Reality-Assisted Evolution of Soft Robots through Large-Scale Physical Experimentation: A Review

Toby Howison*
University of Cambridge
 Bio-Inspired Robotics Lab
 th533@cam.ac.uk

Simon Hauser
University of Cambridge
 Bio-Inspired Robotics Lab

Josie Hughes
University of Cambridge
 Bio-Inspired Robotics Lab

Fumiya Iida
University of Cambridge
 Bio-Inspired Robotics Lab

Abstract We introduce the framework of reality-assisted evolution to summarize a growing trend towards combining model-based and model-free approaches to improve the design of physically embodied soft robots. *In silico*, data-driven models build, adapt, and improve representations of the target system using real-world experimental data. By simulating huge numbers of virtual robots using these data-driven models, optimization algorithms can illuminate multiple design candidates for transference to the real world. *In reality*, large-scale physical experimentation facilitates the fabrication, testing, and analysis of multiple candidate designs. Automated assembly and reconfigurable modular systems enable significantly higher numbers of real-world design evaluations than previously possible. Large volumes of ground-truth data gathered via physical experimentation can be returned to the virtual environment to improve data-driven models and guide optimization. Grounding the design process in physical experimentation ensures that the complexity of virtual robot designs does not outpace the model limitations or available fabrication technologies. We outline key developments in the design of physically embodied soft robots in the framework of reality-assisted evolution.

1 Introduction

From simple cellular organisms to the most complex life forms, biological systems exhibit extraordinary levels of diversity over a large spatiotemporal scale. The apparently coherent behavioral repertoires observed in nature are increasingly explained using an *embodied* view of intelligence that focuses on the intrinsically coupled interactions between the brain, body, and environment [13, 89]. Understanding and harnessing these embodied interactions, therefore, is a key step in building truly lifelike artificial systems.

In this context the field of *soft* robotics is particularly interesting. Soft robots can generally be defined as having highly deformable bodies or elements, often constructed using unconventional (in the robotics sense) materials with highly nonlinear properties [61, 84, 90, 106]. They can be further characterized by their uniquely complex and sustained environmental interactions, for example, in terrestrial or aquatic environments [18]. Given this, the methodologies on which conventional robotics science was developed— for example, rigid-body kinematics and dynamics—are often inapplicable when applied to soft robots. Instead, significant research has focused on how to utilize the characteristics of soft robots in an

---

 * Contact author.

embodied framework. By harnessing the mechanical intelligence of soft bodies, researchers hope to develop robotic systems with comparable performance to biological systems [54].

While the promise of soft embodied intelligence and soft robotics is well documented, the design process by which to realize it is nontrivial [41]. A classical process for designing robotic systems is through the use of models and simulations. *Model-based* approaches often demonstrate the design of virtual soft robots *in silico* via artificial evolution. By mimicking the processes from which embodied intelligence emerged in nature, these methods have successfully demonstrated complex, meaningful robot behaviors [9]. However, evolved robot designs frequently do not perform as expected when transferred into the real world: This is an aspect of the so-called reality gap [77]. Further still, available fabrication technologies may prevent the realization of virtually evolved robot body plans altogether. Alternatively, *model-free* approaches restrict design to the physical world, for example, via top-down imitation of biological systems such as octopus tentacles or elephant trunks [81] or using real-world evolutionary approaches [126]. By evaluating robots *in reality*, the problems associated with transference between models and the real world can be avoided. However, physical experimentation is generally time-consuming and resource intensive, restricting the effective exploration of large design spaces.

In this article we summarize recent developments in the design of soft robots from the perspective of a rapidly growing direction we term *reality-assisted* evolution. There has been a growing interest in design methodologies that combine model-based and model-free approaches to improve the overall design of physically embodied robots (see Table 1). Under this framework, as summarized in Figure 1, simulation-only and simulation-free design methodologies are unified via large-scale physical experimentation and data-driven modeling. *In silico*, data-driven modeling is used to build and improve representations of the target system, using real-world experimental data. Physics engines can be tuned to maximize their predictive accuracy, and auxiliary models can be built to estimate the transferability of virtual robots to the real world [55]. Alternatively, models can be built from scratch to estimate fitness across the design parameter space [108]. These data-driven models can be used to simulate the behavior of huge numbers of virtual robots and, in conjunction with optimization and illumination [78] algorithms, to discover diverse and highly performant designs that are likely to survive crossing the reality gap. *In reality*, large-scale physical experimentation systems can fabricate and test multiple robot designs. Recent developments in automated [42] and scalable [59] fabrication approaches facilitate an increasingly large number of real-world evaluations. Similarly, modular and adaptive robots allow multiple morphologies and controllers to be tested on a single reconfigurable platform [85, 123]. By situating physically embodied robots within a task environment, significant amounts of useful experimental data can be gathered. Grounding the design process in physical experimentation ensures that the complexity of simulated robot designs does not outpace the model accuracy or available fabrication technologies. Further still, modulating complexity in the task environment *in reality* can drive the heterogeneous improvement of data-driven models *in silico* from simple to more challenging design representations.

This review is structured as follows. In Section 2 we outline the open problems in embodied intelligence for soft robots. We highlight three classes of soft robot that typify embodied intelligence in soft robots and drive the need for a reality-assisted framework. In Section 3 we discuss advances in modeling and representation for soft robotics, starting from conventional approaches and finishing with data-driven modeling and transferability methods. In Section 4 we discuss advances in large-scale physical experimentation. We cover the range of possible fabrication methods before exploring how these can be scaled up, for example, via robotic automation or modular and distributed systems. In Section 5 we discuss optimization methods for designing soft robots. We explore design encoding and typical optimization algorithms, then explore how novelty-based search methods offer a more robust approach within the reality-assisted framework. Finally, we conclude our review and provide some remarks on outlook.

2   Embodied Intelligence for Soft Robots

Conventional robotic systems can usually be described using a discrete architecture. The exact position of actuation, sensing, and other morphological elements is known and can be relied upon not to change

Table 1. Highlighted literature for model-based, model-free, and reality-assisted physically embodied robots, showing the target system, design parameters, modeling and simulation tools, design search method, and number of morphologies and/or controllers that were realized *in reality*.

Author reference	Target system	Parameter space	Model / simulation	Search method	Realized designs	
					Morphologies	Controllers
(a) Model-based						
Hiller & Lipson 2012 [38]	Soft robot	M + C	Voxelyze	EA	5	1
Caluwaerts et al. 2014 [5]	Tensegrity robot	M + C	NTRT	EA	1	2
Cellucci et al. 2017 [7]	Recyclable robot	M	ODE	MOEA	3	1
Peng et al. 2018 [88]	Robotic arm	C	MuJoCo	DNN	1	1
(b) Model-free						
Khazanov et al. 2014 [53]	Tensegrity robot	C	—	EA	1	250
Brodbeck et al. 2015 [3]	Modular robot	M + C	—	EA	500	500
Mouret & Clune 2015 [78]	Soft robotic arm	C	—	MAP-elites	1	640
Vujovic et al. 2017 [126]	Soft-legged robot	M + C	—	Evo-devo	75	75
Nygaard et al. 2018 [85]	Quadruped	M + C	—	MOEA	192	192
Veenstra et al. 2018 [123]	Soft fish robot	C	—	EA	1	200
(c) Reality-assisted						
Koos et al. 2013 [55]	Multiple	C	Bullet physics	MOEA	2	2
Cully et al. 2015 [19]	Hexapod	C	ODE	IT&E	10	10
Rosendo et al. 2017 [100]	Modular robot	M + C	GP	BO	25	25
Saar et al. 2018 [108]	Hopping robot	M + C	GP	BO	15	40
Rieffel & Mouret 2018 [96]	Tensegrity robot	C	GP	BO	1	30
Rosser et al. 2020 [101]	Flapping robot	M	PYROSIM	MOEA	16	1
Kwiatkowski & Lipson 2019 [60]	Robotic arm	C	DNN	—	2	2
Howison et al. 2020 [42]	Falling paper	M	KMC	Random	500	—
Howison et al. 2020 [43]	Falling paper	M	GP	BO	40	—

Table 1. (*continued*)

Author reference	Target system	Parameter space	Model / simulation	Search method	Realized designs	
					Morphologies	Controllers
Kriegman et al. 2020 [56]	Living cell robots	M	Voxelyze	EA	5	1
Kriegman et al. 2020 [59]	Modular soft robot	M	Voxelyze	Exhaustive	108	1

Notes. Note that in many cases these publications reported significant numbers of additional experiments, for example, manual design comparisons. (a) Model-based approaches. Designs are evaluated using modeling and simulation tools and are not tested in the real world until the end of the design process. (b) Model-free approaches. Designs are exclusively evaluated in the real world, without the use of simulation or modeling tools. (c) Reality-assisted approach. As categorized in this review, designs are evaluated using a combination of modeling tools and real-world experimentation.
Key: M: Morphology; C: Control; GP: Gaussian process; KMC: *K*-means clustering; ODE: Open dynamics engine; NTRT: NASA tensegrity robotics toolkit; MAP-elites: multidimensional archive of phenotype elites; DNN: deep neural network; EA: Evolutionary algorithm; MO: Multi-objective; MOEA: Multi-objective evolutionary algorithm; BO: Bayesian optimization; IT&E: Intelligent trial and error

during deployment. Interaction with the environment can be actively regulated, for example, in pick-and-place robotic arms. The continuum nature of soft robots means they cannot be described using this discrete architecture, but rather as a set of loosely coupled parallel processes [88] and environmental interactions spanning the microscopic to macroscopic scales. At the microscopic scale, molecular and material interactions induce physical properties such as elasticity or durability, as well as active behaviors such as those seen in electroactive polymers or shape memory alloys [131]. At the organism level these properties manifest as distinct higher-order behaviors, with environmental interactions inducing highly nonlinear dynamics, for example, sustained contact forces or turbulent fluid dynamics [52]. Further still, at the population level soft robots can be placed in the context of modular and distributed robotics, with interaction between agents driving complexity. In terms of embodied intelligence, therefore, the structure and interdependence of these interactions is key for the emergence of useful, nontrivial behaviors. Given this, we are particularly interested in three classes of soft robot:

1. **Soft robots with complex interactions.** A key area of interest is soft robots with a *simple* embodiment but *complex* environmental interactions—for example, a soft extendable tube that exhibits complex behaviors via contact with the environment [37] (Figure 2(a)), a simple water-immersed silicon tentacle whose dynamics can be utilized for real-time information processing [81] (Figure 2(b)), or liquid droplets whose properties drive sensing and motility functionalities [12] (Figure 2(c)). These nontrivial behaviors that emerge via interaction between morphology and the environment represent a fundamental basis on which more complex behaviors can be built.

2. **Soft robots with complex hybrid structures.** Another key area of interest is so-called soft-rigid robots. The rapid progress in additive manufacturing has enabled the construction of heterogeneous continuum structures with anisotropic elasticity profiles. For example, an anthropomorphic hand with rigid bones but soft ligaments utilizes its hybrid structure to achieve complex dexterity tasks [46] (Figure 2(d)). Complex soft structures can also be built using rigid components with soft connections, for example, a tensegrity robot that combines the robustness of rigid components with the versatility of a deformable body [95] (Figure 2(e)). Robots constructed using living tissues have also shown the potential of hybrid structures for encoding functional behaviors [56] (Figure 2(f)). Similarly to biological systems, hybrid robots can diversify their behaviors by complexifying their morphology.
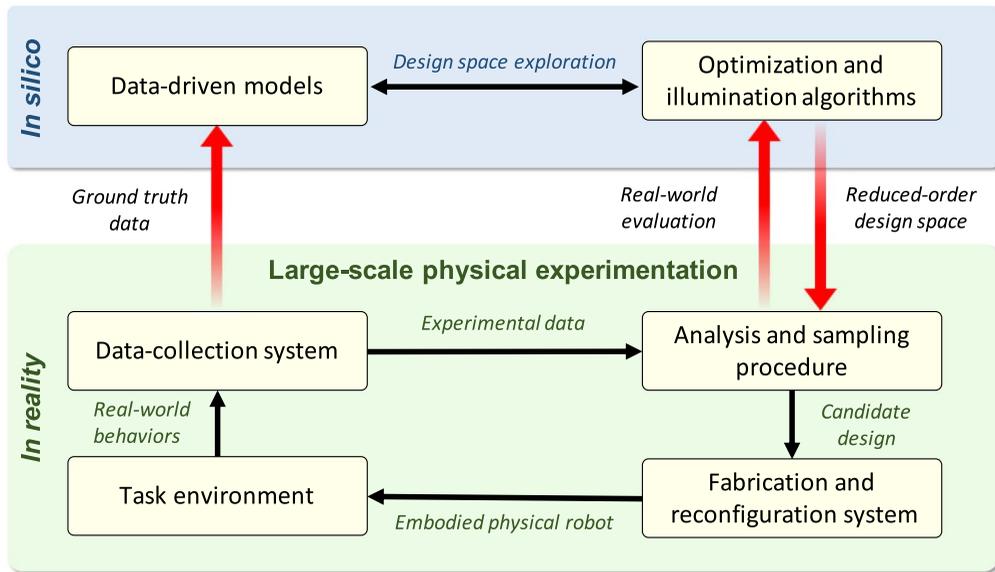
Figure 1. The reality-assisted evolution framework for designing physically embodied soft robots. *In silico*, data-driven models are constructed and adapted based on ground-truth data. Physics engines can be tuned to maximize their predictive accuracy. Alternatively, machine learning can be used to build models from scratch. Auxiliary models can also be built to estimate the performance disparity of virtual robots after transference to the real world. By using data-driven models to simulate huge numbers of possible robot designs, optimization and illumination algorithms can discover a range of diverse and highly performant designs across the parameter space. A reduced-order design space of promising candidates can be established for transference to the real world. *In reality*, large-scale physical experimentation facilitates the fabrication and analysis of multiple candidate designs. Increasingly automated experimental platforms can fabricate and test large numbers of candidate designs without human input. Alternatively, new modular and adaptive robotic systems facilitate the testing of multiple robot designs on one reconfigurable platform. By placing physical robots in a task environment and observing their behaviors, large volumes of useful experimental data can be gathered. This data can inform the sampling procedure for physical experimentation *in reality*, and can be used to update data-driven models and as an input to optimization algorithms *in silico*. From the bottom up, changes to the physical task environment drive the gradual complexification of data-driven models and robot designs toward more complex embodiments and behaviors.

3. **Soft robots that can change their own embodiment.** The final class concerns one of the most fascinating aspects of soft robots: growth and adaptation. One of the key properties separating biological systems from robots is an ability to change one's own embodiment, over the course of a lifetime or in response to the environment. Adaptation has been shown to improve soft robot evolution in real-world [126] (Figure 2(g)) and simulated robots [58] (Figure 2(h)). Morphogenesis has been demonstrated on modular robotic platforms [124] (Figure 2(i)). Understanding how to harness the power of developmental processes is a key step for progressing from simple soft robots to complex, intelligent, and perhaps ultimately conscious machines.

3   Modeling and Representation

Models (mathematical or other logical representations) and simulations (evaluated models) of soft robotic systems facilitate *in silico* experimentation on a scale many orders of magnitude higher than can be achieved *in reality*. This is beneficial for discovering and testing candidate designs before transference to the real world, and for the systematic testing of different design methodologies, for example,

Soft robots with complex interactions

Soft robots with complex hybrid structures

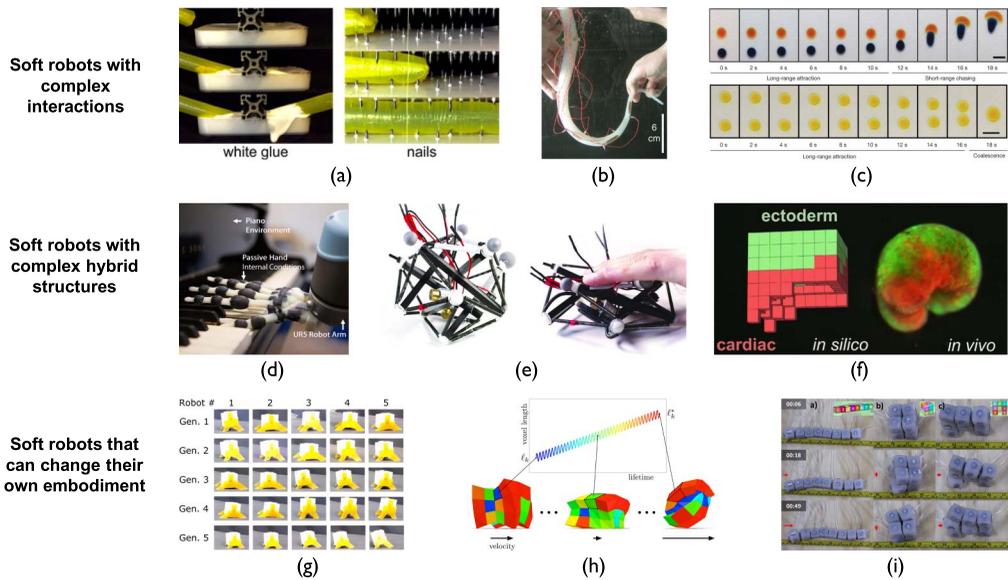Soft robots that can change their own embodiment

Figure 2. Three distinct classes of soft robots with strongly embodied functionalities: soft robots with complex interactions, soft robots with complex hybrid structures, and soft robots that can change their own embodiment. (a) A soft extendable tube that exhibits complex behaviors via environmental interaction [37]. (b) A simple water-immersed silicon tentacle whose dynamics can be utilized for real-time computation [81]. (c) Liquid droplets whose properties drive sensing and motility behaviors [12]. (d) An anthropomorphic hand with rigid bones but soft ligaments utilizes its hybrid structure to achieve complex dexterity tasks [46]. (e) A tensegrity robot that combines the robustness of rigid components with the versatility of a deformable body [95]. (f) A living tissue robot with hybrid structure for locomotion, where green is passive tissue and red is active contractile cardiac tissue [56]. (g) Examples of soft robots produced by real-world evo-devo [126]. (h) A simulated soft robot showing the power of morphological development for guiding evolution [58]. (i) A reconfigurable soft modular robotic platform reproducing morphogenetic processes [124]. All images reproduced with permission from the authors.

evolutionary algorithms. However, all model representations of the real world have some form of reality gap [77]. While it may be possible to construct models of physical phenomena, it may not always be possible to evaluate these models in simulation to a sufficient granularity for the purposes of design. This section discusses approaches for modeling soft robots, from conventional methodologies to the latest physics engines and data-driven modeling techniques.

3.1 Conventional Modeling

Popular modeling approaches for soft robots are at the level of kinematics or second-order full dynamics [68]. Such methods involve deriving precise geometric and dynamic expressions, which are in turn used to derive Jacobian kinematics or equations of motion. For example, elastic systems can be modeled as mass-spring lattices or arrays, providing a simple estimation of deformation. Similar approaches include traditional beam-bending and constant-curvature approximations, which often have analytical solutions. Bespoke models can combine these approaches for different modalities of soft body deformation, for example, continuum structures with constant-curvature models [105, 109, 128]. Finite element methods (FEMs) are also used for modeling soft systems [135], and have seen particular usage for exploring the design parameter spaces of soft pneumatic actuators [16, 23] and controller verification [136]. FEM models are generally computationally expensive, requiring a tradeoff between simulation time and accuracy [92]. However, work on real-time FEMs has shown some promise for the control of soft robots [25, 136].

3.2   Physics Engines and Simulators

Generalized physics engines that can simulate soft robots as they interact with their environment are growing in popularity. A number of physics engines offer soft body simulators, including Bullet Physics,[1] CryEngine,[2] MuJoCo,[3] Open Dynamics Engine,[4] and the NASA Tensegrity Robotics Toolkit.[5] Perhaps the best known physics engine for deformable bodies is Voxelyze,[6] a voxel-based representation that has been used for a large number of soft robotics studies [9, 39, 57, 59] and has become a benchmark on which different design optimization methods are tested (Figure 2(f), 2(h), for example). A recent GPU-accelerated re-implementation of Voxelyze, voxcraft-sim,[7] has recently been released.

There have also been recent advances in differentiable soft simulators, which have the advantage of solvability using gradient-based optimization algorithms. These are particularly efficient for solving optimal control and motion planning problems. However, implementation for soft systems is challenging and, at present, highly computationally expensive. Examples of soft-body differentiable systems include ChainQueen [44] and the differentiable cloth simulator [67]. The ability to use gradient-based optimization methods could allow for far more computationally efficient optimization and exploration of design.

Despite developments in soft body modeling, there are still many limitations. Rigid body approximations, FEMs, and constant-curvature models can be effective at predicting the behavior of specific problems, but do not generalize well. Physics engines such as Voxelyze certainly offer a more generalized simulation environment. Additionally, many physics engines are developed by the video game industry, and so come with certain technical and financial weight behind them. However, with generality can come a loss of accuracy when compared to problem-specific modeling methods. In general, different physics engines offer different tradeoffs and capabilities, each suited to different elements of soft robot simulation [116].

3.3   Data-Driven Modeling

Significant research has been carried out on data-driven modeling techniques that update their representation using ground-truth data. Data-driven approaches offer the ability to incrementally improve predictions as more data becomes available. Some approaches construct models directly from ground-truth data, for example, deriving symbolic equations to describe real-world phenomena [4, 104]. Learnt knowledge of fundamental concepts can be gradually combined for understanding more complex systems [111]. Other methods detect underlying structure in large data sets, for example, dynamic mode decomposition [110].

Alternatively, increasingly black-box approaches can be used to estimate the behaviors of soft systems without explicitly discovering the underlying dynamics. Neural networks, for example, have been used for soft robot pose reconstruction [113], inverse kinematics [33], or control strategies [10], and are effective without having to explicitly model the mechanisms behind soft deformation. The rapidly growing field of neural ordinary differential equations could see particular usage in data-driven modeling for soft robots [102].

More abstract methods bypass direct modeling of the underlying dynamics completely, instead learning surrogate models to map between the design space and fitness landscape. Gaussian process (GP) modeling, for example, is a supervised learning technique for solving regression problems [118]. The power of GP models lies in their leveraging of Bayesian inference to estimate black-box function behaviors in relatively few samples. GP models have been used to estimate design fitness in the

---

1 https://pybullet.org/
2 https://www.cryengine.com/
3 http://www.mujoco.org/
4 https://www.ode.org/
5 https://github.com/NASA-Tensegrity-Robotics-Toolkit
6 https://github.com/jonhiller/Voxelyze
7 https://voxcraft.github.io/

reality-assisted design of a hopping [108] robot, mapping morphological and control parameters to locomotion speed, and a tensegrity robot [96], mapping motor speeds to locomotion speeds.

3.4   Transferability, Robustness, and Sim2Real Performance

Related to data-driven modeling is the idea of transferability. Simulation-to-real (sim2real) performance can be improved by learning the disparity between robot behaviors observed *in silico* and *in reality* (i.e., their transferability). The *transferability approach* augments existing system models with supervised learning to understand the limits of the model and simulator [55]. This so-called robot-in-the-loop method uses a minimal number of physical experiments to build a surrogate model of the sim2real disparity across the design space. By including this disparity measure within a multi-objective optimization framework, the design fitness landscape can be adjusted to reward designs that are likely to cross the reality gap with a low disparity. Incremental testing in the real world improves the sim2real disparity surrogate model's accuracy, driving the design process towards performant *and* transferable solutions. A recent study on a flapping robot, whose dynamics are notoriously challenging to model, used incremental simulated and real-world experimentation to explicitly measure the sim2real disparity across the design space [101].

Robustness filters can be also used to assess how well simulated designs perform under perturbations [50], for example, in their morphology, controller, or environment. If the reality gap is viewed as a large perturbation to the design space, then designs that can withstand high perturbations in simulation and still exhibit the same behaviors are likely to also perform well in the real world. These methods have been used for the design of living tissue robots [56], in which simulated robot designs were passed through a robustness filter that injected noise into their control systems, and a transferability filter that measured their performance once transferred to reality and returned this to the model environment in the form of constraints. Transferability and robustness methods are useful tools because they maximize the utility of existing simulation tools, allowing generalized physics engines to be used in many different design contexts. However, the design process is still fundamentally limited by the accuracy of the model tool. Areas of the design space that cannot be simulated accurately may still provide useful data, but cannot be realized in the form of a physically embodied robot.

4   Large-Scale Physical Experimentation

Those implementing reality-assisted evolution rely on carrying out a sufficient number of physical experiments. In this section we discusses methods and challenges for fabricating and testing physical soft robots on a large scale. First we discuss fabrication, sensing, and actuation approaches for soft robots, drawing attention to the difficulty in realizing simulated designs in the physical world. Next we discuss approaches for scaling up experimentation to enable more design evaluations in the real world, including automated fabrication and modular robotic systems.

4.1   Materials and Fabrication

One of the great opportunities offered by soft robotics is the large pool of potential materials and fabrication technologies available to the designer [112]. Many soft robots are fabricated using casting and molding, typically with silicon elastomers or expanding foam [48, 91]. These approaches offer a flexible and potentially scalable approach for fabrication, but can be highly labor intensive. Additive manufacturing has also recently seen widespread adoption, with 3D printing shown to be especially useful for multi-material soft-rigid robots such as an anthropomorphic hand [46] (Figure 2(d)), and for seamless incorporation of sensing and actuation mechanisms [129]. 3D printing can also be exploited with flexure-based rigid techniques [45], with increasingly high-quality flexible filaments and stereolithography techniques offering significantly more capabilities [35].

There are a number of alternative materials and approaches that are potentially more scalable. These include hot melt adhesives, which have seen widespread usage for soft robots [83, 126], and offer the

advantage of being cheap, accessible, and quick to form. Reconfigurable soft robots are another approach, and can be fabricated using cutting and folding inspired by origami [86, 107, 134]. Similarly, laser cutting is a rapid method for fabricating simple robots [42] or creating 3D-flexure-based actuators [69]. In addition to these well-established techniques, a number of exciting novel fabrication approaches are emerging, including knitted and balloon-structure robots [71, 132].

4.2   Sensing and Actuation

Another key challenge in the development of soft robots is sensing and actuation [90]. Actuation methods such as pneumatically driven systems are popular; however, these often require tethers or large external compressors [119]. Tendon-driven systems are also common and allow for use of motors as an actuation source, providing higher controllability and power density [6]. While these can be efficient, their size and rigidity makes them hard to integrate into continuum bodies. More unconventional approaches use smart materials, for example, dielectric actuators or shape memory alloys [66, 76]. These methods have the clear advantage that actuation can be seamlessly integrated into a robot morphology and are especially useful from the perspective of embodied intelligence. However, it is currently challenging to generate large forces with these technologies [34].

Sensing is challenging due to the large deformations and potentially infinite degrees of freedom of deformation that soft-body systems exhibit [115]. A number of different sensing approaches have been proposed, including piezoresistive materials [27], capacitive sensors [29], ionic metal soft sensors [11], and also sensors that use cameras [30] or exploit physical structures [114]. Again, more novel methods have been presented, for example, harnessing the sensing properties of liquid droplets [12] (Figure 2(c)).

A growing trend in soft robotic sensing and actuation is the use of biohybrid materials. The boundaries between biological and artificial systems can be blurred with the development of biohybrid robots [99]. Some of the capabilities, structures, and materials from biological systems can be incorporated to interact with robots [1]. For example, a biohybrid system can incorporate biological muscles, which are controlled artificially [75]. This approach could allow the functional gap between current soft-robotics systems and biological systems to be closed.

4.3   The Fabrication Gap

The fabrication approaches discussed in Section 4.2 have a complex set of limitations dictating what types of design can and can't be built to sufficient accuracy. Hence, if the fabrication process is not properly included in the design process, we may see a *fabrication gap* [97], that is, a difference between the prescribed design and the physically fabricated end product. This problem can be addressed by considering available fabrication methodologies early in the design process.

One approach is to use fabrication rules to filter designs at the simulation stage, for example, using a build filter to rule out designs that cannot be physically fabricated [56]. Alternatively, designers can use fabrication rules—3D printing commands, for example—as a means to describe designs (e.g., in [97]). *Grammar* -based approaches such as this allow designs to be described via a vocabulary of parts and fabrication methods [62]. These ideas have recently been advanced with the concept of a *robot compiler*, that is, a process for converting a robot design into parts, structures, and fabrication instructions. Robot compilers have been used to convert simulated designs into origami robots whose fabrication is guaranteed [73, 74, 113].

Each fabrication technology introduces its own characteristics into the final designs, and that in turn affects their embodiment and thus their behavior. Selecting the correct fabrication approach could vastly increase the performance of soft robots. Indeed, if fabrication is viewed as a *filter* between the virtual and physical environments, then this could improve the design process by automatically ruling out designs that could not cross the fabrication gap. The recent work on robot compilers and grammars demonstrates, to some extent, that including fabrication at the representation stage can allow us to harness limited fabrication technologies to our advantage in the design process.

4.4   Scaling Up Physical Experimentation

There is a growing trend toward testing large numbers of robot designs *in reality*, and significant research is being carried out to enable more scalable physical experimentation methodologies. Indeed, this is one of the driving factors in presenting the reality-assisted framework as a feasible option for unifying model-based and model-free design methodologies.

Online controller learning is relatively easy to implement with physical experimentation, as the morphology remains fixed, and it has been applied successfully for locomotion [53, 85] and a soft fish robot [123]. Other studies have co-optimized control and morphology in the real world. One platform uses a "mother robot" to automatically construct different robot designs and test them for their locomotive behaviors (Figure 3(g)) [3, 100, 126]. By automating the fabrication process, large numbers of real-world robots can be evaluated with minimal human intervention. These studies reveal the effectiveness of scaling up physical experimentation, but are still fundamentally limited to orders of magnitude fewer design evaluations than is achievable *in silico*.

To address this, methods of rapidly fabricating soft robots have been developed, and robotic automation has been used to partially or fully automate the fabrication process. A number of soft robotic fabrication techniques are in particular suited, or can be adapted, for rapid fabrication. Additive manufacturing using flexible thermoplastic elastomers [35, 127] is one example, as are "1D" printing techniques that can fold a single string of recyclable material into a target morphology [7]. In this approach thermoplastics can be extruded using high-precision robot arms to create structures, or to connect existing components together. This approach offers a high level of accuracy and design complexity in a relatively short time. New printing technologies are also developing where complex 3D structures can be fabricated in one step [129], improving the speed at which robot designs can be fabricated. Alternatively, low-cost soft robot construction kits (voxcraft) have been presented along with appropriate simulation tools to design and test many physical robots [59]. Laser cutting is another fabrication approach that can be used to rapidly create bespoke structures with high precision. When combined with robotic arm automation, this can be used to automatically create complex 3D structures. Laser cutting of paper has been shown to facilitate fabrication of morphological structures in under 10 seconds in significantly large-scale physical experiments (Figure 3) [42].

4.5   Modular and Distributed Systems

Modular robotic systems allow significant physical experimentation without the need to continually fabricate new robots. Instead, modules can be reconfigured to make use of existing fabricated components. Not only does this speed up experimentation, but it allows investigation into bio-inspired topics such as morphogenesis. For example, emergent self-assembly approaches inspired by nature have been replicated in a number of distributed robotic systems [103, 130]. Here, global strategies are converted to local assembly rules via a compiler. Modular robot systems such as these are forced to consider fabrication early in the design process, as modules can only be connected in certain configurations. In doing so, users can create an implicitly "buildable" design space.

Systems where either the assembly or the disassembly process is manually performed include, for example, the programmable-matter systems Robot Pebbles [31] and Miche [32]. Even more interestingly, there is a special type of modular robots that can autonomously self-assemble and self-disassemble, that is, self-reconfigurable modular robots. In theory, these systems could perform experiments autonomously (limited by their operation time), as they would assemble into a design, test it, and reassemble into the next design by themselves. Within the domain of rigid robots there have been a large variety of such modular robotic technologies. Recent examples of these include M-blocks [98], SMORES [20], Soldercubes [82], and Roombots [36]. Realizing soft modular or self-assembling robots is less common, largely due to the inherent difficulties in fabricating and controlling continuum bodies. However, modular soft robots are seeing increasing use [59]—for example, tensegrity systems [133], tendon-driven structures [70], and soft modular cubes for investigating morphogenetic movements of the embryo (Figure 2(i)) [124].
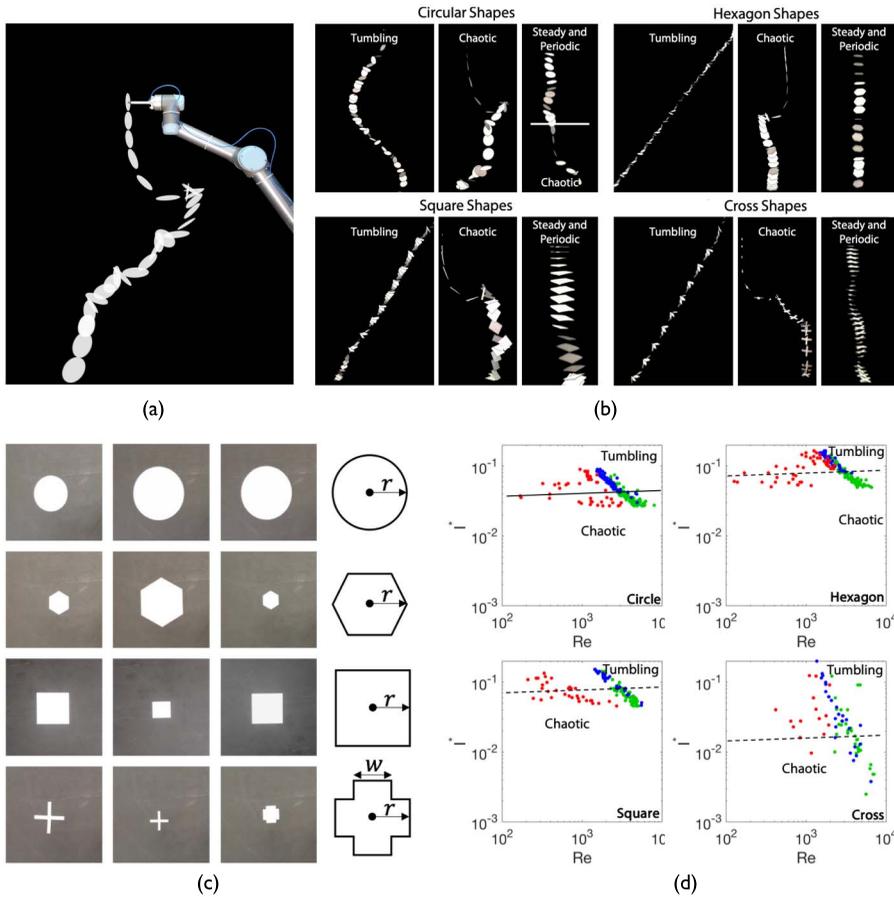
Figure 3. Large-scale physical experimentation and data-driven modeling with falling paper [42]. (a) A large-scale physical experimentation system dropping a paper shape. Different paper shapes are automatically fabricated, picked, and dropped from a range of initial conditions, using a robotic arm. The trajectories of shapes are tracked using computer vision. (b) As the paper shape and initial drop conditions change, different falling behaviors are observed. Falling behaviors are easy to describe visually and simple to investigate experimentally, yet challenging to simulate. (c) Examples of different fabricated morphologies, each with a different design space parameterization. (d) Hundreds of trajectories for different shapes are used to create a data-driven model (based on k-means clustering) of behavioral diversity in an appropriate parameter space, in this case Reynolds number (Re) and dimensionless moment of inertia (I^*). All images reproduced with permission from the authors.

A key related field is self-replicating robotics. Introduced half a century ago by John von Neumann, self-replication has long been a dream of roboticists. Requiring futuristic technologies, it would allow a self-sustaining pipeline of robots to be fabricated autonomously. A number of examples have been developed [120], and 3D printers have provided an imperfect replicator [2]. However, there has not yet been significant progress towards soft self-replicating systems.

5   The Search for Novelty

Key to the success of any design optimization process are the methods used to search for favorable designs and the metrics by which designs are compared. As discussed in Section 4, a key process in reality-assisted evolution is discovering designs in simulation that are likely to transfer well to reality. In this section we summarize advances in optimization techniques for soft robot design.

5.1 Bio-inspired Encoding

Robot designs are typically described via an encoding that systematically maps input parameters to design features. The space of all possible designs is, therefore, defined by the encoding along with the valid range of input parameter values. There is a range of desirable encoding features. Encoding schemes should output feasible designs for a given task environment, but ideally generalize to many task environments. They should be receptive to the influence of optimization algorithms searching for favorable designs within the design space, that is, they should be *evolvable*. Finally, as mentioned previously, having a grounding to the available fabrication technology is advantageous.

Direct encodings map input parameters directly to design features. This can be a powerful approach, as it allows a human designer to specify the key features of the output design, hence ensuring the design space is feasible and can be fabricated. For example, robot foot and leg parameters have been optimized with direct encodings [108]. However, the approach performs poorly in terms of scalability and generality. Since every node in the discretized design space needs a separate, exact description, the total amount of information stored in the direct encoding is as large as the design itself. This can be problematic, especially for soft robots, where a fine design discretization can quickly make the optimization process intractable. Furthermore, a direct encoding scheme suitable for a given task may not transfer to another.

Instead, research has focused on *indirect* or *generative* encoding systems that can describe a complex design space with relatively few parameters [40, 72]. The idea is inspired by biological systems, where phenotypic expression often occurs in repeating patterns that can be described by a singular part of the encoding, in this case a genome. Lindenmayer systems (L-systems) and their variations [49, 125] are generative encodings that incorporate bio-inspired aspects of morphogenesis, the development of morphological characteristics. Their particular properties make them effective for modeling natural plant systems, with directed growth and branching. However, they have not yet found a clear application in the design of soft robots.

Another more promising indirect encoding is *compositional pattern-producing networks* (CPPNs) [15]. CPPNs mimic the natural ontogenetic process without the need to directly simulate the chemical mechanisms involved. Instead, they describe morphology in terms of a network where each node is a mathematical function (e.g., a Gaussian or cosine function), and the final design is the result of design coordinates queried through this network. By including regularity in the encoding [15], design information can be compressed significantly while maintaining diversity within the design space. CPPNs have been combined with various optimization algorithms that evolve their underlying network to design soft robots in a simulation environment [9], with some having been transferred to the real world (Figure 2(g)). Growing evidence has supported the idea that generative encoding schemes using CPPNs or similar networks outperform other approaches [93, 121].

5.2 Optimization Algorithms

Single objective optimization (SOO) strategies aim to maximize performance in a specific behavioral feature or task [122], for example, locomotion speed. Evolutionary algorithms (EAs) mimic natural selection and offer an effective approach to searching for favorable designs, provided the desired phenotypic behaviors can be encoded within a fitness function. In simulation they have been shown to effectively optimize a range of virtual agents [117], including ones for locomotion [9, 24] or navigating a confined space [8]. EAs have also been demonstrated in the real world, evolving modular robots for locomotion [3, 126] and for controlling a soft fish robot [123].

Bayesian optimization (BO) [28] is an alternative strategy for the global optimization of expensive-to-evaluate black box functions, and has seen significant usage in SOO problems for robotics. BO methods sequentially build and improve a surrogate GP model of the underlying function and use this to efficiently sample the parameter space. Significantly, BO allows users to choose a range of acquisition functions to decide the next sample point, some of which include a penalty for evaluation time. The algorithm, therefore, can search for designs that maximize the predictive accuracy of the GP model and design fitness while also minimizing the time spent doing physical experimentation.

BO has been used for a range of physical robot design optimization tasks, including modular robots [100], locomotion control strategies [96], falling-paper shape morphologies [43], and for the cooptimization of morphology and control [108], where it was shown to outperform a human designer. In this study, physical robots were iteratively fabricated and tested. After each test, the design fitness was used to update the GP model, which, in this case, mapped leg parameters to predicted locomotion distance. BO has also been used in *intelligent trial and error* (IT&E), designed to quickly adapt robot controllers to morphological damage by using real-world experimentation to learn optimal control policies [19].

There is a growing trend toward implementing multi-objective optimization (MOO) approaches in the evolution of robotic systems. Since intelligent behaviors can rarely be characterized by a single fitness, design process [122]. Multi-objective evolutionary algorithms (MOEAs) use multiple objectives to drive the evolutionary process, offering the designer a set of solutions with tradeoffs between the various objectives [79, 80]. MOEAs are effective for evolving simulated soft robot behaviors, for example in aquatic environments [18]. Transferability approaches also use the MOO framework, finding Pareto optimal solutions that balance design fitness and providing an estimation of transferability [55]. MOO frameworks are effective for finding a range of possible design candidates, but will not return solutions in areas of the design space that are not Pareto optimal. Hence, many potential candidate designs can be missed, especially in the case of poorly defined objectives.

5.3   Quality Diversity and Illumination Algorithms

Designers can incorporate solution novelty within the optimization objectives. Such algorithms aim to actively create divergence in the solution space, rather than converging to one global maximum, for example, by formulating the optimization problem to search only for behavioral novelty, that is, *novelty search* (NS) [21, 64]. The formulation has been shown to outperform traditional objective-based searches for solving task-based problems such as maze solving or obstacle avoidance [80], and for the online morphological adaptation of a simulated underwater robot [17]. In the context of design optimization, this offers an alternative way of evaluating designs based on their behavior, rather than directly on a fitness function. Because many points in the design space may map to the similarly performing behaviors, this approach might significantly improve search efficiency. However, without any direct measure of solution fitness, searches based on novelty can be too divergent to ever present an optimal solution candidate.

To address this, so-called *illumination* or *quality diversity* (QD) algorithms have been presented, which hybridize the concepts of novelty search and direct fitness optimization [93]. QD algorithms aim to discover the range of behavioral niches in the system, as well as the associated optimal solution of each niche. One example, *novelty search with local competition* (NS+LC) [65], lets similarly behaved solutions compete based on a fitness function. When evolving virtual agents for locomotion, NS+LC found more functional morphological diversity than a global fitness function did. Similarly, the *multi-objective landscape exploration* (MOLE) algorithm [14] searches for diverse solutions that are as far away from each other as possible in a user-defined feature space. One of the most popular QD implementations is the *multidimensional archive of phenotype elites* (MAP-Elites) [78] algorithm (Figure 4). Here, a set of highly performant solutions are discovered across a discretized feature space defined by the user. The holistic nature of MAP-Elites allows the human designer to define interesting robot behaviors and use these to structure the evolutionary search, and it has been reported to outperform traditional EAs in a range of tasks.

The QD approach may be particularly effective for the design of soft robots because it is more accommodating to unknown system behaviors. In the case of soft robotics, we often do not know how a particular soft system will behave. Optimizing a range of solutions with different behaviors makes it more likely some of these solutions will be effective when transferred into the real world.

5.4   Developmental Robotics

Taking inspiration from nature, there is growing evidence that mimicking ontogenesis and allowing a developmental phase, where a robot can alter its morphology or controller, can be highly beneficial [22,
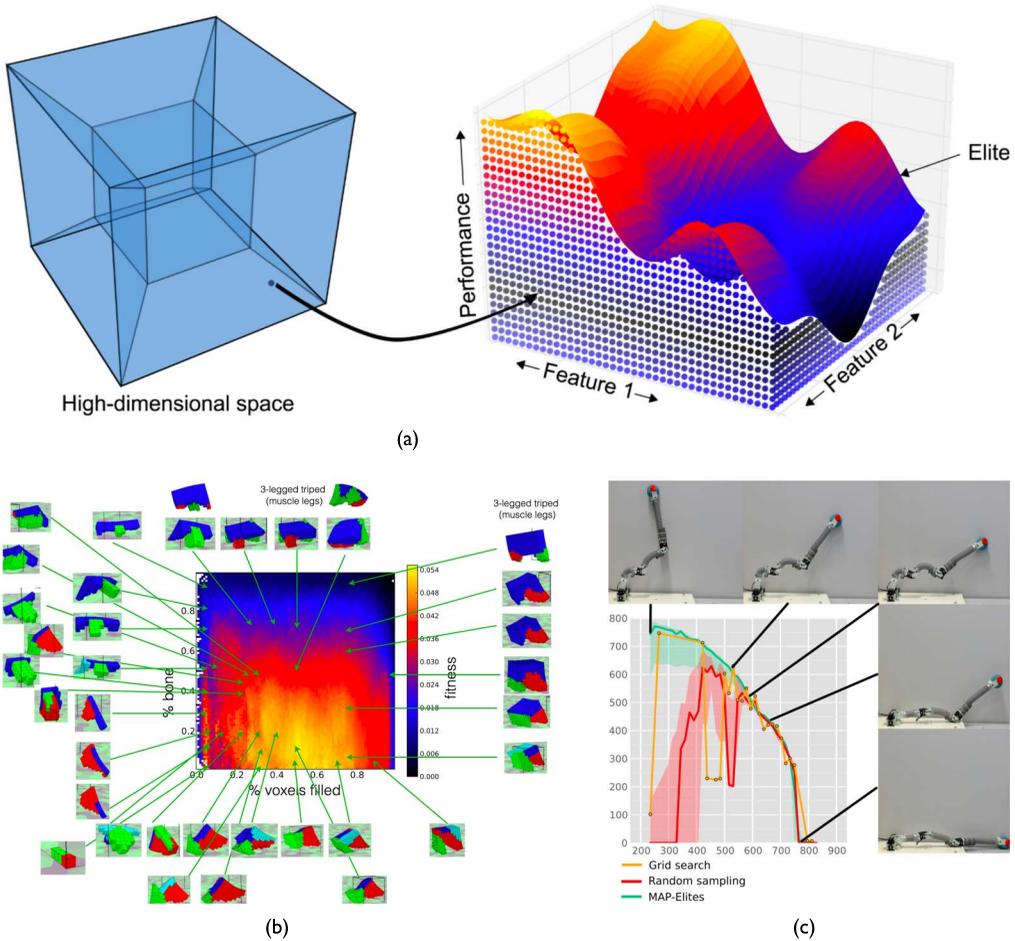
Figure 4. Multidimensional archive of phenotype elites (MAP-Elites) algorithm [78], an illumination algorithm that searches for diverse and highly performant solutions across a feature space defined by the user. (a) MAP-Elites searches a high-dimensional parameter space to find highly performant solutions in a user-defined low-dimensional feature space. (b) Examples of different virtual soft robot behaviors found via MAP-Elites. Robots were evaluated for their locomotive fitness across a two-dimensional feature space defined by the morphological parameters (% bone and % voxels filled). (c) A soft robotic arm whose controller was discovered using MAP-Elites. The method consistently finds better-performing (positive y axis) solutions in the feature space (x axis) than a grid search or random sampling. All images reproduced with permission from the authors.

26, 95]. Incorporating a developmental process into the design optimization framework adds a number of benefits. First, the design-space complexity can be reduced and offloaded to the developmental interaction between the robot and its environment. Second, performance disparities introduced by the reality gap can be corrected via developmental processes in the real world. Including developmental processes also means a robot can adapt to a changing task environment, or repair itself if damaged. Similarly, controller development allows robots to correct for damage or an unexpected change in task [19]. Third, it could allow the design space of embodied robots to be explored more efficiently and effectively. It has been demonstrated that implementing a developmental framework combined with a novelty search is more effective for evolving simulated soft robots than using a traditional fitness-driven approach [51]. A key study [58] demonstrated how phenotypic plasticity can guide and improve evolution (so-called evo-devo), and increase the overall evolvability across the design space. Large-scale

developmental processes have seen only limited implementation for real-world embodied soft robots, but the preliminary results indicate their potential [126].

6   Conclusions and Outlook

This review is written in the context of two key problems in the design of soft robots. First, although model-based methods are effective for searching large design spaces, we are currently unable to sufficiently model many physical processes within soft robots, and are also unable to physically fabricate many virtual soft robot designs. These reality and fabrication gaps have severely limited the scope of designing physically embodied soft robots with a model-based approach. If we subscribe to the view that intelligent behaviors result from complex embodied interaction within the environment, then there is a clear need for significant physical experimentation in lieu of highly accurate modeling and simulation. Second, while model-free physical experimentation does fully capture the embodied behaviors of soft robots, the approach is not scalable to the size achievable with a model-based approach. Designers cannot, for example, explore the evolutionary design of complex soft robots, since exploration of these design spaces requires a significant number of evaluations.

The challenges associated with designing soft robots combined with the potential benefits of utilizing soft robots in the context of embodied intelligence are forcing roboticists to rethink their design methodologies and philosophies. The literature presented here (as highlighted in Table 1) demonstrates that an effective strategy is a reality-assisted evolution framework in which model-based and model-free physical experimentation methods are unified to improve the design of physically embodied soft robots that exhibit useful, meaningful behaviors. *In silico*, data-driven modeling can be used to build and update models of real-world systems. Tuning physics simulations [56], building models from scratch [108], and learning auxiliary transferability models [55] are all data-driven methods for reducing the reality-gap disparity. *In reality*, large-scale physical experimentation methods are facilitating significant numbers of real-world evaluations. Automated [42] and scalable [59] methods show promise, as do modular and reconfigurable systems [85, 124]. At a high level, novel optimization techniques can guide design exploration *in silico* and *in reality*. QD and illumination algorithms such as MAP-Elites [78] seem particularly suited to modulating the design process by discovering multiple diverse candidate designs to be tested in the real world. Bayesian optimization [96] methods also show promise in that they allow designers to include the cost of physical experimentation directly in the objective function.

Looking forward, we expect to see a continuation of the trend toward a more unified approach to designing soft robots. This will be partially driven by the further development of fabrication, material, sensing, and actuation technologies. As these become better understood, so will our ability to include them within models and deploy them via large-scale physical experimentation. In parallel, developments in data-driven modeling and transferability approaches will improve the utility of simulation tools, facilitating better predictions of robot behaviors and, crucially, more informed studies of optimal design methods. In the long term, research on *open-ended evolution* (e.g., [47, 63]) that aims to indefinitely evolve systems without converging to a particular solution could be significant. Developments in these search and optimization methods are key for structuring the design process toward discovering diverse behaviors. Finally, moving beyond soft robotics, we expect to see a trend toward more complex hybrid systems. Biological systems tend to be neither soft nor rigid, so understanding how the combination of different materials improves embodied functionality is a key milestone toward designing complex, intelligent, and perhaps ultimately conscious machines.

References

1. Alapan, Y., Yasa, O., Yigit, B., Yasa, I. C., Erkoc, P., & Sitti, M. (2019). Microrobotics and microorganisms: Biohybrid autonomous cellular robots. *Annual Review of Control, Robotics, and Systems*, *2*(1), 205–230. DOI: https://doi.org/10.1146/annurev-control-053018-023803

2. Bowyer, A. (2014). 3D printing and humanity's first imperfect replicator. *3D Printing and Additive Manufacturing*, *1*(1), 4–5. DOI: https://doi.org/10.1089/3dp.2013.0003

3. Brodbeck, L., Hauser, S., & Iida, F. (2015). Morphological evolution of physical robots through model-free phenotype development. *PLOS ONE*, *10*(6), e0128444. DOI: https://doi.org/10.1371/journal.pone.0128444, PMID: 26091255, PMCID: PMC4474803

4. Brunton, S. L., Proctor, J. L., & Kutz, J. N. (2016). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences of the USA*, *113*(15), 3932–3937. DOI: https://doi.org/10.1073/pnas.1517384113, PMID: 27035946, PMCID: PMC4839439

5. Caluwaerts, K., Despraz, J., Işçen, A., Sabelhaus, A. P., Bruce, J., Schrauwen, B., & SunSpiral, V. (2014). Design and control of compliant tensegrity robots through simulation and hardware validation. *Journal of The Royal Society Interface*, *11*(98), 20140520. DOI: https://doi.org/10.1098/rsif.2014.0520, PMID: 24990292, PMCID: PMC4233701

6. Camarillo, D. B., Milne, C. F., Carlson, C. R., Zinn, M. R., & Salisbury, J. K. (2008). Mechanics modeling of tendon-driven continuum manipulators. *IEEE Transactions on Robotics*, *24*(6), 1262–1273. DOI: https://doi.org/10.1109/TRO.2008.2002311

7. Cellucci, D., MacCurdy, R., Lipson, H., & Risi, S. (2017). 1D printing of recyclable robots. *IEEE Robotics and Automation Letters*, *2*(4), 1964–1971. DOI: https://doi.org/10.1109/LRA.2017.2716418

8. Cheney, N., Bongard, J., & Lipson, H. (2015). Evolving soft robots in tight spaces. In *Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation* (pp. 935–942). New York: ACM. DOI: https://doi.org/10.1145/2739480.2754662

9. Cheney, N., MacCurdy, R., Clune, J., & Lipson, H. (2013). Unshackling evolution: Evolving soft robots with multiple materials and a powerful generative encoding. In *Proceedings of the 15th Annual Conference on Genetic and Evolutionary Computation* (pp. 167–174). New York: ACM.

10. Choi, C., Schwarting, W., DelPreto, J., & Rus, D. (2018). Learning object grasping for soft robot hands. *IEEE Robotics and Automation Letters*, *3*(3), 2370–2377. DOI: https://doi.org/10.1109/LRA.2018.2810544

11. Chossat, J., Park, Y., Wood, R. J., & Duchaine, V. (2013). A soft strain sensor based on ionic and metal liquids. *IEEE Sensors Journal*, *13*(9), 3405–3414. DOI: https://doi.org/10.1109/JSEN.2013.2263797

12. Cira, N. J., Benusiglio, A., & Prakash, M. (2015). Vapour-mediated sensing and motility in two-component droplets. *Nature*, *519*(7544), 446–450. DOI: https://doi.org/10.1038/nature14272, PMID: 25762146

13. Clark, A. (2008). *Supersizing the mind: Embodiment, action, and cognitive extension*. Oxford, UK: Oxford University Press. DOI: https://doi.org/10.1093/acprof:oso/9780195333213.001.0001

14. Clune, J., Mouret, J.-B., & Lipson, H. (2013). The evolutionary origins of modularity. *Proceedings of the Royal Society B: Biological Sciences*, *280*(1755), 20122863. DOI: https://doi.org/10.1098/rspb.2012.2863, PMID: 23363632, PMCID: PMC3574393

15. Clune, J., Stanley, K. O., Pennock, R. T., & Ofria, C. (2011). On the performance of indirect encoding across the continuum of regularity. *IEEE Transactions on Evolutionary Computation*, *15*(3), 346–367. DOI: https://doi.org/10.1109/TEVC.2010.2104157

16. Connolly, F., Polygerinos, P., Walsh, C. J., & Bertoldi, K. (2015). Mechanical programming of soft actuators by varying fiber angle. *Soft Robotics*, *2*(1), 26–32. DOI: https://doi.org/10.1089/soro.2015.0001

17. Corucci, F., Calisti, M., Hauser, H., & Laschi, C. (2015). Novelty-based evolutionary design of morphing underwater robots. In *Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation* (pp. 145–152). New York: ACM. DOI: https://doi.org/10.1145/2739480.2754686

18. Corucci, F., Cheney, N., Giorgio-Serchi, F., Bongard, J., & Laschi, C. (2018). Evolving soft locomotion in aquatic and terrestrial environments: Effects of material properties and environmental transitions. *Soft Robotics*, *5*(4), 475–495. DOI: https://doi.org/10.1089/soro.2017.0055, PMID: 29985740

19. Cully, A., Clune, J., Tarapore, D., & Mouret, J.-B. (2015). Robots that can adapt like animals. *Nature*, *521*(7553), 503–507. DOI: https://doi.org/10.1038/nature14422, PMID: 26017452

20. Davey, J., Kwok, N., & Yim, M. (2012). Emulating self-reconfigurable robots—design of the SMORES system. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 4464–4469). New York: IEEE. DOI: https://doi.org/10.1109/IROS.2012.6385845

21. Doncieux, S., Laflaquière, A., & Coninx, A. (2019). Novelty search: A theoretical perspective. In *Proceedings of the Genetic and Evolutionary Computation Conference* (pp. 99–106). New York: ACM. DOI: https://doi .org/10.1145/3321707.3321752

22. Doursat, R., & Sánchez, C. (2014). Growing fine-grained multicellular robots. *Soft Robotics*, *1*(2), 110–121. DOI: https://doi.org/10.1089/soro.2014.0014

23. Drotman, D., Jadhav, S., Karimi, M., de Zonia, P., & Tolley, M. T. (2017). 3D printed soft actuators for a legged robot capable of navigating unstructured terrain. In *2017 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 5532–5538). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2017 .7989652

24. Duarte, M., Gomes, J., Oliveira, S. M., & Christensen, A. L. (2018). Evolution of repertoire-based control for robots with complex locomotor systems. *IEEE Transactions on Evolutionary Computation*, *22*(2), 314–328. DOI: https://doi.org/10.1109/TEVC.2017.2722101

25. Duriez, C. (2013). Control of elastic soft robots based on real-time finite element method. In *2013 IEEE International Conference on Robotics and Automation* (pp. 3982–3987). New York: IEEE. DOI: https://doi.org /10.1109/ICRA.2013.6631138

26. Eiben, A., Bredeche, N., Hoogendoorn, M., Stradner, J., Timmis, J., Tyrrell, A., & Winfield, A. (2013). The triangle of life: Evolving robots in real-time and real-space. In *ECAL 2013: The Twelfth European Conference on Artificial Life* (pp. 1056–1063). Cambridge, MA: MIT Press. DOI: https://doi.org/10.7551/978-0-262 -31709-2-ch157

27. Firouzeh, A., Amon-Junior, A. F., & Paik, J. (2015). Soft piezoresistive sensor model and characterization with varying design parameters. *Sensors and Actuators A: Physical*, *233*, 158–168. DOI: https://doi.org/10 .1016/j.sna.2015.06.007

28. Frazier, P. I. (2018). A tutorial on Bayesian optimization. *arXiv Preprint arXiv:1807.02811*.

29. Frutiger, A., Muth, J. T., Vogt, D. M., Mengüç, Y., Campo, A., Valentine, A. D., Walsh, C. J., & Lewis, J. A. (2015). Capacitive soft strain sensors via multicore–shell fiber printing. *Advanced Materials*, *27*(15), 2440–2446. DOI: https://doi.org/10.1002/adma.201500072, PMID: 25754237

30. Gilday, K., Thuruthel, T. G., & Iida, F. (2020). A vision-based collocated actuation-sensing scheme for a compliant tendon-driven robotic hand. In *2020 3rd IEEE International Conference on Soft Robotics (RoboSoft)* (pp. 760–765). New York: IEEE. DOI: https://doi.org/10.1109/RoboSoft48309.2020 .9116054

31. Gilpin, K., Knaian, A., & Rus, D. (2010). Robot pebbles: One centimeter modules for programmable matter through self-disassembly. In *2010 IEEE International Conference on Robotics and Automation* (pp. 2485–2492). New York: IEEE. DOI: https://doi.org/10.1109/ROBOT.2010.5509817

32. Gilpin, K., Kotay, K., Rus, D., & Vasilescu, I. (2008). Miche: Modular shape formation by self-disassembly. *The International Journal of Robotics Research*, *27*(3–4), 345–372. DOI: https://doi.org/10.1177/0278364907085557

33. Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823–834. DOI: https://doi.org/10.1109/TRO.2015.2428511

34. Gu, G.-Y., Zhu, J., Zhu, L.-M., & Zhu, X. (2017). A survey on dielectric elastomer actuators for soft robots. *Bioinspiration & Biomimetics*, *12*(1), 011003. DOI: https://doi.org/10.1088/1748-3190/12/1/011003, PMID: 28114111

35. Gul, J. Z., Sajid, M., Rehman, M. M., Siddiqui, G. U., Shah, I., Kim, K.-H., Lee, J.-W., & Choi, K. H. (2018). 3D printing for soft robotics—a review. *Science and Technology of Advanced Materials*, *19*(1), 243–262. DOI: https://doi.org/10.1080/14686996.2018.1431862, PMID: 29707065, PMCID: PMC5917433

36. Hauser, S., Mutlu, M., Léziart, P. A., Khodr, H., Bernardino, A., & Ijspeert, A. J. (2020). Roombots extended: Challenges in the next generation of self-reconfigurable modular robots and their application in adaptive and assistive furniture. *Robotics and Autonomous Systems*, *127*, 103467. DOI: https://doi.org/10.1016/j.robot .2020.103467

37. Hawkes, E. W., Blumenschein, L. H., Greer, J. D., & Okamura, A. M. (2017). A soft robot that navigates its environment through growth. *Science Robotics*, *2*(8), eaan3028. DOI: https://doi.org/10.1126/scirobotics.aan3028, PMID: 33157883

38. Hiller, J., & Lipson, H. (2012). Automatic design and manufacture of soft robots. *IEEE Transactions on Robotics*, *28*(2), 457–466. DOI: https://doi.org/10.1109/TRO.2011.2172702

39. Hiller, J., & Lipson, H. (2014). Dynamic simulation of soft multimaterial 3D-printed objects. *Soft Robotics*, *1*(1), 88–101. DOI: https://doi.org/10.1089/soro.2013.0010

40. Hornby, G. S., & Pollack, J. B. (2001). The advantages of generative grammatical encodings for physical design. In *Proceedings of the 2001 Congress on Evolutionary Computation, Volume 1* (pp. 600–607). New York: IEEE.

41. Howard, D., Eiben, A. E., Kennedy, D. F., Mouret, J.-B., Valencia, P., & Winkler, D. (2019). Evolving embodied intelligence from materials to machines. *Nature Machine Intelligence*, *1*(1), 12–19. DOI: https://doi.org/10.1038/s42256-018-0009-9

42. Howison, T., Hughes, J., & Iida, F. (2020). Large-scale automated investigation of free-falling paper shapes via iterative physical experimentation. *Nature Machine Intelligence*, *2*(1), 68–75. DOI: https://doi.org/10.1038/s42256-019-0135-z

43. Howison, T., Hughes, J., & Iida, F. (2020). Morphologically programming the interactions of V-shaped falling papers. In *ALIFE 2020: The 2020 Conference on Artificial Life* (pp. 359–366). Cambridge, MA: MIT Press. DOI: https://doi.org/10.1162/isal_a_00306

44. Hu, Y., Liu, J., Spielberg, A., Tenenbaum, J. B., Freeman, W. T., Wu, J., Rus, D., & Matusik, W. (2019). ChainQueen: A real-time differentiable physical simulator for soft robotics. In *2019 International Conference on Robotics and Automation (ICRA)* (pp. 6265–6271). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2019.8794333

45. Hughes, J., & Iida, F. (2017). 3D printed sensorized soft robotic manipulator design. In Y. Gao, S. Fallah, Y. Jin, & C. Lekakou (Eds.), *Towards autonomous robotic systems* (pp. 627–636). Cham: Springer. DOI: https://doi.org/10.1007/978-3-319-64107-2_51

46. Hughes, J. A. E., Maiolino, P., & Iida, F. (2018). An anthropomorphic soft skeleton hand exploiting conditional models for piano playing. *Science Robotics*, *3*(25), eaau3098. DOI: https://doi.org/10.1126/scirobotics.aau3098, PMID: 33141692

47. Huizinga, J., Stanley, K. O., & Clune, J. (2018). The emergence of canalization and evolvability in an open-ended, interactive evolutionary system. *Artificial Life*, *24*(3), 157–181. DOI: https://doi.org/10.1162/artl_a_00263, PMID: 30485140

48. Ilievski, F., Mazzeo, A. D., Shepherd, R. F., Chen, X., & Whitesides, G. M. (2011). Soft robotics for chemists. *Angewandte Chemie International Edition*, *50*(8), 1890–1895. DOI: https://doi.org/10.1002/anie.201006464, PMID: 21328664

49. Jacob, C. (1994). Genetic L-system programming. In Y. Davidor, H.-P. Schwefel, & R. Männer (Eds.), *Parallel problem solving from nature* (pp. 333–343). Berlin, Heidelberg: Springer. DOI: https://doi.org/10.1007/3-540-58484-6_277

50. Jakobi, N. (1997). Evolutionary robotics and the radical envelope-of-noise hypothesis. *Adaptive Behavior*, *6*(2), 325–368. DOI: https://doi.org/10.1177/105971239700600205

51. Joachimczak, M., Suzuki, R., & Arita, T. (2015). Improving evolvability of morphologies and controllers of developmental soft-bodied robots with novelty search. *Frontiers in Robotics and AI*, *2*, 33. DOI: https://doi.org/10.3389/frobt.2015.00033

52. Katzschmann, R. K., Marchese, A. D., & Rus, D. (2016). Hydraulic autonomous soft robotic fish for 3D swimming. In M. A. Hsieh, O. Khatib, & V. Kumar (Eds.), *Experimental robotics: The 14th International Symposium on Experimental Robotics* (pp. 405–420). Cham: Springer. DOI: https://doi.org/10.1007/978-3-319-23778-7_27

53. Khazanov, M., Jocque, J., & Rieffel, J. (2014). Evolution of locomotion on a physical tensegrity robot. In *ALIFE 14: The Fourteenth International Conference on the Synthesis and Simulation of Living Systems* (pp. 232–238). Cambridge, MA: MIT Press.

54. Kim, S., Laschi, C., & Trimmer, B. (2013). Soft robotics: A bioinspired evolution in robotics. *Trends in Biotechnology*, *31*(5), 287–294. DOI: https://doi.org/10.1016/j.tibtech.2013.03.002, PMID: 23582470

55. Koos, S., Mouret, J., & Doncieux, S. (2013). The transferability approach: Crossing the reality gap in evolutionary robotics. *IEEE Transactions on Evolutionary Computation*, *17*(1), 122–145. DOI: https://doi .org/10.1109/TEVC.2012.2185849

56. Kriegman, S., Blackiston, D., Levin, M., & Bongard, J. (2020). A scalable pipeline for designing reconfigurable organisms. *Proceedings of the National Academy of Sciences of the USA*, *117*(4), 1853–1859. DOI: https://doi.org /10.1073/pnas.1910837117, PMID: 31932426, PMCID: PMC6994979

57. Kriegman, S., Cappelle, C., Corucci, F., Bernatskiy, A., Cheney, N., & Bongard, J. C. (2017). Simulating the evolution of soft and rigid-body robots. In *Proceedings of the Genetic and Evolutionary Computation Conference companion* (pp. 1117–1120). New York: ACM. DOI: https://doi.org/10.1145/3067695.3082051

58. Kriegman, S., Cheney, N., & Bongard, J. (2018). How morphological development can guide evolution. *Scientific Reports*, *8*(1), 1–10. DOI: https://doi.org/10.1038/s41598-018-31868-7, PMID: 30224743, PMCID: PMC6141532

59. Kriegman, S., Nasab, A. M., Shah, D., Steele, H., Branin, G., Levin, M., Bongard, J., & Kramer-Bottiglio, R. (2020). Scalable sim-to-real transfer of soft robot designs. In *2020 3rd IEEE International Conference on Soft Robotics (RoboSoft)* (pp. 359–366). New York: IEEE. DOI: https://doi.org/10.1109/RoboSoft48309.2020 .9116004

60. Kwiatkowski, R., & Lipson, H. (2019). Task-agnostic self-modeling machines. *Science Robotics*, *4*(26), eaau9354. DOI: https://doi.org/10.1126/scirobotics.aau9354, PMID: 33137761

61. Laschi, C., Mazzolai, B., & Cianchetti, M. (2016). Soft robotics: Technologies and systems pushing the boundaries of robot abilities. *Science Robotics*, *1*(1), aah3690. DOI: https://doi.org/10.1126/scirobotics .aah3690, PMID: 33157856

62. Lau, M., Ohgawara, A., Mitani, J., & Igarashi, T. (2011). Converting 3D furniture models to fabricatable parts and connectors. *ACM Transactions on Graphics*, *30*(4), 1–6. DOI: https://doi.org/10.1145/2010324.1964980

63. Lehman, J., & Miikkulainen, R. (2015). Enhancing divergent search through extinction events. In *Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation* (pp. 951–958). New York: ACM. DOI: https://doi.org/10.1145/2739480.2754668

64. Lehman, J., & Stanley, K. O. (2011). Abandoning objectives: Evolution through the search for novelty alone. *Evolutionary Computation*, *19*(2), 189–223. DOI: https://doi.org/10.1162/EVCO_a_00025, PMID: 20868264

65. Lehman, J., & Stanley, K. O. (2011). Evolving a diversity of virtual creatures through novelty search and local competition. In *Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation* (pp. 211–218). New York: ACM. DOI: https://doi.org/10.1145/2001576.2001606

66. Li, J., Liu, L., Liu, Y., & Leng, J. (2019). Dielectric elastomer spring-roll bending actuators: Applications in soft robotics and design. *Soft Robotics*, *6*(1), 69–81. DOI: https://doi.org/10.1089/soro.2018.0037, PMID: 30335571

67. Liang, J., Lin, M., & Koltun, V. (2019). Differentiable cloth simulation for inverse problems. In H. Wallach, H. Larochelle, A. Beygelzimer, F. dAlché Buc, E. Fox, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems 32* (pp. 772–781). Red Hook, NY: Curran Associates Inc.

68. Lipson, H. (2014). Challenges and opportunities for design, simulation, and fabrication of soft robots. *Soft Robotics*, *1*(1), 21–27. DOI: https://doi.org/10.1089/soro.2013.0007

69. Lipton, J. I., MacCurdy, R., Manchester, Z., Chin, L., Cellucci, D., & Rus, D. (2018). Handedness in shearing auxetics creates rigid and compliant structures. *Science*, *360*(6389), 632–635. DOI: https://doi .org/10.1126/science.aar4586, PMID: 29748279

70. Malley, M., Rubenstein, M., & Nagpal, R. (2017). Flippy: A soft, autonomous climber with simple sensing and control. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 6533–6540). New York: IEEE. DOI: https://doi.org/10.1109/IROS.2017.8206563

71. Maziz, A., Concas, A., Khaldi, A., Stålhand, J., Persson, N.-K., & Jager, E. W. H. (2017). Knitting and weaving artificial muscles. *Science Advances*, *3*(1), e1600327. DOI: https://doi.org/10.1126/sciadv .1600327, PMID: 28138542, PMCID: PMC5266480

72. McCormack, J., Dorin, A., & Innocent, T. (2005). Generative design: A paradigm for design research. In J. Redmond, D. Durling, & A. de Bono (Eds.), *Futureground, volume 2*. Melbourne: Monash University.

73. Mehta, A. M., DelPreto, J., Shaya, B., & Rus, D. (2014). Cogeneration of mechanical, electrical, and software designs for printable robots from structural specifications. In *2014 IEEE/RSJ International Conference on*

Intelligent Robots and Systems (pp. 2892–2897). New York: IEEE. DOI: https://doi.org/10.1109/IROS.2014 .6942960

74. Mehta, A. M., & Rus, D. (2014). An end-to-end system for designing mechanical structures for print-and-fold robots. In *2014 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 1460–1465). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2014.6907044

75. Morimoto, Y., Onoe, H., & Takeuchi, S. (2018). Biohybrid robot powered by an antagonistic pair of skeletal muscle tissues. *Science Robotics*, *3*(18), eaat4440. DOI: https://doi.org/10.1126/scirobotics.aat4440, PMID: 33141706

76. Motzki, P., Khelfa, F., Zimmer, L., Schmidt, M., & Seelecke, S. (2019). Design and validation of a reconfigurable robotic end-effector based on shape memory alloys. *IEEE/ASME Transactions on Mechatronics*, *24*(1), 293–303. DOI: https://doi.org/10.1109/TMECH.2019.2891348

77. Mouret, J.-B., & Chatzilygeroudis, K. (2017). 20 years of reality gap: A few thoughts about simulators in evolutionary robotics. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 1121–1124). New York: ACM. DOI: https://doi.org/10.1145/3067695.3082052

78. Mouret, J.-B., & Clune, J. (2015). Illuminating search spaces by mapping elites. *arXiv Preprint arXiv:1504 .04909*.

79. Mouret, J.-B., & Doncieux, S. (2008). Incremental evolution of animats' behaviors as a multi-objective optimization. In M. Asada, J. C. T. Hallam, J.-A. Meyer, & J. Tani (Eds.), *From Animals to Animats 10* (pp. 210–219). Berlin, Heidelberg: Springer. DOI: https://doi.org/10.1007/978-3-540-69134-1_21

80. Mouret, J.-B., & Doncieux, S. (2012). Encouraging behavioral diversity in evolutionary robotics: An empirical study. *Evolutionary Computation*, *20*(1), 91–133. DOI: https://doi.org/10.1162/EVCO_a_00048, PMID: 21838553

81. Nakajima, K., Hauser, H., Li, T., & Pfeifer, R. (2015). Information processing via physical soft body. *Scientific Reports*, *5*, 10487. DOI: https://doi.org/10.1038/srep10487, PMID: 26014748, PMCID: PMC4444959

82. Neubert, J., & Lipson, H. (2015). Soldercubes: A self-soldering self-reconfiguring modular robot system. *Autonomous Robots*, *40*, 139–158. DOI: https://doi.org/10.1007/s10514-015-9441-4

83. Nurzaman, S. G., Culha, U., Brodbeck, L., Wang, L., & Iida, F. (2013). Active sensing system with in situ adjustable sensor morphology. PLOS ONE, *8*(12), e84090. DOI: https://doi.org/10.1371/journal.pone .0084090, PMID: 24416094, PMCID: PMC3887119

84. Nurzaman, S. G., Iida, F., Margheri, L., & Laschi, C. (2014). Soft robotics on the move: Scientific networks, activities, and future challenges. *Soft Robotics*, *1*, 154–158. DOI: https://doi.org/10.1089/soro.2014.0012

85. Nygaard, T. F., Martin, C. P., Samuelsen, E., Torresen, J., & Glette, K. (2018). Real-world evolution adapts robot morphology and control to hardware limitations. In *Proceedings of the Genetic and Evolutionary Computation Conference* (pp. 125–132). New York: ACM. DOI: https://doi.org/10.1145/3205455 .3205567

86. Onal, C. D., Wood, R. J., & Rus, D. (2011). Towards printable robotics: Origami-inspired planar fabrication of three-dimensional mechanisms. In *2011 IEEE International Conference on Robotics and Automation* (pp. 4608–4613). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2011.5980139

87. Peng, X. B., Andrychowicz, M., Zaremba, W., & Abbeel, P. (2018). Sim-to-real transfer of robotic control with dynamics randomization. In *2018 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 3803–3810). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2018.8460528

88. Pfeifer, R., & Bongard, J. (2006). *How the body shapes the way we think: a new view of intelligence*. Cambridge, MA: MIT Press.

89. Pfeifer, R., Lungarella, M., & Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. *Science*, *318*(5853), 1088–1093. DOI: https://doi.org/10.1126/science.1145803, PMID: 18006736

90. Pfeifer, R., Lungarella, M., & Iida, F. (2012). The challenges ahead for bio-inspired 'soft' robotics. *Communications of the ACM*, *55*(11), 76–87. DOI: https://doi.org/10.1145/2366316.2366335

91. Polygerinos, P., Correll, N., Morin, S. A., Mosadegh, B., Onal, C. D., Petersen, K., Cianchetti, M., Tolley, M. T., & Shepherd, R. F. (2017). Soft robotics: Review of fluid-driven intrinsically soft devices; manufacturing, sensing, control, and applications in human-robot interaction. *Advanced Engineering Materials*, *19*(12), 1700016. DOI: https://doi.org/10.1002/adem.201700016

92. Pozzi, M., Miguel, E., Deimel, R., Malvezzi, M., Bickel, B., Brock, O., & Prattichizzo, D. (2018). Efficient FEM-based simulation of soft robots modeled as kinematic chains. In *2018 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 1–8). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2018.8461106

93. Pugh, J. K., Soros, L. B., & Stanley, K. O. (2016). Quality diversity: A new frontier for evolutionary computation. *Frontiers in Robotics and AI*, *3*, 40. DOI: https://doi.org/10.3389/frobt.2016.00040

94. Richards, D., & Amos, M. (2014). Evolving morphologies with CPPN-NEAT and a dynamic substrate. In *ALIFE 2014: The Fourteenth International Conference on the Synthesis and Simulation of Living Systems* (pp. 255–262). Cambridge, MA: MIT Press. DOI: https://doi.org/10.7551/978-0-262-32621-6-ch042

95. Rieffel, J., Knox, D., Smith, S., & Trimmer, B. (2014). Growing and evolving soft robots. *Artificial Life*, *20*(1), 143–162. DOI: https://doi.org/10.1162/ARTL_a_00101, PMID: 23373976

96. Rieffel, J., & Mouret, J.-B. (2018). Adaptive and resilient soft tensegrity robots. *Soft Robotics*, *5*(3), 318–329. DOI: https://doi.org/10.1089/soro.2017.0066, PMID: 29664708, PMCID: PMC6001847

97. Rieffel, J., & Pollack, J. (2005). Crossing the fabrication gap: Evolving assembly plans to build 3D objects. In *2005 IEEE Congress on Evolutionary Computation, volume 1* (pp. 529–536). New York: IEEE.

98. Romanishin, J. W., Gilpin, K., & Rus, D. (2013). M-blocks: Momentum-driven, magnetic modular robots. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 4288–4295). New York: IEEE. DOI: https://doi.org/10.1109/IROS.2013.6696971

99. Romano, D., Donati, E., Benelli, G., & Stefanini, C. (2019). A review on animal–robot interaction: From bio-hybrid organisms to mixed societies. *Biological Cybernetics*, *113*(3), 201–225. DOI: https://doi.org/10.1007/s00422-018-0787-5, PMID: 30430234

100. Rosendo, A., von Atzigen, M., & Iida, F. (2017). The trade-off between morphology and control in the co-optimized design of robots. *PLOS ONE*, *12*, e0186107. DOI: https://doi.org/10.1371/journal.pone.0186107, PMID: 29023482, PMCID: PMC5638323

101. Rosser, K., Kok, J., Chahl, J., & Bongard, J. (2020). Sim2real gap is non-monotonic with robot complexity for morphology-in-the-loop flapping wing design. In *2020 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 7001–7007). New York: IEEE. DOI: https://doi.org/10.1109/ICRA40945.2020.9196539

102. Rubanova, Y., Chen, R. T. Q., & Duvenaud, D. K. (2019). Latent ordinary differential equations for irregularly-sampled time series. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché Buc, E. Fox, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems 32* (pp. 5320–5330). Red Hook, NY: Curran Associates Inc.

103. Rubenstein, M., Cornejo, A., & Nagpal, R. (2014). Programmable self-assembly in a thousand-robot swarm. *Science*, *345*(6198), 795–799. DOI: https://doi.org/10.1126/science.1254295, PMID: 25124435

101. Rudy, S. H., Brunton, S. L., Proctor, J. L., & Kutz, J. N. (2017). Data-driven discovery of partial differential equations. *Science Advances*, *3*(4), e1602614. DOI: https://doi.org/10.1126/sciadv.1602614, PMID: 28508044, PMCID: PMC5406137

105. Runge, G., Wiese, M., Günther, L., & Raatz, A. (2017). A framework for the kinematic modeling of soft material robots combining finite element analysis and piecewise constant curvature kinematics. In *2017 3rd International Conference on Control, Automation and Robotics (ICCAR)* (pp. 7–14). New York: IEEE. DOI: https://doi.org/10.1109/ICCAR.2017.7942652

106. Rus, D., & Tolley, M. T. (2015). Design, fabrication and control of soft robots. *Nature*, *521*(7553), 467–475. DOI: https://doi.org/10.1038/nature14543, PMID: 26017446

107. Rus, D., & Tolley, M. T. (2018). Design, fabrication and control of origami robots. *Nature Reviews Materials*, *3*(6), 101. DOI: https://doi.org/10.1038/s41578-018-0009-8

108. Saar, K. A., Giardina, F., & Iida, F. (2018). Model-free design optimization of a hopping robot and its comparison with a human designer. *IEEE Robotics and Automation Letters*, *3*(2), 1245–1251. DOI: https://doi.org/10.1109/LRA.2018.2795646

109. Santina, C. D., & Rus, D. (2020). Control oriented modeling of soft robots: The polynomial curvature case. *IEEE Robotics and Automation Letters*, *5*(2), 290–298. DOI: https://doi.org/10.1109/LRA.2019.2955936

110. Schmid, P. J. (2010). Dynamic mode decomposition of numerical and experimental data. *Journal of Fluid Mechanics*, *656*, 5–28. DOI: https://doi.org/10.1017/S0022112010001217

111. Schmidt, M., & Lipson, H. (2009). Distilling free-form natural laws from experimental data. *Science*, *324*(5923), 81–85. DOI: https://doi.org/10.1126/science.1165893, PMID: 19342586

112. Schmitt, F., Piccin, O., Barbé, L., & Bayle, B. (2018). Soft robots manufacturing: A review. *Frontiers in Robotics and AI*, *5*, 84. DOI: https://doi.org/10.3389/frobt.2018.00084

113. Schulz, A., Sung, C., Spielberg, A., Zhao, W., Cheng, R., Grinspun, E., Rus, D., & Matusik, W. (2017). Interactive robogami: An end-to-end system for design of robots with ground locomotion. *The International Journal of Robotics Research*, *36*(10), 1131–1147. DOI: https://doi.org/10.1177/0278364917723465

114. Scimeca, L., Hughes, J., Maiolino, P., & Iida, F. (2019). Model-free soft-structure reconstruction for proprioception using tactile arrays. *IEEE Robotics and Automation Letters*, *4*(3), 2479–2484. DOI: https://doi.org/10.1109/LRA.2019.2906548

115. Shih, B., Shah, D., Li, J., Thuruthel, T. G., Park, Y.-L., Iida, F., Bao, Z., Kramer-Bottiglio, R., & Tolley, M. T. (2020). Electronic skins and machine learning for intelligent soft robots. *Science Robotics*, *5*(41), eaaz9239. DOI: https://doi.org/10.1126/scirobotics.aaz9239, PMID: 33022628

116. Silva, D. F., & Maciel, A. (2012). A comparative study of physics engines for modeling soft tissue deformation. In *2012 XXXVIII Conferencia Latinoamericana En Informatica (CLEI)* (pp. 1–7). New York: IEEE. DOI: https://doi.org/10.1109/CLEI.2012.6427120

117. Sims, K. (1994). Evolving 3D morphology and behavior by competition. *Artificial Life*, *1*(4), 353–372. DOI: https://doi.org/10.1162/artl.1994.1.4.353

118. Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical Bayesian optimization of machine learning algorithms. In *Proceedings of the 25th International Conference on Neural Information Processing Systems—Volume 2* (pp. 2951–2959). Red Hook, NY: Curran Associates Inc.

119. Sun, Y., Song, Y. S., & Paik, J. (2013). Characterization of silicone rubber based soft pneumatic actuators. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 4446–4453). New York: IEEE.

120. Suthakorn, J., Cushing, A. B., & Chirikjian, G. S. (2003). An autonomous self-replicating robotic system. In *Proceedings 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM 2003)* (pp. 137–142). New York: IEEE.

121. Tarapore, D., & Mouret, J.-B. (2015). Evolvability signatures of generative encodings: Beyond standard performance benchmarks. *Information Sciences*, *313*, 43–61. DOI: https://doi.org/10.1016/j.ins.2015.03.046

122. Trianni, V., & López-Ibáñez, M. (2015). Advantages of task-specific multi-objective optimisation in evolutionary robotics. *PLOS ONE*, *10*(8), e0136406. DOI: https://doi.org/10.1371/journal.pone.0136406, PMID: 26295151, PMCID: PMC4546428

123. Veenstra, F., Jørgensen, J., & Risi, S. (2018). Evolution of fin undulation on a physical knifefish-inspired soft robot. In *Proceedings of the Genetic and Evolutionary Computation Conference* (pp. 157–164). New York: ACM. DOI: https://doi.org/10.1145/3205455.3205583

124. Vergara, A., Lau, Y.-S., Mendoza-Garcia, R.-F., & Zagal, J. C. (2017). Soft modular robotic cubes: Toward replicating morphogenetic movements of the embryo. *PLOS ONE*, *12*(1), e0169179. DOI: https://doi.org/10.1371/journal.pone.0169179, PMID: 28060878, PMCID: PMC5218564

125. von Mammen, S., & Jacob, C. (2007). Genetic swarm grammar programming: Ecological breeding like a gardener. In *2007 IEEE Congress on Evolutionary Computation* (pp. 851–858). New York: IEEE. DOI: https://doi.org/10.1109/CEC.2007.4424559

126. Vujovic, V., Rosendo, A., Brodbeck, L., & Iida, F. (2017). Evolutionary developmental robotics: Improving morphology and control of physical robots. *Artificial Life*, *23*(2), 169–185. DOI: https://doi.org/10.1162/ARTL_a_00228, PMID: 28513207

127. Wallin, T., Pikul, J., & Shepherd, R. (2018). 3D printing of soft robotic systems. *Nature Reviews Materials*, *3*(6), 84–100. DOI: https://doi.org/10.1038/s41578-018-0002-2

128. Webster, R. J. III, & Jones, B. A. (2010). Design and kinematic modeling of constant curvature continuum robots: A review. *The International Journal of Robotics Research*, *29*(13), 1661–1683. DOI: https://doi.org/10.1177/0278364910368147

129. Wehner, M., Truby, R. L., Fitzgerald, D. J., Mosadegh, B., Whitesides, G. M., Lewis, J. A., & Wood, R. J. (2016). An integrated design and fabrication strategy for entirely soft, autonomous robots. *Nature*, *536*(7617), 451–455. DOI: https://doi.org/10.1038/nature19100, PMID: 27558065

130. Werfel, J., Petersen, K., & Nagpal, R. (2014). Designing collective behavior in a termite-inspired robot construction team. *Science*, *343*(6172), 754–758. DOI: https://doi.org/10.1126/science.1245842, PMID: 24531967

131. Whitesides, G. M. (2018). Soft robotics. *Angewandte Chemie International Edition*, *57*(16), 4258–4273. DOI: https://doi.org/10.1002/anie.201800907, PMID: 29517838

132. Yarbasi, E. Y., & Samur, E. (2018). Design and evaluation of a continuum robot with extendable balloons. *Mechanical Sciences*, *9*(1), 51–60. DOI: https://doi.org/10.5194/ms-9-51-2018

133. Zappetti, D., Mintchev, S., Shintake, J., & Floreano, D. (2017). Bio-inspired tensegrity soft modular robots. In M. Mangan, M. Cutkosky, A. Mura, P. F. Verschure, T. Prescott, & N. Lepora (Eds.), *Biomimetic and biohybrid systems* (pp. 497–508). Cham: Springer. DOI: https://doi.org/10.1007/978-3 -319-63537-8_42

134. Zhakypov, Z., & Paik, J. (2018). Design methodology for constructing multimaterial origami robots and machines. *IEEE Transactions on Robotics*, *34*(1), 151–165. DOI: https://doi.org/10.1109/TRO .2017.2775655

135. Zhang, J., Zhou, M., Huang, Y., Ren, P., Wu, Z., Wang, X., & Zhao, S. F. (2017). A smoothed finite element-based elasticity model for soft bodies. *Mathematical Problems in Engineering*, *2017*, 467356. DOI: https://doi.org/10.1155/2017/1467356

136. Zhang, Z., Dequidt, J., Kruszewski, A., Largilliere, F., & Duriez, C. (2016). Kinematic modeling and observer based control of soft robot using real-time finite element method. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 5509–5514). New York: IEEE. DOI: https://doi.org/10.1109/IROS.2016.7759810

137. Zheng, G., Goury, O., Thieffry, M., Kruszewski, A., & Duriez, C. (2019). Controllability pre-verification of silicone soft robots based on finite-element method. In *2019 International Conference on Robotics and Automation (ICRA)* (pp. 7395–7400). New York: IEEE. DOI: https://doi.org/10.1109/ICRA.2019 .8794370