soft wearable robotic device.[40] (L) Soft robotic sleeve supports heart function.[41] (M) An organosynthetic dynamic heart model.[42]

(Figure 5E). Pasquier et al.[35] introduced a modular pneumatic toolkit for assembling locomotion units, including a crawling caterpillar robot actuated by alternating inflation and deflation (Figure 5F). Building on these concepts, Wang et al.[36] developed ultrathin soft robots that are capable of multimodal terrestrial locomotion in confined spaces, employing dual-actuation dielectric elastomer structures to achieve both linear and undulating gaits (Figure 5G). Zhu et al.[37] further reported a light-driven mini soft robot that fused inchworm-like crawling with rapid gait switching, enhancing adaptability to varied ground conditions (Figure 5H). In the second category, vertical mobility, efforts have focused on extending locomotion capabilities into climbing and multi-terrain transitions. Ching et al.[38] demonstrated the FiBa platform, a versatile system capable of crawling, climbing, perching, and even flight by switching between animal-inspired gaits (Figure 5I). This illustrates how vertical mobility complements terrestrial motion, allowing soft robots to navigate complex three-dimensional environments with enhanced adaptability.

Circulation and muscular actuation. Biological muscular and circulatory systems provide powerful inspiration for soft robotic design, which is broadly introduced through muscle actuation and circulatory regulation. In the first category, muscle actuation, artificial muscles replicate the contractile efficiency of animal muscle tissue. A striking example is a skeletal muscle–based swimming robot that used a 3D-printed serpentine spring skeleton to support cell maturation and self-stimulation (Figure 5J).[39] On the wearable side, Park et al.[40] developed pneumatic artificial muscle actuators to power ankle–foot and lower-leg devices for human assistance (Figure 5K). These studies highlight how muscle-inspired actuation enables both autonomous locomotion and human-assistive functions. In the second category, circulatory regulation, physiological functions of the heart have inspired the development of robotic pumping systems. A Harvard team built a soft robotic heart pump (Figure 5L),[41] while another group led by Park et al.[42] created a cardiac-motion-mimicking robot comprising a skeleton, membrane, and shells (Figure 5M). These examples demonstrate how circulation-inspired designs can be translated into robotic systems to reproduce rhythmic pumping and support physiological assistance. Collectively, these studies show that principles of muscle actuation and circulatory regulation can be directly integrated into soft robotic systems to achieve lifelike motion and biomedical functionality.

Taken together, the third section has reviewed biomimetic design in soft robots from two complementary perspectives: morphological biomimetics, covering underwater, ground, and aerial morphological designs, and functional biomimetics, including grasping and manipulation, locomotion and gaits, and circulation and muscular actuation. These approaches demonstrate the remarkable potential of biological inspiration in enabling soft robots to achieve adaptability, versatility, and lifelike performance. At the same time, they reveal inherent limitations: designs are often constrained to simplified morphologies, performance is difficult to predict prior to prototyping, and trial-and-error remains a central part of the development process. These challenges underline the need for strategies beyond direct imitation, motivating the discussion of morphological computation in the next section.

INVERSE DESIGN: MORPHOLOGICAL COMPUTATION

Forward biomimetic approaches are widely used in soft robot design but often rely on researchers' experience and intuition. By contrast, morphological computation seeks the morphology that realizes a specified function, without relying on an assumed initial morphology or expert heuristics, expanding the design space for soft robot and enabling more innovative morphology. Note that, in soft robots, and specifically in this design methodologies review, the term of morphological computation refers to design process of morphology for soft robots using computational methods, different from connotations of morphological computation in biomechanics or cognitive science. Morphological computation can be used as a powerful tool for inverse design. Topology optimization-based morphological computation methods and learning-based morphological computation methods are reviewed in this section.

Topology optimization-based morphological computation

To model and design soft robots within a theoretical framework, the design problem is often cast as a topology optimization problem of continuum compliant mechanisms.[45] The workflow typically begins with an initial design and iteratively evaluates performance and updates the design variables until the convergence criteria are satisfied. Within this paradigm, diverse soft robots have been realized, such as soft pneumatic actuators,[46] cable-driven fingers,[47] electrolyte-driven soft robots,[48] ferromagnetic soft systems,[49] and dielectric elastomer soft actuators.[50]

Topology optimization can be regarded as a mathematical formulation to design soft robots. In general, the problem can be formulated as an optimization problem:

$$\begin{aligned} &\underset{x}{\operatorname{argmin}}\, J(x), \\ s.t.\quad &G(x) \le 0, \\ &H(x) = 0, \end{aligned} \tag{1}$$

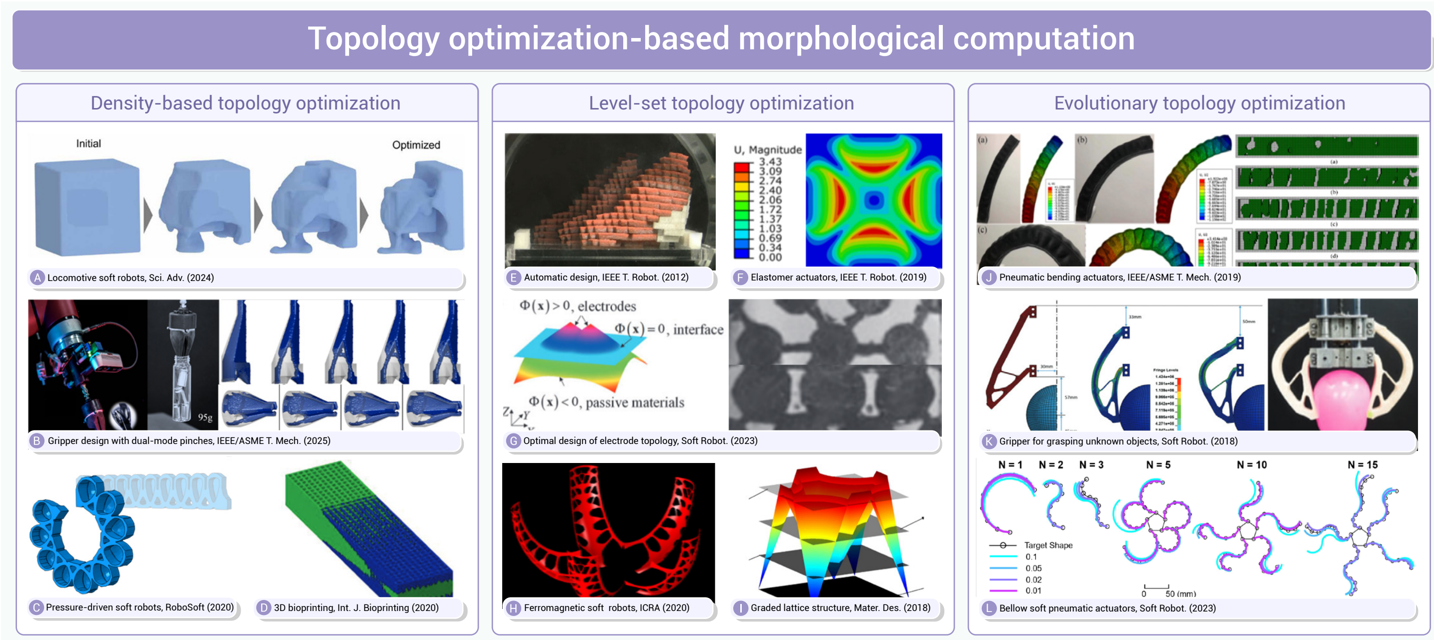

Figure 6. Topology optimization-based morphological computation for soft robot design (A) Computational synthesis of locomotive soft robots.[59] (B) Topology-optimized multimaterial pinch gripper.[60] (C) Polygonal mesh and nonlinear FE for soft materials.[61] (D) Multimaterial topology optimization-enhanced 3D bioprinted soft actuator.[48] (E) Automatic design of soft robots.[62] (F) Soft dielectric elastomer actuators.[63] (G) Topology optimization of electrodes in dielectric elastomer actuators.[64] (H) Design of ferromagnetic soft active structures.[49] (I) Graded lattice topology optimization.[65] (J) Pneumatic bending actuators.[66] (K) Motor-driven compliant gripper design.[53] (L) Design optimization for bellow soft pneumatic actuators.[67]

where, x denotes the design variables, $J(x)$ denotes the objective function, $G(x)$ and $H(x)$ denote the inequality and equality constraints, respectively, that the design must satisfy. In topology optimization for soft robots, the parameterization of the design variables depends on the method: density-based approaches use an element- or voxel-level pseudo-density that takes values between zero and one; level-set approaches use a scalar field whose zero level-set defines the boundary, with positive values interpreted as solid and negative values as void; evolutionary approaches use element-level binary variables indicating whether material is kept or removed.[51-53] Common objectives include maximizing stiffness, achieving target deformations, and minimizing strain energy. Typical inequality constraints impose bounds on mass or volume fraction, stress, and displacements, whereas equality constraints usually encode governing equations such as force equilibrium and structural vibration.

Topology optimization addresses the fundamental engineering question of how to distribute material within a prescribed design domain to achieve task-specific morphological performance.[54] By now, it is developing into several methodological families[55,54] including "density-based",[56] "level-set",[57] "evolutionary",[58] and several others, all of which have been applied in the field of soft robots. Figure 6 illustrates representative results for these three principal approaches.

Density-based topology optimization. Density-based topology optimization represents a structure as a continuous elementwise density field and updates the design with a gradient based scheme driven by adjoint sensitivities.[68] Traditionally, material properties are interpolated using schemes, most commonly the solid isotropic material with penalization and the rational approximation of material properties,[69–71] often with penalization to discourage intermediate gray densities and to approach a solid and void layout. Minimum manufacturable feature sizes are typically enforced through filtering or projection, which can also mitigate checkerboard artifacts.

Methods based on the solid isotropic material with penalization framework have been widely applied, including compliant grippers and porous structures.[72,73] Notably, several recent studies have coupled solid isotropic material with penalization-based design methods with differentiable multiphysics simulations, thereby enabling more efficient soft-structure synthesis. For example, Kobayashi et al.[59] proposed a methodology for pneumatically actuated soft robots that integrates gradient-based topology optimization with a multi-physics material point method simulation, yielding locomotive soft robots under coupled physics (Figure 6A).

Density-based formulations that do not rely on explicit penalization have been proposed with the advancement of multimaterial additive manufacturing.[74,75] For example, Chen et al.[60] applied a multimaterial topology optimization framework to design a soft gripper whose internal architecture comprises two materials, fabricated via a customized voxel level 3D printing strategy that controls the local mixing ratio of soft and hard inks (Figure 6B).

Objective and the constraints specification is the key to density-based framework. Beyond single objective, multiple objectives can be handled through different weights. Wang et al.[47] developed a cable-driven soft robotic gripper with multi-input and multi-output using topology optimization considering geometric non-linearity, which not only performs adaptive grasping but also enables finer manipulations such as rotating or panning the target. However, the effectiveness of these weight-summation methods often relies on carefully selected tuning parameters, which may constrain robustness and practical applicability. For constraints, design-dependent load constraints are a common challenge of topology optimization. Souza and Silva used mixed displacement-pressure finite elements to solve it.[46] And for validation, they designed soft actuators driven by pressure loads. Three numerical examples were explored to evaluate the effectiveness of the formulation: a bending, a linear, and an inverter actuator. The numerical results demonstrated that the proposed projection technique was effective in producing optimized closed designs for the studied cases. Similarly, Caasenbrood et al.[61] introduced facial connectivity in polygonal meshes and explored nonlinear finite element formulations to address the challenges of adaptive topology and the hyperelastic nature of soft materials (Figure 6C). And a pressure-driven soft robot was tested. To impose multi-materials as constraints, Zolfagharian et al.[48] enforced the volume fraction constraint applied using two different materials for each layer (Figure 6D). And they fabricated and analyzed the design of the electrolyte driven, multi-material soft actuator as a practical application.

Level-set topology optimization. Level-set topology optimization represents geometry by an implicit scalar field, where the zero-level contour defines the boundary. By updating the field values the boundary is advanced according to shape sensitivities, and perimeter or curvature regularization promotes crisp, binary geometries suitable for computer-aided design reconstruction.

In the classical level-set method, the evolution of the level-set function is governed by the Hamilton–Jacobi equation, which makes it difficult to nucleate new holes during shape optimization. To address this limitation, parametric or parameterized level-set formulations represent the level-set function as a linear combination of basis expansions and parametric representations, such as radial basis function, discrete wavelet transform, discrete cosine transform,[76] compositional pattern producing network,[77] Gaussian mixture and Bezier curve (Figure 6E).[62,78]

In the design of soft dielectric elastomer actuators, due to the level-set method representing geometry as a smooth and sharp interface that can move and change topology on a fixed mesh, allowing direct optimization with consistent design dependent voltage boundary conditions and accurate control of electric field concentration and Maxwell stress (Figures 6F & I).[63,65] For example, Zhang et al.[64] employed a parameterized level-set formulation coupled with nonlinear electromechanical finite elements based on the absolute nodal coordinate formulation to optimize dielectric elastomers actuations electrode topology by directly evolving the sharp electrode and dielectric interface under design dependent voltage conditions, thereby enabling precise control of electric field concentration and Maxwell stress (Figure 6G).

Level-set methods have been widely used in locomotion robots. Hiller and Lipson presented the automated design and manufacture of static and locomotion robots in which functionality is obtained purely by the unconstrained 3-D distribution of materials.[62] Also, the actuation source can be ferromagnetic. Tian et al.[49] used the level-set-based topology optimization method to design ferromagnetic soft robots, with three examples, including a gripper, an actuator, and a flytrap structure, which validate the effectiveness of the proposed framework (Figure 6H).

Evolutionary topology optimization. Evolutionary topology optimization is a discrete, heuristic design framework in which a structure is represented by a finite set of discrete variables, typically binary element occupancy at the element level, either solid or void. Representative methods include genetic algorithms, evolutionary morphological optimization, and bi-directional evolutionary morphological optimization. Researchers have demonstrated applications of evolutionary algorithms in the design of soft locomotion robots,[66] magnetic soft continuum robots,[79] and soft robotic grippers for unknown objects (Figure 6K).[53]

Genetic algorithms are population-based, derivative-free optimization methods inspired by the principles of natural selection. Successive generations arise from selection, crossover, and mutation, with elitism often incorporated to preserve the best-performing individuals. In soft robot design, genetic algorithms typically serve as global search strategies for navigating expensive, black-box morphological and geometric spaces. They have been applied in diverse ways: Pagoli et al.[80] employed them as non-dominated sorting genetic algorithm II–based Pareto optimizers on finite-element–evaluated variables; Yao et al.[67] utilized them as surrogate-assisted explorers operating on trained neural-network surrogates for high-dimensional shape matching (Figure 6L); and Mannam et al.[81] applied them as morphology search engines coupled with policy transfer for design-control co-optimization.

Another important branch of evolutionary methods is the bi-directional evolutionary morphological optimization method,[82–84] developed from the evolutionary morphological optimization method.[85] This approach combines mathematical derivation with heuristic search strategies, and related studies have shown its effectiveness.[66] The bi-directional evolutionary morphological optimization method was applied to areas such as nonlinear material and large deformation,[86] energy absorption, periodic structures, multiple materials, and multiple constraints.[87–91] More recently, updated versions of the method have been employed in a wide range of morphological design problems. In the work of Chen et al.[66] addressed pneumatic design-dependent load problems by calculating element sensitivity using a rational approximation of material properties interpolation (Figure 6J). This algorithm simplifies the sensitivity calculation procedure and reduces iteration time, and the final layouts were validated through nonlinear finite element analysis simulation and experiment.

Topology optimization is a numerical design methodology that has played a pioneering role in addressing inverse morphological design problems. Through iterative optimization, robotic morphologies can evolve in response to their environments, thereby providing viable solutions for practical applications. This practical potential has motivated extensive research efforts.

Nevertheless, several challenges remain in extending topology optimization to broader applications in soft robots. Most existing studies have relied on simplified single-mode assumptions, such as maximizing bending displacement,[66] maximizing morphological stiffness,[65] maximizing energy,[53] or withstanding fluid load constraints.[92] Such linear and single-objective formulations are insufficient to capture the inherently complex physical behaviors of soft robotic systems. Future developments should consider multi-mode modeling (incorporating multiple objectives or constraints), material hyperelasticity, nonlinear and diverse behaviors, as well as the complexity of design spaces and application scenarios. Incorporating these aspects will enable the exploration of diverse motion modes in soft robots, including extension, contraction, bending, and twisting, also enable more versatile applications.[93]

Learning-based morphological computation

With rapid progress in machine learning and the emergence of fast predictive surrogates that can reduce reliance on costly finite-element and multiphysics simulations in the evaluation loop, learning-based methods are increasingly applied to the morphological design of soft robots to accelerate design-space exploration,[94] quantify performance, and guide optimization under tight computational budgets.[95] Based on the learning model employed, methods fall into statistical learning methods or deep neural network methods. Representative learning-based pipelines for the morphological design of soft robots are illustrated in Figure 7.

Statistical learning methods. Statistical learning approaches to soft-robot design construct surrogate models, commonly Gaussian process regressors, trained on a limited set of high-fidelity simulations or experiments to predict behavior and performance. These surrogates reduce reliance on repeated high-fidelity evaluations in the design loop, enabling optimization via methods such as evolutionary algorithms or Bayesian optimization with Gaussian-process models.

Many contemporary studies adopt Bayesian optimization with a Gaussian-process surrogate because Gaussian-process provide probabilistic predictions with quantified uncertainty and flexible nonparametric modeling of the design–performance map. Paired with acquisition strategies, Bayesian optimization enables uncertainty-aware active sampling and sample-efficient, globally oriented exploration for expensive black-box objectives. Representative works include the Fin-Bayes framework for Fin-Ray fingers proposed by Wang et al.[96] which trains Gaussian process surrogates on nonlinear finite element method outputs and applies multi-objective Bayesian optimization to navigate compliance–force trade-offs (Figure 7A). The bi-level design of multi-actuator soft catheters developed by Ghoreishi et al. (Figure 7B),[97] where the upper level uses a Gaussian process prior with a knowledge-gradient policy to select geometry and material parameters. And the Bayesian optimization of fiber-based biomimetic actuators presented by Kaczmarski et al. (Figure 7C),[98] coupling a Matérn-kernel Gaussian process with an expected-improvement acquisition to minimize actuation energy and outperform random search under matched evaluation budgets.

Deep neural network methods. Compared with statistical learning methods that typically rely on simpler, lower-capacity models, deep neural network approaches employ multilayer architectures to learn complex, design-relevant mappings. With large numbers of trainable parameters and greater representational capacity, they can capture input to output relationships that exceed the expressiveness of conventional statistical surrogates. In the morphological design of soft robots, deep neural networks play two distinct roles: neural surrogates and deep generative models.

As neural surrogates for evaluation or prediction, deep networks are fitted to high-fidelity simulation and experimental data, then paired with search procedures such as genetic algorithms and stochastic exploration with cost-efficient simulators to emulate expensive solvers, reduce inner-loop evaluations, and accelerate end-to-end design. For example, the soft pneumatic actuator design automation toolbox fit an artificial neural network surrogate to finite-element and kinematic datasets and queries it within a genetic algorithm to solve end-to-end shape matching for bellows-type pneumatic actuators, achieving millimeter-level accuracy while avoiding repeated inner-loop finite-element solves (Figure 7D).[99] Extending surrogate-assisted exploration to functional materials, data-driven design of shape-programmable magnetic soft materials use stochastic design variations guided by a predictive neural network together with cost-efficient simulation to co-explore morphology and magnetization, uncovering non-intuitive designs with verified simulation-

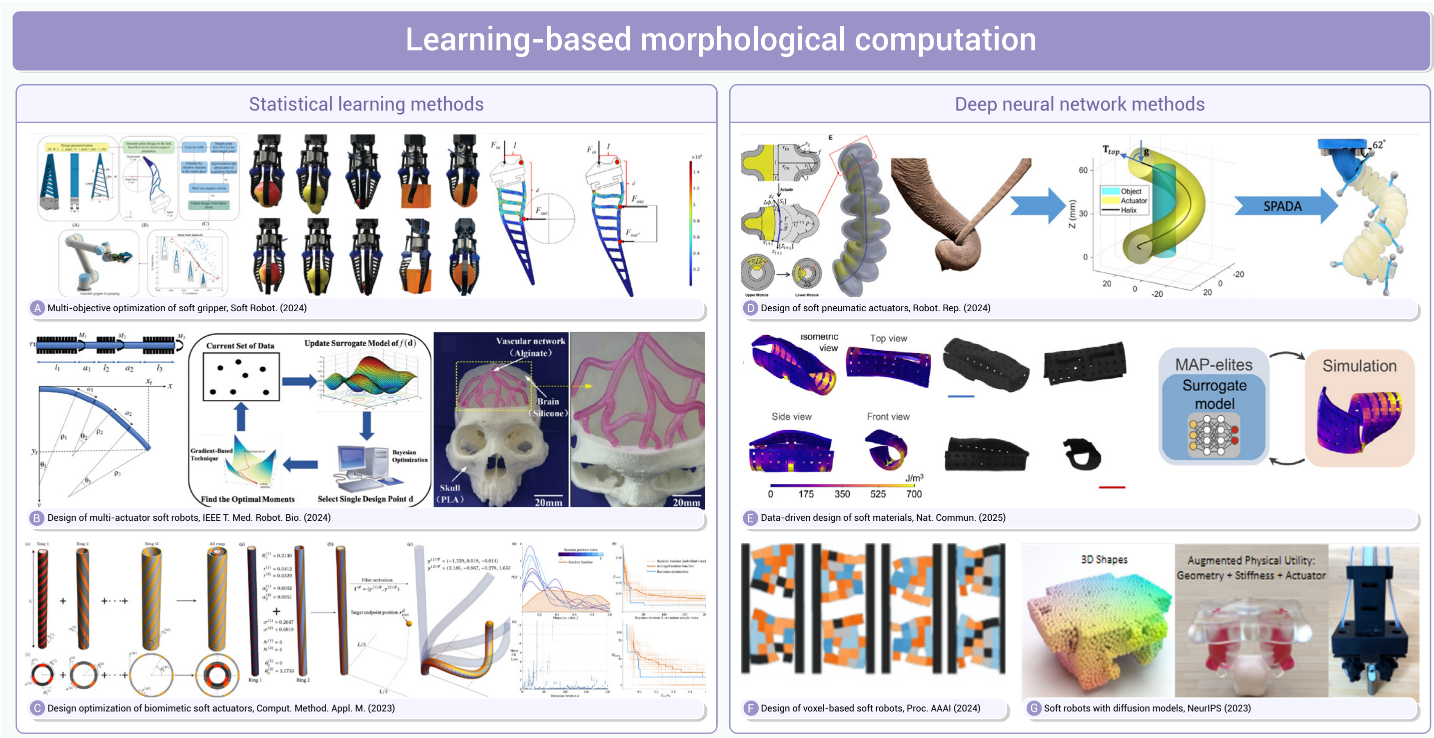

Figure 7. Learning-based morphological computation for soft robot design (A) Multi-objective optimization.[96] (B) Design of multi-actuator soft robots.[97] (C) Bayesian design optimization of biomimetic soft actuators.[98] (D) A toolbox of designing soft pneumatic actuators.[99] (E) Data-driven design of magnetic soft materials.[100] (F) Advancing morphological design of voxel-based soft robots.[101] (G) Breeding soft robots with physics-augmented generative diffusion models.[102]

to-hardware transfer (Figure 7E).[100]

As deep generative models, neural networks synthesize morphologies directly in physics-aware, differentiable loops to propose candidates, incorporate performance signals, and accelerate discovery. MorphVAE trains a task-conditioned variational autoencoder to generate voxelized robot bodies and improves sampling efficiency through continuous natural selection that reuses evaluated designs across tasks (Figure 7F).[101] DiffuseBot couples a three-dimensional diffusion generator with differentiable physics, treating sampling as co-design of morphology and control (Figure 7G).[102] The simulator provides performance certificates and gradients, enabling design that transfer from simulation to hardware.

Learning-based methods constitute a data-driven design methodology that addresses inverse morphological problems by learning predictive or generative mappings between morphology and performance. By training statistical surrogates or deep neural networks on simulation and experimental data, these approaches reduce reliance on costly evaluations and guide optimization toward high-performing designs. Their capacity to accelerate design cycles, reveal counterintuitive solutions, and transfer from simulation to hardware has motivated extensive research in soft-robot morphological design. However, learning-based methods have important limitations that warrant emphasis. Many pipelines require substantial training data to adequately cover the design space; without sufficient coverage, models generalize brittlely and exhibit poorly calibrated uncertainty. Heavy dependence on simulated data introduces a sim-to-real gap, and models may overfit to numerical artifacts or idealized physics, yielding designs that erode performance under fabrication tolerances or unmodeled contact and friction. Training large neural surrogates or generative models is computationally and energy intensive, with outcomes sensitive to hyperparameter choices, complicating reproducibility. Looking ahead, broader practical impact will hinge on data-efficient learning, physics-informed training, domain randomization, transfer learning, and calibrated uncertainty continue to narrow the sim-to-real gap and improve reliability.

Taken together, the fourth section has reviewed inverse design methods from two perspectives: topology optimization and learning-based methods. The design space of soft robots is extremely large, including materials, geometry, actuation layout. Traditional biomimetic approaches typically draw inspiration from natural forms or mechanisms and rely on experiential parameter tuning, struggle to efficiently explore such a high dimensional, strongly coupled space and often lead to simplified morphologies and repeated trial and error. By contrast, morphological computation encodes task objectives and engineering constraints directly into the objective and constraints of the optimization problem, while tightly coupling simulation-based evaluation with optimization algorithms to enable efficient search of the design space. By reducing dependence on human intuition, it often yields structures and chamber layouts that go beyond intuition and deliver superior performance. For example, morphology optimization can produce soft robot arms that realize prescribed complex spatial deformations under specified pressure inputs, with validation in simulation and experiments.[103] Overall, morphological computation holds strong promise for soft robot design, while substantial challenges remain to be overcome.

CHALLENGES AND PERSPECTIVES

So far, the basic morphological design problem of soft robots has been clearly presented. The basic morphological design problem of soft robots concerns a single static objective, such as achieving a prescribed deformation or executing interactions with a specific object. In morphological computation, we formalize this requirement as a static constraint and provide it, together with the initial topology, as input to the algorithm. Existing topology optimization-based and learning-based computational design methods are capable of providing acceptable and useful solutions to this problem.

The key feature of the basic morphological design problem above is the static constraint. However, along with the research and development of soft robotics, the applications of soft robots are rapidly extending to new application scenarios, such as special services and biomedical applications. A soft robot is expected to perform multi-object manipulation or time-varying object interaction, where the robot must handle dynamic constraints arising from variation across objects or from the timely variation of a single object through its specific morphology. Different from the basic morphological design problem, the key feature of the above scenarios is dynamic constraints. As shown in Figure 8, based on the above-mentioned new application scenarios, the morphological design needs to solve two types of new problems. (I) Morphological design of soft robots for multi-object manipulation in special service scenarios. For example, in soft-gripper design, a single morphology must handle a family of objects while meeting object-dependent deformation

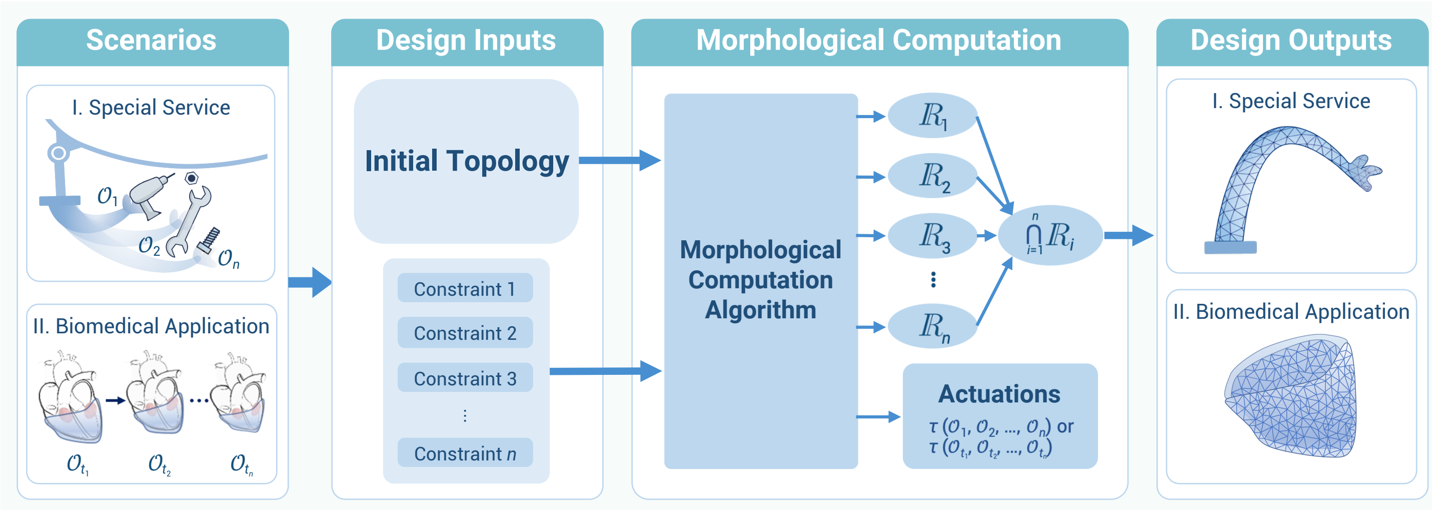

Figure 8. A preliminary morphological design of soft robots for new application scenarios for special services or biomedical applications.

targets. (II) Morphological design of soft robots for time-varying organ assistance in biomedical scenarios. For example, in cardiac sleeve design, the target set varies over the cardiac cycle: as the heart contracts and relaxes, its size, shape, and loading conditions change, and the design must remain feasible along the entire trajectory with a synthesized, time-parameterized actuation profile.

The generalized morphological design methodology for soft robots regarding the above-mentioned application scenarios can be described as follows. The algorithm takes two types of input, the initial topology instantiated from the application scenario, and a set of dynamic constraints viewed as combinations of the basic morphological design problem, indexed either by a set of switching objects, for type (I) or by the time varying form of the same object, for type (II). Each constraint corresponds to one basic problem that specifies a target behavior to be achieved. Therefore, there are two open issues to be resolved. First, characterize the solvability boundary by determining the conditions under which a morphological computation algorithm can compute a single morphology together with appropriate actuation, so that for each object or time index the robot attains the desired behavior. Second, provided the problem is solvable, design a balanced morphological computation algorithm that computes a single morphology together with either a task-specific or a time-parameterized actuation strategy, while striking an appropriate balance among computational efficiency, accuracy, robustness, and manufacturability.

Although current research has reported some progress in certain relevant scenarios, developing a systematic morphological computation framework that integrates dynamic constraints remains a significant challenge. We believe that the systematic mathematical description and a complete solution to this problem will be of substantial importance for the deployment of soft robots in special services and biomedical scenarios.

CONCLUSION

This survey has outlined the methodologies, challenges, and perspectives in soft robot design, underscoring the fundamental interplay between morphology and functionality. To clarify this relationship, we categorized the discussion into forward methodologies and inverse methodologies, encompassing both general design principles and specific methodological directions. Forward design primarily proceeds via biomimetic methods, drawing inspiration from natural organisms and refining candidates through analysis, simulation, and experimental validation. By contrast, inverse design employs computational methods to derive morphology from functional goals, producing morphologies that satisfy specified requirements. Despite their promise, such approaches remain limited by modeling accuracy and computational tractability. Recent explorations of topology optimization and learning-based methods offer tools for adapting morphologies to task-specific requirements, indicating a shift toward systematic and automated design frameworks. Looking ahead, advances will depend on strengthening the mathematical foundations of morphological computation, improving computational efficiency, and embedding inverse design into integrated, end-to-end pipelines. Ultimately, these developments are expected to enhance the functionality, adaptability, and reliability of soft robots, broadening their impact across science, industry, and society.

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AUTHOR CONTRIBUTIONS

Z. X. contributed to the conceptualization, materials organization and analysis, manuscript writing and revision, visualization, funding acquisition, supervision of the study; B. Z. and J. S. contributed to the materials collection and analysis, manuscript writing and revision, visualization; Z. H. contributed to the materials analysis, visualization and manuscript revision; Q. W. contributed to the materials analysis and manuscript revision; J. X. contributed to the conceptualization, materials analysis, manuscript revision, funding acquisition, and co-supervision of the study. All authors contributed to this manuscript, read and approved the submitted version.

DECLARATION OF INTERESTS

Zeyang Xia is an Academic Editor of The Innovation Informatics and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.

DATA AND CODE AVAILABILITY

No new data were created or analyzed in this study.