From Bioinspiration to Computer Generation: Developments in Autonomous Soft Robot Design

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The emerging field of soft robotics presents a new paradigm for robot design in which “precision through rigidity” is replaced by “cognition through compliance.” Lightweight and flexible, soft robots have vast potential to interact with fragile objects and navigate unstructured environments. Like octopuses and worms in nature, soft robots’ flexible bodies conform to hard objects and reconfigure for different tasks, delegating the burden of control from brain to body through embodied cognition. However, because of the lack of efficient modeling and simulation tools, soft robots are primarily designed by hand. Typically, hard components from rigid robots or living creatures are heuristically substituted for comparable soft ones. Autonomous design and manufacturing methodologies are urgently required to produce bespoke, high-performing robots. Currently, design methodologies exist between simple but realistic parametric optimizations, and evolutionary algorithms which simulate morphology and control coevolution. To find high-performing designs, novel high-fidelity simulators and high-throughput manufacturing and testing processes are required to explore the complex soft material, morphology and control landscape, blending simulation, and experimental data. This article reviews the state of the art in autonomous soft robotic design. Existing manual and automated designs are surveyed and future directions to automate soft robot design and manufacturing are presented.

1. Introduction

Throughout their history, robots have been characterized by their demand for high speed, precision, and repeatability. Guided by these requirements, their designs have converged toward rigid-bodied designs with discrete joints. Rigid links have the mechanical stiffness to support large loads, as required in automated assembly lines and other common applications. Discrete joints constrain motion to specified degrees of freedom (DOFs), with controllable finite-dimensional kinematics. However, the resulting hard and heavy robots require sophisticated sensing and control systems to operate outside of carefully structured environments.

The nascent field of soft robotics over-turns the paradigm of rigid robotics. Using materials with an elastic modulus in the order of kilopascals to megapascals, soft robots are designed to be lightweight and compliant. Their deformable bodies can safely interact with delicate objects, conform to the shape of unknown objects or terrain, and reconfigure to suit task requirements.[1,2] Their monolithic designs and absence of moving parts are also ideal for multimaterial additive manufacturing, simplifying their production. Combining hard, soft, elastic, and conductive materials, entire functional soft robots can now be printed including sensors and actuators.[3,4] While existing research has focused on the applications of soft grasping and soft locomotion, soft robots have the potential to revolutionize robotics operating in uncertain, confined, and fragile environments, for example, fruit picking, human assistance, or search and rescue robots.

By using materials’ functional properties to control their position and orientation (pose), soft robots embody intelligence, reducing the need for sensing and perception. Sharing control between embodied intelligence (or morphological computation) and digital computation exploits the robot’s materials and morphology to enhance task performance, enabling simple soft robots to outperform sophisticated rigid ones when undertaking delicate tasks. Compared with their simplified control, the design of soft robots is complicated by their nonlinear materials and multiphysics coupling. The resulting large deformations, hyperelasticity, and viscoelasticity produce high-dimensional design spaces, which are complex and unintuitive, even for experienced designers. Nevertheless, in the absence of accurate analytical models and efficient simulation tools, soft robot design remains a primarily manual process in which models are heuristically designed and experimentally verified.

Recently, efforts to automate their design have centered on parametric optimizations of existing soft robots. Typically, a gradient-based algorithm optimizes the geometry, materials, or actuation within specified bounds.[5] While these create
tractable optimizations, they require extensive designer input which introduces human bias to the outcome and yields only incremental improvements. More general physics simulator-based optimizations have generated unique qualitative behaviors, but lack physical replicability. Therefore, a designer is still required to interpret and postprocess results.

A gap exists between the potential for adaptable, safe, and inexpensive soft robots, and the tools required to design them. A reusable method is needed which can optimize material properties, actuation, morphology, and control for any task. To bridge this gap, novel autonomous design methodologies and accurate simulators are required to efficiently optimize the high-dimensional, nonlinear, multiphysics problems. Autonomous design completely removes humans from the process, instead using task specifications to computationally generate and assess designs.

Numerous reviews have been published in recent years, discussing the fundamental characteristics of soft robotics, including their materials, actuation, fabrication, sensing, and control. Motivated by the urgent demand for novel tools to rapidly produce bespoke soft robots, this article reviews the state of the art in autonomous soft robot design. In contrast to reviews on soft design principles and optimizations, we focus on progress toward the high-level design autonomy required to rapidly generate high-performance, realizable soft robots. By studying existing manual, parametric, and evolutionary methodologies, we evaluate limitations in current practice and barriers to the end-to-end computational generation of physically realizable soft robots. Soft materials present a revolutionary opportunity for the robotics field. Combined with recent advances in 3D and 4D printing, they create the possibility for fleets of low-cost, lightweight robots to explore unknown environments, handle delicate goods, and safely cooperate with humans. We hope this review will inspire practitioners to develop the autonomous tools required to create them.

1.1. Soft Robot Design Requirements

Robotic design is a multiphase process through which a set of high-level task objectives are mapped into a detailed design, with specified geometry, materials, actuators, sensors, and controllers. The design process applies to both soft and rigid robots and is shown in Figure 1. Through several intermediate steps, high-level objectives are translated into a final design. Objectives are first mapped onto a morphology, then a mechanical structure, and finally a detailed design. For example, an assembly robot's objective is to safely and reliably grasp an object and place it in a resting location; a mobile robot's objective could be to quickly and stably navigate unknown terrain. Both have traditionally used rigid-links, but the relative simplicity of the assembly task allows it to be performed with single manipulator and 3–7 DOFs. In contrast, legged mobile robots require multiple limbs, each with several DOFs.

Rigid robots with finite DOFs have been studied for decades, resulting in accurate analytical methods to evaluate their kinematics and dynamics, and a common set of components (actuators, joints, links) upon which most designs are based. This reduces the design process to selecting the appropriate combination of components to fulfill the mechanical requirements. As a result, automated design methods have been developed for both fixed and mobile robots and detailed design procedures exist for numerous morphologies. In soft robots, motion is infinite dimensional and no analogous set of standard

![Figure 1. Robotic design and evaluation process. High-level objectives are sequentially mapped into design features, simulated, and refined.](image-url)
components exist. Hence, converting task requirements into a morphology and detailed design requires extensive numerical and experimental evaluation.

In the absence of a standardized process, researchers have investigated several methods to expedite design exploration and optimization. To minimize designer input, entire robot morphologies have been generated through heuristic evolutionary algorithms and evaluated in soft robotic simulators. These algorithms imitate the natural process by which species evolve to find evolutionary niches suited to their survival; given enough computational resources they can find efficient and original designs. However, the simulators’ simplified mechanics cannot reliably capture the depth and breadth of real-world physics, resulting in a gap between the simulated and true performance, the so-called “reality gap.” As they evolve for fitness without considering manufacturing, optimized robots are both challenging to make and ineffectual in the real world. At the opposite extreme, manual designs draw inspiration directly from biology, identifying animals which efficiently perform the desired task and mimicking their morphology and mechanics. The success of this approach relies on finding soft materials and actuators which replicate natural characteristics. Between the two exists a range of computational techniques which partially automate the design process: computational parametric optimizations find the optimal geometry or set of components for the design within a specified range, and topology optimizations find the material distribution which maximizes fitness given a set of loads and boundary conditions. All these methods occupy a continuum of designer input, complexity, generality, and detail, as shown in Figure 2. The ongoing challenge is to develop a closed-loop method which is able to generate high-performance robots and behaviors and captures environmental interactions and manufacturing constraints.

The requirements of additive manufacturing and casting are particularly relevant, owing to their popularity in soft robots. Additive manufacturing is generally preferred as it can print complex geometries with minimal human processing, and allows multiple materials including rigid, soft, and blended materials. Common techniques include fused deposition modeling (FDM), direct ink writing (DIW), and stereolithography (SLA). FDM is simple to operate and inexpensive, but cannot produce details smaller than \( \approx 0.2 \text{mm} \) or manufacture materials softer than Shore 60A and generates anisotropic prints. In contrast, SLA can produce materials down to Shore 30A with layers of less than 20 \( \mu \text{m} \) and enables material blending. However, the soft materials degrade quickly in UV light and lack durability. DIW can print highly flexible silicones with high precision. However, only a single material can be printed, and print rates and sizes are limited by the material’s curing rate and viscosity. Silicone rubbers are well suited to soft robots because of their elasticity, flexibility, and durability. As a result, silicone casting remains popular for large and complex parts despite its laborious processing requirements.

Because current automated design methods are largely unable to incorporate these critical manufacturing details, soft robots continue to be designed manually. As this relies on human designers to identify and transfer learnings, the rate of advancement is slow. An intermediate, mixed reality, method is needed, which trains simulators to match physical reality and directly predicts high-performance designs. This would reduce the

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**Figure 2.** Overview of soft robotic design methods ranging from most to least automated (a) Voxel-based computational evolution of walking virtual soft robots. Adapted with permission. Copyright 2013, ACM. (b) Computational generation of walking and swimming virtual soft robots using cellular growth model. Adapted under the terms of the CC-BY-4.0 license. Copyright 2015, The Authors. Published by Frontiers Media S.A. (c) Multimaterial evolutionary topology optimization capable of solving multiobjective problems without sensitivity information. Adapted with permission. Copyright 2012, IEEE. (d) Sensitivity-based topology optimization of pneumatic soft fingers guided by a rigid exoskeleton. Adapted with permission. Copyright 2019, IEEE. (e) Parametric optimization of three chambered pneumatic soft robot to reduce ballooning and buckling. Adapted with permission. Copyright 2017, IEEE. (f) Chamber shape optimization of 3D-printed pneumatic actuator. Reproduced under the terms of the CC-BY-4.0 license. Copyright 2020, The Authors. Published by Wiley-VCH. (g) Geckobot, a gecko-inspired pneumatic climbing soft robot. Reproduced under the terms of the CC-BY-4.0 license. Copyright 2019, The Authors. Published by Frontiers Media S.A.
computational and experimental burdens of evaluating soft robots and the need for human intervention, enabling the high-level design autonomy needed for bespoke soft robots. The remainder of this article discusses existing soft robotic design methodologies in detail, evaluating their relative levels of autonomy, complexity, speed, and modeling accuracy.

2. Manual Design

The principle of soft robotics dates back to the 1950, when the first pneumatic actuator was designed to function as an artificial human muscle.[32] Despite its long history, the field has only proliferated in the recent years, fueled by the development of soft material 3D printing and increased computing power. However, in the absence of efficient modeling tools, prototypes are predominantly still developed manually. Using common actuators as design primitives, robots are developed to perform intuitive actions or imitate natural designs. In addition to pneumatic actuators, cable-actuation, shape-memory alloys, electroactive polymers, and jamming actuation have also gained widespread acceptance.[6,11,33] From inspiration to validation, a linear process is routinely followed, with experimental knowledge used initially and results transferred only qualitatively to new designs. However, as results are established experimentally, there is no simulation-reality gap in the finished design. The ability to produce functional, easily manufacturable designs explains the ongoing appeal of this suboptimal method.

2.1. Intuitive Manual Design

The simplest soft robots are created to perform a specific action. As the robot's objective is also its behavior, they are directly specified in engineering terms, as set of forces and displacements. Soft robotic grippers, for example, require compression of the grasped object;[33,14] jumping robots require a force exceeding the robot's weight to be exerted downward.[35–37] Actions including rotating,[38,39] climbing, crawling,[2,40–42] and stiffening,[43,44] have been demonstrated.[15] While effective for simple behaviors, the method quickly becomes infeasible as more is demanded of the robot.

2.2. Bioinspired Manual Design

As sown in Figure 3, more sophisticated robots draw inspiration from the world of biology to mimic soft animals such as worms and octopuses, and soft features such as those in fish tails and

Figure 3. Bioinspired soft robots. a) Remote operable hydraulic soft fish capable of 3D trajectory tracking. Reproduced with permission.[159] Copyright 2018, Science. b) Meshworm, a shape memory alloy (SMA) actuated soft worm robot. Reproduced with permission.[160] Copyright 2013, IEEE. c) Cockroach-inspired robot which compresses its body to fit through small crevasses. Reproduced under the terms of the CC-BY-4.0 license.[1] Copyright 2016, The Authors. Published by National Academy of Sciences.
Water striders have superhydrophobic feet to dry adhesion to climb smooth vertical surfaces and walk on the surface of water. Insects and other small animals often rely on these material properties to overcome their biomechanical limitations, increase energy efficiency, and enhance locomotive capabilities. The growing knowledge of functional materials has allowed miniature soft robots to be produced in recent years which replicate many of these natural properties. However, miniaturization of actuators and power supplies presents a barrier to untethered insect-sized robots, which instead rely on external stimuli such as light, acoustic, or magnetic energy. A summary of bioinspired soft robot designs is shown in Table 1. The list is not intended to be comprehensive, rather it demonstrates the extent of inspiration which soft roboticists have drawn from nature.

Nature has evolved animals which are capable of performing a wide range of tasks necessary for survival in different evolutionary niches. Given the size and complexity of the search space presented by nature, such animals are not likely to be optimal, even within their niche. Drawing inspiration from nature may thus simplify the design process compared with directly designing for specific actions, but the resulting robots remain suboptimal for the selected task. The underlying complexity of the design space is too great for expensive manual evaluation, which lacks the means for efficient data capture.

3. Model-Based Design Optimization

To accelerate soft robotic development, researchers have used model-based optimization methods, which automate the parameter optimization phase of robotic design. Analytical and computational models relate a robot’s behavior to geometric and other design parameters, enabling numerical optimization of the parameterized design space. For example, an analytical strain energy density function modeled the deformation (extension, contraction, bending, and twisting) of a fiber-reinforced pneumatic actuator and optimized its deformed trajectory. Meaningful analytical models reduce a high-order design space to intuitive features without significantly compromising accuracy. Their value lies in either directly enabling numerical optimizations or finding quantitative design insights for future heuristic designs, but their development relies on the designer’s ability to select and capture relevant features in the mathematical formulation. In contrast, general purpose numerical finite element analysis (FEA) can be applied to arbitrary complex systems without expert domain knowledge. By decomposing a system into discrete elements, physical interactions can be calculated elementally with large scale solvers. However, the geometric non-linearities, hyperelastic materials, and multiphysics couplings present in soft robots are both computationally expensive and frequently nonconvergent in FEA simulations. Despite its maturity as a design tool, nonlinear and multiphysics FEA requires heuristic selection of numerous simulation parameters. Finding tractable formulations is challenging, especially where contact occurs between deformable bodies. Therefore, robots are commonly modeled in isolation, with environmental interactions reduced to a set of point and surface loads. As a general-purpose design optimization tool, FEA excels at finding the detailed design parameters which maximize performance, and with appropriate modeling and parameters, simulated results closely match reality. However, accurate simulations are computationally expensive, which prevents detailed modeling of environmental interactions or the exploration large design spaces.
| Animal/Feature | Bioinspiration | Applications | Actuation/Movement principle | References |
|---------------|----------------|--------------|------------------------------|------------|
| Octopus/Cephalopod arms | Kinematics of muscular hydrostats | Soft grasping | Pneumatic artificial muscles | [161–163] |
| Octopus | Soft body | Soft mobile robots | Fluidic via a chemical reaction | [166] |
| Fish tail | High-speed maneuverability of flexible tail | Aquatic mobile robots | Electroactive polymer bending | [46] |
| Fish | Underwater navigation through tail and fin movement | Aquatic mobile robots | Pneumatic bending via synthetic vascular system | [168] |
| Gecko feet | Passive adhesion caused by directionally compliant microstructures | Climbing mobile robots | Passive adhesion | [158,169] |
| Gecko | Climbing through adhesion and gait | Climbing mobile robots | Pneumnet kinematics/active suction | [170] |
| Worm | Muscular hydrostatic locomotion through propagating waves | Complex terrain navigation | Braided mesh with radial shape memory alloy | [160] |
| Caterpillar | Ballistic caterpillar rolling dynamics | High-speed mobile locomotion in confined spaces | Longitudinal shape memory alloy | [52] |
| Snake | Climbing locomotion through coiled grasping | Tree climbing | Pneumatic | [177] |
| Turtle | Marine locomotion through flapping flippers | Aquatic locomotion | Shape memory alloy | [178] |
| Elephant trunk | Controllable compliant tubing for fluid transport | Bulk liquid transportation | Cable | [179] |
| Rays/Batoid | Swimming through undulatory flapping motion | Aquatic locomotion | Electroactive polymer bending | [181] |
| Jellyfish | Efficient wake-based propulsion | Autonomous aquatic surveillance | Shape memory alloy | [185,186] |
| Frog | Synchronous swimming gait | Aquatic locomotion | Shape memory alloy | [188] |
| Cockroach/Insect | Shape shifting soft-body and gait | Confined space crawling | Electric motor | [1] |
| Quadruped | Walking gait | Human assistance | Pneumatic actuation with cable guides | [190] |
| Starfish | Multigait locomotion | Rough terrain exploration | Shape memory alloy | [192] |

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Table 1. Continued.

| Animal/Feature | Bioinspiration       | Applications                          | Actuation/Movement principle         | References       |
|----------------|----------------------|---------------------------------------|--------------------------------------|------------------|
| Finger/Hand    | Gripping mechanics   | Dextrous grasping                     | Pneumatic bending actuator           | [48,195,196]     |
|                |                      | Human assistance/rehabilitation       | Pneumatic                            | [195,197,198]    |
|                |                      |                                       | Cable                                | [199]            |
| Human elbow    | Elastic ligament damping | Safe humanoid robots                  | Pneumatic artificial muscles        | [200]            |
|                |                      |                                       | Preneut                              | [50]             |

3.1. Parametric Optimization of Soft Actuators

Given their central role in soft robot designs, the optimization of soft actuators to increase displacement/rotation and force is of significant interest. In pneumatic bending actuators (pneunets), which produce bending by inflating a series of chambers about an inextensible membrane, parametric studies have investigated the relationship between the chamber dimensions and performance.\[59-62\] Using FEA and experimental methods, they found increasing surface area of pneumatic chambers and reducing their wall thickness increases bending.\[28,63,64\] However, chamber shape was not a significant determinant of bending as semi-circular, square, and triangular chambers all produced similar pressure-bending relationships.\[65\] Similarly, parametric optimizations of 3-DOF (Z-Tilt-Tip) pneumatic actuators have maximized bending subject to ballooning and buckling constraints.\[66,67\] Ballooning occurs in thin walled pneumatic chambers when hyperelasticity causes excessive local deformation under pressure, and can lead to bursting.

As a design optimization technique, parametric methods are inherently incremental, relying on the designer to specify variables of interest. However, fitting analytical models to the simulated data facilitates both model-based control and future design predictions. In pneumatic actuators alone, line-segment, pseudorigid body, piecewise constant curvature (PCC), Newtonian models, and rod-based models have been proposed,\[59-61,68-71\] while artificial neural networks (ANNs) have predicted the pose for closed-loop control of an optimized 3-DOF bending actuator.\[66,72\] Given their few design parameters and relevance only to a single design, the models are valuable only in predicting the performance of minor design changes. While each model shows agreement with experimental data, they lack generality, and therefore are seldom used for new design predictions.

3.2. Parametric Optimization of Soft Objects

When applied to entire soft robots, the absence of tractable environmental interaction modeling restricts parametric optimizations to cases where the objective is defined independently of the operating environment. This is directly applicable to serial arms, which are parameterized by their link geometries and characterized by their reach and payload.\[73,74\] and soft robots which do not act on the environment. Motivated by the need to physically realize animated soft characters, Skouras et al. developed a framework to automatically design cable-driven soft robots with defined deformations. Because the animated characters have a predetermined shape, it solved an actuator placement and material distribution problem. The layout of driving cables, and distribution of soft and rigid material were optimized to minimize the distance between control points and their target location.\[75\] Ma et al. presented a similar framework to design and manufacture pneumatic soft robots with desired deformations.\[76\] It resolved an initial design into pneumatic chambers with supporting rigid frames and allocates soft and stiff materials to match the desired actuated shapes while minimizing total work energy. The result is a 3D printable pneumatic object, which requires only the air inlet to be manually placed. While these are among the few examples of highly automated soft robotic design methodologies, the resulting robots are limited to deforming to target shapes and lack the locomotive, lifting or grasping capabilities required in most robotic tasks.

An alternative strategy to optimize mobile robots is to divide a robot into mechanical features and hierarchically optimizing them. This reduces the problem size and enables optimization of component specific objectives, but only heuristically relates the component’s objective to the robot’s. For example, using energy storage as a measure of locomotive capabilities in a hexapedal robot, soft robot legs were optimized to maximize energy output subject to a torque constraint.\[77\] The leg’s shape was represented by the area between 2D splines, whose control points are the design variables. Rather than increasing design autonomy, parameter optimizations (either hierarchical or concurrent) are mainly seen as a final step in manual designs, which validate a design by adjusting a handful of design parameters, rather than searching a meaningful space.

4. Topology Optimization

Over the past three decades, topology optimization (TO) has established itself as an industrially relevant, design optimization tool. Rather than the user specifying a base design and optimization parameters, TO distributes material within a defined design space to find the structure which maximizes a fitness function. The design space is configured as an FEA problem, with a set of elements, loads, and constraints and an FEA solver. Because the optimizer allocates material without human bias, novel designs have been generated in applications, including structural design, compliant mechanism design, crashworthiness design, and heat transfer problems and in multiobjective and multiphysics problem.\[78-83\] Despite its obvious value in optimizing immobile soft components, TO has only recently attracted attention within the soft robotics field. It has primarily been used to optimize single-material soft grippers, which are conveniently formulated as a linear structural problem. However, with an appropriate design space and formulation, entire multimaterial soft robots could be topology optimized in the near future. This
section presents a brief overview of the state of the art in topology optimization and its application to soft robotics.

4.1. Topology Optimization Algorithms

Three unique methods have gained widespread acceptance in TO research, the solid isotropic material with penalization (SIMP), (bidirectional) evolutionary structural optimization (BESO/ESO), and level set methods. While each is capable of optimizing complex nonlinear spaces with multiple materials, the differences in their distribution policies are of relevance in soft robot TO and summarized here. For a comprehensive review of topology optimization methods, see Sigmund and Maute. ESO/BESO uses a binary material distribution in which elements are either solid or void. It optimizes the structure by removing elements from regions of low fitness and inserting them in high fitness areas. In contrast, SIMP implements a virtual density to transform the discrete material distribution problem into a continuous one. Elements occupy a density space between a void and solid element, but have a penalty applied to drive convergence toward a final binary design. The level set method defines the structure according to the boundaries between material phases. This allows crisp boundaries to be defined; however, auxiliary methods are required to form new holes during the optimization process and mesh the resulting shapes for FEA evaluation. Without new hole formation, the problem reduces to a shape optimization. Soft grippers optimized using each of the three methods are shown in Figure 4. While SIMP is the most common soft-optimization method, the clearly defined boundaries produced by BESO and level set are advantageous when optimizing robots with pneumatic actuation, as discussed in Section 4.4. In addition to the three common methods, numerous bespoke ones have been developed. Most notably, Hiller and Lipson developed a multiamaterial topology optimization based on their own physics simulator. Its formulation enabled a nongradient solver to search the multimaterial landscape and find solutions unavailable using conventional techniques. The simulation environment formed the basis of the VoxCad environment, which is widely used in evolutionary soft robotic design and discussed in Section 5.1.

4.2. Solvers

4.2.1. Sensitivity-Based Solver

Conventionally, the three TO algorithms all use sensitivity functions, the objective function’s derivative with respect to the design variables, to specify the search direction of a gradient-based algorithm. Among the most widely used solver is the method of moving asymptotes, a convex approximation method designed for large-scale structural optimizations. Gradient methods are computationally efficient, but they limit the search smooth problems and exclude discontinuous contact problems, such as soft grasping. To avoid this problem, soft gripping devices have been modeled as displacement actuators, such as the pneumatically actuated semisoft finger, as shown in Figure 4a. The gripping finger was modeled as an inflatable internal chamber with a surrounding rigid shell. The shell was then optimized using the SIMP method to maximize output displacement. Compared with fully soft pneunets, the exoskeletal design increased the finger’s strength, however, linear material assumptions in FEA lead to excessive ballooning of the manufactured prototype (Figure 4b). By converting the elastic modulus to a strain energy within the SIMP framework, hyperelastic soft devices have also been optimized. Given the ubiquity of hyperelastic materials in soft robotics, modeling the nonlinearity is critical for meaningful results.

4.2.2. Nongradient Solvers

Because of their nonlinear materials, large deformations, and distributed actuation, soft robotic design spaces are highly nonlinear and misleading. In these spaces, gradient-based searches quickly become trapped in a local optimum. Nongradient (also called Black-Box) and evolutionary solvers have been proposed as an alternative. This class of solver comprises numerous heuristic and stochastic search algorithms, several of which are inspired by natural processes, such as particle swarm optimization, simulated annealing, and ant colony optimization. They apply metaheuristic rules to search large and nonlinear spaces, enabling them to avoid local minima and potentially reach a global optimum in nonconvex problems, without problem-specific knowledge. These heuristic methods explore a significantly larger region of the design space than greedy gradient-based methods, allowing fitter candidates to be found. However, they are vastly more computationally expensive than their gradient-based counterparts. Where gradient-based TOs typically converge in hundreds of iterations, genetic TOs typically require thousands or tens of thousands. In addition, stochastic nongradient methods also suffer from connectivity problems, where infeasible, discontinuous regions of elements occur within the design space. In the context of soft robots, these manifest as open chambers in pneumatic devices or disconnected parts.

4.2.3. Machine Learning

Where analytical sensitivities are not available, researchers have generally used one of two strategies: the first is the numerical calculation of sensitivities through a finite difference approach; the second is to avoid the need for sensitivities altogether by using a nongradient solver. Recently, learning sensitivities has been proposed as an intermediate solution between gradient and nongradient solvers, reducing the computational burden of nongradient methods without requiring analytical sensitivities and reducing their susceptibility to local minima compared with gradient methods. Topology optimization by predicting state features (TOPS) uses machine learning models to estimate sensitivities by drawing on features of the simulation which predict its behavior. Using a principle similar to BESO’s heuristic movement of elements from low stress to high stress regions, local state information specific to each problem (e.g., stress, displacement, energy) can be used to update the search direction. Evolutionary algorithms, neural network, and regression models have all been developed to map state information to design updates, demonstrating efficacy in benchmark and nonlinear...
4.3. Encodings

Regardless of the solver used, state features are implicitly subject to selective pressure by the optimizer. In evolutionary terms, they form part of the phenotype, the set of observable characteristics which can be measured by the fitness function. In contrast, the optimization variables form the genotype, the set of genes which encode the design. Unlike phenotypes, genotypes are generally not directly observable, instead forming a hidden inner layer of the evolutionary process. In the simple case of a pneumatic actuator optimization, geometric and material parameters (length, width, thickness, modulus, etc.) form the basis of the genotype, while the chamber volume and external dimensions are its phenotype.

In nature, the mapping from genotype to phenotype is encoded in DNA, but in numerical optimizations it is part of crashworthiness problems. Discontinuous and nonlinear crashworthiness problems present similar challenges to modeling soft robots with contact; learning sensitivities presents a tractable method to optimize them.
the problem design. The encoding determines both the dimension of the search space and its fitness landscape, and ideally should include optimal phenotypes within an easily searchable space. As discussed previously, BESO and SIMP directly encode the design as elements in an FEA mesh, such that each element has a corresponding variable. The conceptually simple encoding is suitable for gradient-based optimization, and has proven viable in small nongradient topology optimizations such as deformed shape matching.\[^{[95]}\] However, a 2D design space \(n\) elements long requires \(O(n^2)\) variables, which is infeasible for usable robots. If entire soft devices are to be tractably optimized, a more compact representation is required.

Geometric encodings use a set of shape primitives (e.g., size, location, curvature) to define the phenotype. Bezier curves, Voronoi cells, and level sets are examples of this method. In the level set method, the shape boundaries are encoded as the level set of a shape function, indirectly representing the topology through polynomials or radial basis functions.\[^{[96]}\] Bezier curves represent a structure through the curves’ shape and thickness, which are parameterized by their control points. When compared with direct encoding in compliant mechanism optimizations, a Bezier curve optimization reduced the number of design variables from \(n^2\) pixels to approximately 20 without connectivity problems.\[^{[100,101]}\] Alternately, indirect and generative encodings, such as Lindenmayer systems (L-systems), minimal spanning trees, and compositional pattern producing networks (CPPNs) have efficiently solved single and multiobjective optimization problems.\[^{[81,102–105]}\] Using grammar rules or mathematical formulations, they can efficiently encode symmetric and repeating patterns, accelerating convergence to valid soft robotic designs. Further detail on these encoding can be found in Section 5. To date, soft robotic TO has primarily applied direct encodings to the workspace, restricting optimizations to square and cuboid domains. However, moving beyond gripping fingers requires denser representations.

### 4.4 Soft Actuation Modeling

In soft robots, actuation forces are distributed throughout the robot’s body, rather than lumped at points. Distributed loading is a feature of soft actuation, and also necessary to avoid dangerous stress concentrations within the soft material. However, conventional TO requires fixed loads at specified locations and cannot be directly applied to pneumatic actuators or cable-driven actuators with internal routing. While the problem can be circumvented by designing the robot around optimization constraints, it severely restricts the algorithms relevance. For example, cable-driven robots have used external routing to create a point contact, but it increased the device’s footprint and required careful control to avoid self-contact. Therefore, reformulating the TO problem to capture soft robotic actuation methods is of significant interest.

#### 4.4.1 Displacement-Based Loading

Where soft robotic components are attached to a rigid base, a displacement load can be directly applied in FEA. Chen et al. used the level set method to optimize a cable-driven soft robotic fingers to grasp specific objects\[^{[106]}\] (Figure 4c). For simplicity, the driving cable was affixed only to its endpoint, rather than through the design space. The resulting servo-actuated, single-material finger was then 3D printed; its grasping capabilities were experimentally investigated in a three-fingered configuration (Figure 4d). A soft robotic gripper was similarly optimized using BESO. It was actuated by the relative displacement of two rigid plates.\[^{[107,108]}\] To improve the design’s ability to grasp irregular objects, the output displacement was measured at multiple points. In addition to the static optimizations, the gaits and motion of soft robots have been optimized dynamically. For example, the fin structure of a bateauid fish was optimized using SIMP to match an ideal motion profile, given a known rotation.\[^{[109]}\]

Numerous similar studies can be found within the related field of compliant mechanism design, in which the design of compliant grippers through TO is a benchmark problem.\[^{[89,100–103]}\] While the optimizations are conceptually similar, in compliant mechanisms the driving force is applied externally and transferred to an output location, where in soft robots the energy source is typically internal and distributed across the body. Therefore, compliant mechanisms require hard, linear elastic materials such as metals and plastics, rather than soft elastomers. To be of relevance to the broader soft robotics field, common nonlinear actuation methods, including internally routed cable actuation and pneumatic actuation, must be considered.\[^{[90]}\]

#### 4.4.2 Surface Loading

In pneumatic actuation, displacement results from pressure exerted by the actuating fluid on the pneumatic chamber. Uniform chambers expand and contract when pressurized, but more complex chamber geometries can bend or twist.\[^{[33,114]}\] Both the widely used pneumatic artificial muscles (McKibben actuators) and pneumatic bending actuators (pneunets) constrain a chamber’s inflation to generate a desired deformation. The pressure force is modeled in FEA as a surface load with a constant normal force applied to each exposed node at the solid-fluid boundary. This creates a problem of design dependence in TO, where the boundary moves as the structure evolves. Because the optimization is specified by a set of nodal loads, the optimization problem changes when the boundary moves.

As the boundary must be known to the optimizer, the sharp boundaries produced by level-set optimizations are ideal for pneumatic actuation.\[^{[115]}\] In contrast, the intermediate density regions in SIMP optimizations create an ambiguous boundary and uncertain forces. This can be resolved in two ways: by estimating the solid-fluid boundary, or through a mixed pressure-displacement formulation. The mixed formulation removes the requirement for a defined boundary by creating a density-based optimization with solid/liquid/void phases. The introduction of the fluid phase allows transfer of surface forces throughout the design space, in proportion with its elemental density.\[^{[116,117]}\] Chen et al.\[^{[118]}\] explicitly considered design-dependent loads when optimizing a pneumatic bending actuator. Using the BESO method, they adjusted the loading at each iteration by applying a uniform normal force to each exposed face within
the design domain. To avoid any open sections the design space was bounded by a solid square tube (Figure 4e). However, the optimal topology contained multiple, disjoint cavities. Therefore, postprocessing was required to manufacture and experimentally evaluate a design with a single pneumatic chamber (Figure 4f). The problem of topology optimizing a soft actuator while maintaining a variable sized, closed actuation chamber is addressed using a mixed formulation SIMP approach. A projection technique is developed which avoids the formation of holes in the solid material layer by forming a solid boundary between interior and exterior regions. In both cases, linear materials and deformations were assumed in the FEA solver resulting in physically unrealizable or undesirable solutions. While improved modeling methodologies could remove some of these artifacts, the physical characteristics could be directly included through a multiphysics topology optimization. Multiphysics optimizations of electrothermal actuators, microfluidic devices, aero-thermal problems, and more have been solver using both gradient and evolutionary algorithms. Despite the reduced need for designer input, TO design remains a direct process in which mechanical specifications are used to generate a detailed structural design. Because of its reliance on FEA for performance evaluation, existing TO methods are unable to efficiently model environmental interactions and therefore are limited to stationary soft robots or components.

5. Generative and Evolutionary Design

Evolutionary robots are designed in simulation using heuristic algorithms, inspired by nature, to efficiently search the design space and find high-performing designs. Rather than optimizing a single candidate by iteratively evaluating the optimal search direction, evolutionary algorithms evaluate populations of candidates which evolve over generations. In each generation, high-fitness candidates are selected from the population and have mutation and crossover operations performed to produce offspring candidates for the next generation. The research builds on the seminal work of Sims, who developed a method for the evolution of rigid-bodied “virtual creatures” using a robot simulator (Figure 5a). Using a genetic algorithm and a graph-based encoding, it coevolved a creature’s morphology and control through a set of rigid links, joints, and sensors. By shifting environmental pressures, creatures were evolved for walking, jumping, swimming, and light-following. Given the dependence of the robot’s behaviors on its design, high-level evolutionary approaches which autonomously coevolve “body and brain” facilitate the development of complex behaviors (e.g., walking gaits) and frequently outperform conventional designs in their simulated environments. However, because of the large simulation-to-reality gap, few evolved soft robots have ever been manufactured. Because of their

Figure 5. Generative soft robot designs. a) Swimming creatures generated in Sims’ seminal work on rigid robot evolution. Reproduced with permission. Copyright 1994, ACM. b) An initial generative design approach based on VoxCad and experimentally evaluated. Reproduced with permission. Copyright 2012, IEEE. c) The CPPN encoding used to generate complex virtual soft robots using four materials and d) resulting generated designs. Reproduced with permission. Copyright 2013, ACM. e) GRN generated soft robot growth process. Reproduced under the terms of the CC-BY-4.0 license. Copyright 2015, The Authors. Published by Frontiers Media S.A.
cumbersome manufacturing and actuation requirements, the few manufactured examples were only viable as proof-of-concept devices.

As with evolutionary algorithms in topology optimization, the design space’s encoding is critical to their efficient operation and the fitness of their solution. At the simplest level, these encodings are a binary matrix, representing the presence or absence of material at each pixel/voxel. However, complex robots have been compactly represented using Bezier curves, L-systems, gene-regulatory networks, and CPPNs. Morphogenetic methods based on DNA encoding have also been proposed to reduce the complexity of soft robot representation while incorporating greater detail. For a detailed review of encodings used in topology and soft robotic optimization, see Guirguis et al. A summary of evolutionary soft robot optimizations is shown in Table 2.

### 5.1. VoxCad

The majority of evolutionary soft robotics research has used the VoxCad simulator developed by Hiller and Lipson. It uses a mass-spring-based particle formulation to estimate the nonlinear soft body dynamics. Compared with FEA, the mass-spring model significantly increases computational efficiency and tractably handles contact, gravity, and friction modeling, at the cost of reduced accuracy. Despite the speedup, the computational expense of evolving soft robots has limited the optimizations to grids of 20 × 20 voxels or fewer, with four or fewer discrete materials. While the diverse range of evolved behaviors have proven qualitatively beneficial, the resulting designs are unable to cross the reality gap and cannot be directly transferred into physical robots. The results are unable to cross the reality gap. When experimentally tested, neither the quantitative nor qualitative behavior of physical models matched the simulations. Furthermore, they are actuated through volumetric expansion of a specified voxels in the design space, which cyclically expand and contract in several phases, creating relative motion. While this is convenient to implement in simulation, its physical implementation is impractically laborious. However, modular assemblies of magnetic “soft” voxels, each containing a rigid magnetic frame and air supply, have recently been developed to expedite experimental comparisons with VoxCad.

In their groundbreaking work, Hiller and Lipson attempted to fully automate the design of mobile soft robots with an evolutionary algorithm by using 3D-printable materials in simulation. Through the combination of a passive material and one whose volume varies with air pressure, a “scooting” soft robot was evolved and then 3D printed (Figure 5b). However, it could only be actuated by varying the pressure within a pressure/vacuum chamber. Cheney et al. incorporated four materials: a soft and an active passive material, and two active materials which counter-phased expansion. A CPPN was used to encode the genome (Figure 5d). CPPNs are similar to ANNs, but where ANN use a single activation function, CPPNs select from several math functions at each node facilitating natural patterns of symmetry and repetition. A range of locomotive strategies were evolved using the CPPN encoding, resulting in vastly fitter designs than those evolved with a direct encoding (Figure 5c). However, in the absence of a penalty on its use, the best designs almost exclusively contained active material. The resulting mass and energy consumption of the robot may prove disadvantageous in practice. Cheney et al. subsequently investigated evolving electrophysiological soft robots, which embodies the robot’s cognition by allowing electrical signals to propagate through the robot body. Complex patterns of electrical wave propagation were evolved, producing greater diversity of locomotive gaits than previous works. Rather than using the fitness-based NEAT

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**Table 2.** Summary of evolved mobile soft robots. MCD, mass center displacement; CPPN, compositional pattern producing network; GRN, gene regulatory network; ANN, artificial neural network; GA, genetic algorithm; EA, evolutionary algorithm; NEAT, neuroevolution of augmented topologies.

| Author | Aim | Fitness function | Encoding | Algorithm |
|--------|-----|------------------|----------|-----------|
| Sims²⁴ | Terrestrial and aquatic robots | Speed, jumping height | MCD | Directed graph | GA |
| Lipson and Pollack²⁰¹ | Terrestrial robots | MCD | Direct graph | GA |
| Lehman and Stanley²⁰² | Terrestrial robots | MCD | Nested graph | Novelty search |
| Auerbach and Bongard²⁰³,²⁰⁴ | Terrestrial robots | MCD with penalization | CPPN | CPPN-NEAT |
| Rieffel et al.²⁰⁵,²⁰⁶ | Terrestrial robots | Linear displacement | Face-encoding L-system | GA |
| Schram et al.²⁰⁷ | Swimming robots | MCD with penalization | GRN | EA |
| Hiller and Lipson²⁰⁸ | Terrestrial robots | MCD | Gaussian mixtures | Deterministic Crowding |
| Cheney et al.²⁰⁹,²¹⁰ | Terrestrial robots | MCD with penalization | CPPN | CPPN-NEAT |
| Cacucciolo et al.²¹¹ | Batoid fish | Strouhal number | Direct | GA |
| Joachimczak et al.²¹²,²¹³ | Terrestrial and aquatic robots | MCD with penalization | GRN | NEAT/Novelty search |
| Menthenitis et al.²¹⁴ | Low-gravity soft robots | Novelty based | CPPN | Novelty search |
| Veenstra et al.²¹⁵ | Plant generation | Sun absorption | L-system | Steady state GA |
| Corucci et al.²¹⁶,²¹⁷ | Plant generation | Plant growth | CPPN | CPPN-NEAT |
| Kriegman et al.²¹⁸ | Terrestrial robots | MCD | Direct | Age-fitness-pareto optimization |
| Talamini et al.²¹⁹ | Terrestrial robots | MCD | ANN | EA |

²° Rigid robot optimization.
algorithm, Methenitis et al. implemented a novelty search in an attempt to evolve soft animals with greater diversity. The use of a novelty search not only increased morphological diversity, but also increased fitness.134

The aforementioned works investigate the evolution of soft robots, but not their development. That is, the robot’s body is fixed during its lifetime. Corucci et al. explored the role of robotic growth in their behavioral development.135 Two CPPNs encoded the structure and volume change of voxels, respectively, in virtual plants. They found softer virtual plants were better exploited morphological computation, with high fitness candidates requiring less actuation and control. A similar effect was found in virtual swimming robots; however, in locomotive terrestrial soft robots, stiffer material increased velocity.136 Kriegman explicitly considered soft robot development by enabling robots to both evolve and develop on different time scales.137 Adding development to evolution allows the optimizer to find beneficial behaviors at each stage of evolution, accelerating and enhancing the process.

5.2. Alternative Simulators

In addition to VoxCad, several other simulation tools have been investigated to evolve soft robots or soft robotic components. For a detailed review of robotic simulators, see Collins et al.138 When evolving entire soft robots outside of VoxCad, formal grammars have typically been used to grow the robots, rather than relying on a voxel matrix. Rieffel et al.139,140 developed a face encoding L-systems to evolve tetrahedral soft robots. The encoding addresses a major criticism of evolved robots as it enables 3D printing of the body without postprocessing. However, the shape memory alloy actuators would have to be assembled after printing. The robots are simulated using the NVidia PhysX physics engine, which supports a wide range of materials in tetrahedral meshes. Preliminary studies evolved muscle placement, gait, and material properties within a fixed morphology. However, to simplify the development, the evolved robot was actuated through a uniform change in material stiffness during simulations. As the encoding provides variable meshing density, nonlinear motion is produced, as smaller tetrahedrons compress more than larger ones, acting like muscles.

Building on earlier work of Schram et al.,141 Joachimczak et al.127,128,142 used a lower level gene regulatory network to evolve 2D soft robots cell-by-cell. This removes some of the restrictions placed on evolution by formal grammars and allows arbitrary shapes to be generated. The GRN is based on a series of circular disks, joined by springs, which evolves though a process of cell division and death, followed by a soft-bodied locomotion simulation, as shown in Figure 5e. The simulation uses a mass-spring model, with point masses located at the center of each cell. The model is actuated by the expansion of connecting springs, subject to a pressure constraint on cells, which resists excessive compression. In addition to terrestrial and swimming virtual soft robots, morphing soft robots were also developed which transform in either direction between aquatic and terrestrial between terrestrial and adult stages of evolution. Both fitness-based and novelty-based searches were undertaken, with the novelty search producing fitter candidates in the metamorphosis task.

Where they exist in large design spaces, soft actuators and end-effectors are also candidates for evolution. Granular jamming grippers contain material grains within a membrane. Because of the frictional coupling between adjacent grains, vacuum pressure can be applied to switch from a deformable to a solid state. Because little knowledge exists about the large space of possible grain morphologies, Fitzgerald et al. used the nondominated sorting genetic algorithm III (NSGA-III) to evolve grain to maximize gripping force within a discrete element method environment.143 Finally, while it has not been used for any genetic optimizations, the simulation open framework architecture (SOFA) simulator and its soft robotics plugin also models deformable objects and has been used as the basis of soft robot optimizations. It uses a multimodal representation to simulate different physics features, with finite element modeling used for deformable objects.77,144

5.3. Fitness Versus Novelty

In the majority of the terrestrial animal studies discussed, fitness was defined as the animals displacement in a fixed time frame, which is analogous to velocity. In contrast, nature produces animals with a diverse range of phenotypes, which exploit unique evolutionary niches rather than directly competing on a single metric. Studying a wider range of single or multiobjective fitness functions could produce greater phenotypic diversity, resulting in designs better suited to specific tasks. For example, taking energy efficiency as the fitness function may be beneficial in mobile robots. However, given the large search space, conducting multiple optimizations for comparison is impractical; therefore, researchers have generally conformed to the displacement-based fitness. Novelty searches have been shown to encourage phenotypic diversity in evolved soft robots by exploring larger sections of the search space, however often fails to find high-performing candidates. Algorithms which combine fitness and novelty such as novelty search with local competition or MAP-Elites hold promise for uncovering fitter and more diverse candidates.

6. Future Directions

Since the 1960s, science fiction has predicted a near future in which mass produced, intelligent humanoid robots perform routine chores in every home and business (and occasionally turn rogue). While service robots are not yet ubiquitous, the prediction embodies the rigid paradigm that the vast majority of robotic designs still follow. From fixed assembly arms to hexapedal field robots, rigid bodied robots dominate the field. They rely on stiff components and discrete joints for their precise location. Because they are hard and heavy, precision is essential to prevent damage to the robot and its surrounding environment. The resilience of this design model can be attributed to its strong theoretical underpinnings, compatibility with industrial components and processes, and the snowballing effects of growth after reaching a critical mass. Despite this, rigid robots continue to struggle in unstructured environments. Because of their reliance on dynamic and environmental models, minor variations in task or terrain are enough to cause failure and surfaces which
humans routinely traverse (sand, mud, gravel) remain impassable.

An alternative perspective has recently emerged which replaces precision with flexibility and adaptability. In this model, stiff becomes flexible, hard becomes soft, precise becomes robust, and computed control becomes morphological control. By conforming around an object or terrain, soft robots negate the need to precisely predict pose. Their low mass, compliance, and damping increase stability while reducing the risk of harming objects and users. Through this lens, a competing vision for the future of robotics can be seen where evolved soft robots freely navigate fields, forests, and oceans. Fleets of artificial animals could roam free, gathering data, harvesting crops, manufacturing goods, and safely interacting with humans. The ability to realize this vision is limited by the slow process of designing and manufacturing soft robots. Their nonlinear design spaces are unintuitive and cumbersome for human designers, and because of their recent emergence, they have a relatively shallow literature base to draw on. To bring the soft robotic vision to reality, autonomous design tools are required which efficiently convert a task definition into a manufacturable design. Beyond incremental manual and parametric methods, two methods have been documented for partially automated soft robotic design. Adapted from structural design, topology optimization has automated the design of soft robotic grippers. Because problems are formulated in terms of loads and constraints, it is best suited to optimizing fixed mechanical components. While narrowly applicable, topology optimization with geometric and material nonlinearities is an accurate method for component scale optimization. In contrast, adapted from evolutionary robotics, soft robot evolution is a general but imprecise optimization method. Rather than FEA solvers, they rely on computationally inexpensive physics engines, which sacrifice accuracy for speed, but tractably handle common environmental interactions such as contact, friction, drag, and gravity. The reduced computational burden facilitates higher level, task-based optimizations, and morphologies and controllers can coevolve to generate sophisticated behaviors in simulation. However, using the approach, the reality gap is insurmountably large in the short term and the manufacture of simulated robots is unlikely. An intermediate solution is desperately required which draws on both to efficiently search a large design space to find fit candidates for specific tasks while considering physical, engineering, and manufacturing constraints.

6.1. Optimization Environment

The ultimate goal of soft robot design is to produce an embodied device capable of performing physical tasks in the real world. By systematically creating and evaluating candidate designs and identifying high-performing features, automated design methodologies accelerate the design process compared with manual processes. Because of the time and expense of manufacturing soft robots, the design evaluation is typically performed in simulation, making some degree of reality gap inevitable. However, the gap can be reduced by simulating smaller models with greater detail. Therefore, two methods have been proposed to refine the scale of models being solved: hierarchical optimizations and adaptive optimizations. Both can be combined with machine learning to generate efficient mixed reality solutions, as shown in Figure 6.

6.1.1. Hierarchical Optimization

Hierarchical optimization divides the design problem into multiple levels and optimizes them hierarchically from bottom to top. The levels mirror those generally used in robot design: the lowest level is materials; above that is the component level, containing sensors actuators, joints, and limbs; and on top is the complete robot, its gait, and dynamics. At each level, libraries of high-performing candidates are evolved by assembling parts from the lower levels. A framework for multilevel evolution (MLE) of robots is outlined in Howard et al.,[145] with robots evolved using the MLE framework and a shape grammar in the PyBullet simulation in Chand and Howard.[146]

They use a three level optimization hierarchy comprising materials, limbs and components. However, levels can be added or removed to match the desired design space. Metamaterials, sensors and actuators, and manufacturing methods could all be optimized in addition to morphology and mechanics. Similar approaches have proven effective in evolving muscle placement and control in simulated bipeds,[147] and evolving sensing controllers in fixed morphology simulated soft robots.[148]

6.1.2. Adaptive Optimization

While the hierarchical method evolves a robot from the bottom up, top-down methodologies are also of research interest. When optimizing top down, the high-level behaviors are first optimized crudely and then more detail is progressively added. The solver resolution and detail level are refined adaptively until the predictions converge. In the context of soft robots, the simulations are initialized in a physics engine. The optimal gait and morphology for the specified environment are found using a minimal set of materials, joints, and geometries. Key features of the resulting design and its dynamics would then be extracted and solved in FEA, with feature resolution and mesh density gradually increased. At very fine resolutions, the robot's microstructure can be optimized into composite metamaterials.

6.1.3. Machine Learning Models

Both hierarchical and adaptive optimizations retain the underlying assumption that simulations accurately represent reality and can be transferred into a physical device without a significant performance degradation. However, current literature on soft robotics only verifies this assumption superficially, by experimentally evaluating the accuracy of a small number of design candidates.

In contrast to the simulation-based methods which rely on physical or dynamical models, model-free methods have been investigated which remove the reality gap completely by learning predictive models from experimental data. Despite the obvious advantage of grounding evolution in the real world, physical experimentation is generally too resource intensive to evolve detailed design spaces. Machine learning (ML), especially deep learning, methods are data hungry, requiring thousands of
points at a minimum. Therefore, learning and predicting robot designs from physical experimentation is realistic only if the desired robots can be manufactured and tested autonomously, in a high-throughput environment.

ML can also be used to generate surrogate models which predict high-performing regions of the design space from simulated fitness values. Clearly, this has no impact on the reality gap, but enables interpolation of the design space, reducing the computational burden of making new predictions. ML models including support vector regression and deep reinforcement learning have demonstrated efficacy in predicting performance of parameterized soft actuators when trained against FEA, at the cost of a computationally expensive training phase.\cite{28,149}

Reality-assisted evolution, which combines model-based and model-free methods, is a promising method to unite the simulation and experimental methods. Large-scale experiments are used to train and refine a ML model from real world data. The modeled design space can then be widely searched in simulation to illuminate high-performing regions, with the best candidates physically verified and used to update the model.\cite{150} Alternatively, the experimental data can be used to refine a simulation environment by tuning its hyperparameters to minimize the reality gap and generate digital twins. In both cases, because the search is done in silico, a vastly larger region of the design space is exploitable compared with fully experimental methods.

Regardless of whether it is physical or simulated, performance evaluation consumes the vast majority of resources. Therefore, the most efficient design optimizer will be one that can predict designs (or at least filter out low performing designs). With a large enough supply of computational resources, a simulated model could be generated with current methods, but experimental data must also be incorporated if designs are to be manufactured. Therefore, the question is how to efficiently blend physical and computed results to minimize the need for costly experiments. Is it necessary to use objective based searches, or should we instead explore the design space and fish for designs and candidates?

6.2. Materials and Manufacturing

Soft robotics research is still in its infancy, and many fundamental questions remain unsolved. To compliment improved design methodologies, automated manufacturing methodologies and advanced materials should be investigated and developed.

6.2.1. Semisoft Robots

The relationship between a design’s performance across different terrains and material properties remains an open question in soft robotics. In nature, animals range from completely soft...
(e.g., worms, squid) to bony and muscular (cheetahs, springbok) and individual animals combine numerous materials to produce locomotion. In mammals muscle tissue, bones, tendons, cartilage, and ligaments are all involved in locomotion, and each contains multiple materials. As a result, bioinspired robots have exploited a wide array of material properties to produce complex functions, while other design methods have largely been limited to a select few. However, bioinspiration and comparisons with nature restrict the realm of possibility to animals which exist, rather than those that could exist. Nature has evolved fit designs over thousands of generations, but that provides no guarantee of optimality within their evolutionary niche, let alone outside it.

The computational burden of increasing resolution and the range of available materials has limited optimizations to coarse soft designs, without structural elements. Hybrid soft/hard or semisoft designs allow beneficial aspects of soft and rigid robots to be combined. In the near future, we expect the visions of hard and soft robotics to converge such that hard, soft, and hybrid systems all exist in complimentary settings.

6.2.2. Automated Manufacturing

The development of computational design techniques has historically been restricted by their manufacturability. Until a suitable automated manufacturing method exists, the use of these design techniques is primarily academic. However, as occurred with topology optimization and 3D printing, their use can explode with efficient fabrication methods.

The development of additive manufacturing now allows automatic production of complex, monolithic multimaterial parts. Materials ranging from soft elastomers up to solid metals and ceramics can be fabricated through either resin, ink, filament, or powder-based methods, with resolutions down to 100 nm. However, printed materials contain anisotropies and microstructural defects which reduce their mechanical performance compared with bulk materials, and multimaterial printing remains limited to a single class of materials, such as thermoplastics or photopolymers. Current methods pale in comparison to the complex cellular processes by which natural materials grow and organize. In the near term, a fusion of additive manufacturing and robotic assembly line is required, such that multiple printing and assembly processes can be performed on a single part. Diverse hard and soft structural materials, sensors, actuators, and other functional components could be automatically assembled in a single environment, facilitating high-throughput testing. However, the minimum resolution using conventional processes remains large in comparison with natural ones. Therefore, in the longer term, molecular self-assembly and engineered cellular growth are more promising methods to increase design complexity.

Simple automated manufacturing has recently been demonstrated in rigid robots. By evolving both the robot’s body design and its manufacturing process (tool paths), a rigid robot was automatically assembled from both printed and prefabricated components. Similarly, “one-shot” printing of complete granular jamming grippers (membrane, grains, and frame) has recently proven the ability 3D print soft actuators for high-throughput experimentation. In mobile soft robots, which utilize distributed deformation and actuation, prefabricated components need to be embedded within the soft material, rather than assembled to it. Automated printing and embedding of conductive fibers has been demonstrated in stretchable substrates, but the goal of embedded sensing and actuation remains distant.

7. Conclusion

Soft robotics has the ability to revolutionize robots by delegating computation from brain to body and allowing soft material to implicitly undertake distributed sensing and control. This article reviewed the state of the art in soft robotic design, highlighting the progress from manual to automated methods. Despite recent advances, soft robot design continues to be predominantly manual as human designers intuitively capture manufacturing and physical constraints which automated methods cannot. An efficient intermediate solution is required which explores the large, nonlinear design space and resolves it into a smooth, manufacturable design. How best to search the space remains the key problem, given the expense of experiments. Motivated by the immense possibilities of soft robotics, we propose several future directions to advance autonomous soft robotic design. We hope this article will inspire researchers and practitioners to take up the challenge.

Conflict of Interest

The authors declare no conflict of interest.

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autonomous design, material robotics, soft robotics

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