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Shape Changing Robots: Bioinspiration, Simulation, and Physical Realization

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One of the key differentiators between biological and artificial systems is the dynamic plasticity of living tissues, enabling adaptation to different environmental conditions, tasks, or damage by reconfiguring physical structure and behavioral control policies. Lack of dynamic plasticity is a significant limitation for artificial systems that must robustly operate in the natural world. Recently, researchers have begun to leverage insights from regenerating and metamorphosing organisms, designing robots capable of editing their own structure to more efficiently perform tasks under changing demands and creating new algorithms to control these changing anatomies. Here, an overview of the literature related to robots that change shape to enhance and expand their functionality is presented. Related grand challenges, including shape sensing, finding, and changing, which rely on innovations in multifunctional materials, distributed actuation and sensing, and somatic control to enable next-generation shape changing robots are also discussed.

1. Introduction

Biological organisms are able to adjust their body structure, stiffness, and behavior toward a complex anatomy that accommodates a variety of environmental demands and external perturbations. For example, octopuses have been observed to squeeze through apertures that are much smaller than their body, hydrostatic caterpillars use peristaltic shape change to locomote across numerous environments,[1] and moth larvae have been observed to curl up to roll away from predators.[2] In contrast, robots often are specialized for a single task, and cannot adapt their body to accomplish additional tasks after manufacture. Moreover, biological bodies are often highly regenerative, and able to repair and reconfigure their large-scale architecture in the face of significant damage or radical changes to their components.[3] For example, salamanders regenerate amputated limbs,[4] and fragments cut from arbitrary portions of planaria flatworms can rebuild (and rescale) their bodies to recover a full, correct anatomy.[3] Remarkably, many of these systems are able to retain information, such as learned memories, despite drastic reconfiguration or total replacement of their brains.[5] In these integrated living systems, intelligence, memory, learning, behavior, and body structure are all intertwined and emerge from the multiscale dynamics of the same robust and highly fault-tolerant medium.

Evolution did not result in hard-coded body plans purely determined by genetic factors, but rather produced diverse examples of intelligent self-modifying systems which adapt to numerous extragenomic influences.[6] In this way, biology serves as an important proof-of-principle, and design challenge, for artificial intelligence and shape changing robots. Despite having access to this extensive set of model systems, the realization of general-purpose, adaptive robots has remained elusive. Researchers have proposed modular robots that can be attached to each other to expand functionality,[7] passively conforming universal grippers,[8] reconfigurable robotic skins,[9] self-assembling robot swarms,[10] gait-switching mechanisms[11] and controllers,[12,13] and algorithms that quickly re-adapt to multiple distinct tasks.[14] Such approaches succeed at adaptation but operate under the assumption that the robot's body is only reconfigured or reshaped due to external forces, and do not explore the possibility of synthetic machines that actively grow, regenerate, deform, or otherwise change the resting shape of their constituent components.

With the introduction of a conformable gripper by Hirose in 1978,[15] followed by continuum robot arms,[16] silicone grippers,[17] and variable stiffness actuators,[18] robots that can adapt to real-world environments by changing their shape are becoming closer to reality. In particular, the idea of passively conforming around objects during grasping has been quite successful.[17,19,20] Soft robots have shown potential in other applications, including human–robot interaction and exploration, as reviewed by Kim et al.,[21] Rus et al.,[22] and others.[23,24] For a comprehensive review of the role of deformation in single-function soft robots, the reader is referred to Wang et al.[25]

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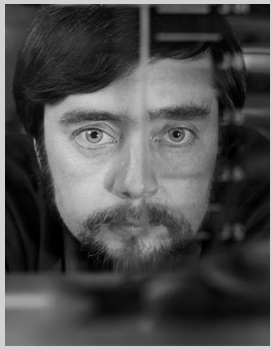
Several recent works have begun to explore the idea of using the resting (non-actuated) shape of a robot's body as a way to expand the robot's functionality. For example, one robot could switch between spherical and cylindrical shapes for medical applications such as navigating the digestive system.[26,27] Another robot used origami techniques to change the diameter of its wheels to crawl over steps and under overhangs.[28] Nygaard et al. introduced a quadrupedal robot that adjusted its leg length to maximize locomotion speed across different surfaces.[29] In another recent study, robotic skins were attached to sculptable materials to create a robot that could change its shape to navigate over an obstacle, rather than searching for a path around the obstacle.[30] Shape change can also be used to allow robots to recover from damage, sometimes outperforming adaptations in control policy.[31] In such examples, even relatively small changes in resting body shape proved useful, pointing toward future general-purpose robots that leverage shape change to adapt to challenging real-world environments, as envisioned in **Figure 1**.

Despite the intense interest in the genesis and implications of shape for many fields, including medicine,[32] developmental biology,[33] swarm robotics,[34] and evolutionary robotics,[35] a consensus on how to quantify changes in shape has not been reached. Taha et al., for instance, reported that 20 distinct shape metrics are commonly used for 3D medical image segmentation.[32] For robots, one natural approach to measure shape change is calculating a virtual "elastic deformation energy," which can be thought of as the energy required to stretch an elastic membrane from one shape to another.[36] However, for many robots, it is difficult to generate meshes or analytic expressions to represent their shape in real time, and it is common in robotics to quantify shape-estimation errors using a small subset of surface points and evaluating root-mean-squared error (RMSE) or mean absolute error.[37–42] Several other discrete measurements of shape similarity have been proposed in the robotics community, including Procrustes analysis (a modification of RMSE that is invariant to rotation, scaling, and translation errors),[40] a "shape index" ($S = \text{Perimeter}/\left(2\sqrt{\pi \times \text{area}}\right)$, which does not define a true metric),[10] and the Hausdorff distance.[43]

Here, we will use the term "shape changing robots" to refer to robots that actively change their shape to adapt to their environment or gain new functionalities. Although this definition does not divide robots into two mutually exclusive sets, it provides a framework to critically evaluate the state-of-the-art design paradigms and materials used in robotics. Through such introspection, and by observing biological mechanisms for shape change, we present several avenues where fundamental advances in materials science can enable the next generation of adaptive, shape changing robots, potentially one day rivaling biological systems that locally encode shape information to enable dynamic plasticity and regeneration.[33]

2. Biological Control of Shape

In organisms ranging from flatworms to mammals, hierarchical processes regulate shape throughout development to ensure the organism can succeed in its ecological niche throughout its life cycle.[33] Each normal fertilized egg reliably



Michael Levin is interested in embodiments of mind at multiple scales of biology and engineering. He received B.S. degrees in computer science and biology, followed by a Ph.D. (Harvard University). After a post-doc (Harvard Medical School), he started his independent lab focusing on the biophysics of cell:cell communication during embryogenesis, regeneration, and cancer. His group at Tufts uses biophysical and computational approaches to study decision-making and basal cognition in cells, tissues, and artificial living machines. He holds the Vannevar Bush chair, and directs the Allen Discovery Center, working to crack the morphogenetic code for applications in regenerative medicine and machine learning.

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Figure 1. Next-generation shape changing soft robots will sense their environment and adjust their shape and behavior to accommodate environmental or terrain changes.

self-assembles a default 3D anatomical structure with very precise tolerances to a standard "target morphology" for that species. This process is remarkably robust—for example, mammalian embryos can be cut in half and each will result in a complete, normal body. In another example, land-based mammalian embryos thrive in an aqueous environment during fetal development, yet prior to birth grow skeletal structures more suitable for terrestrial locomotion.

Regenerative animals provide a unique example of how shape change can be used to recover from damage. When the limbs of a salamander are amputated, the cells are called upon to proliferate, perform morphogenesis, and stop when a correct salamander limb is complete.[4] How the cells are able to ascertain the current morphology of the much larger limb, and continually compare it to an intrinsic model of the target limb morphology to control individual cell behaviors toward self-limiting repair, is largely unknown.[44] However, it is clear that this somatic decision-making is an ancient, pre-neural example of intelligence and distributed computation in biological systems.[45–47] The tissue undergoing dynamic shape change is the same tissue that is processing information on-the-fly and making decisions about growth and form. Regenerative systems thus challenge engineers to implement a kind of integrated, robust computational medium that can continue to guide its own shape even as it is being deformed.

Recent progress in genomics and molecular biology have shed crucial light on the origin of biological hardware: genes encode signaling and structural components (proteins) at the sub-cellular level. However, the genome does not directly encode the target morphology, nor the algorithms sufficient to perform the kind of error correction seen during regeneration.[6] The search for the biological software that runs on the genome-specified hardware has only begun, and two key features are now apparent. First, the software is biophysical in implementation. Bioelectric networks[48] enable cell collectives to store pattern memories, generate spontaneous symmetry-breaking morphogenesis, recognize patterns, and integrate information across large distances in the body[49]—all occurring outside the brain. Second, this embodied software strategy enables dynamic plasticity. For example, caterpillars that learn conditioned responses to a chemical in their environment retain that information as butterflies, despite complete brain reconstruction during metamorphosis.[50] Planaria retain their memories across total brain removal and regeneration.[51,52] Oviedo et al. showed a technique for creating two-headed flatworms whose pieces continue to regenerate as two-headed forms in subsequent rounds of damage and regrowth without further treatment.[53] Tadpoles made to have eyes only on their tails can see quite well, despite this unprecedented change in sensory system architecture.[54] Next-generation robots can learn from these examples of basal cognition coupled to physical shape change,[45,55] perhaps embedding information-processing tools that guide shape change directly into the robot's body.[56,57]

3. Simulated Shape Changing Robots

Although numerous organisms successfully exploit shape change as a mechanism for adaptation and survival, it is unclear when and how robots should change their shape. To address these questions, it would be useful to evaluate a large number of diverse shape changing robots in different environments. However, manufacturing and deploying multiple robots can be expensive, time consuming, and even dangerous. Thus, simulations are often used to weed out undesirable designs before attempting to build them in reality.[43,58–60]

Yet, under realistic design conditions, simulations cannot exhaustively search the design space. Even using a small number of mechanical parts, the size of the design space is enormous. For example, in voxel-based robot simulators,[61,62] which use voxels as structural building blocks, there are 4.5×10^8 unique ways to arrange 12 voxels to form a robot, and the design space (the number of possible designs) increases exponentially with each additional block.[63] As a result, evolutionary[64–67] and learning[68,69] algorithms are usually employed to efficiently explore the vast space of possible robot designs.[70]

Directly incorporating biologically inspired mechanisms of shape change—for example, slowly extruding limbs during optimization rather than optimizing controllers only for the

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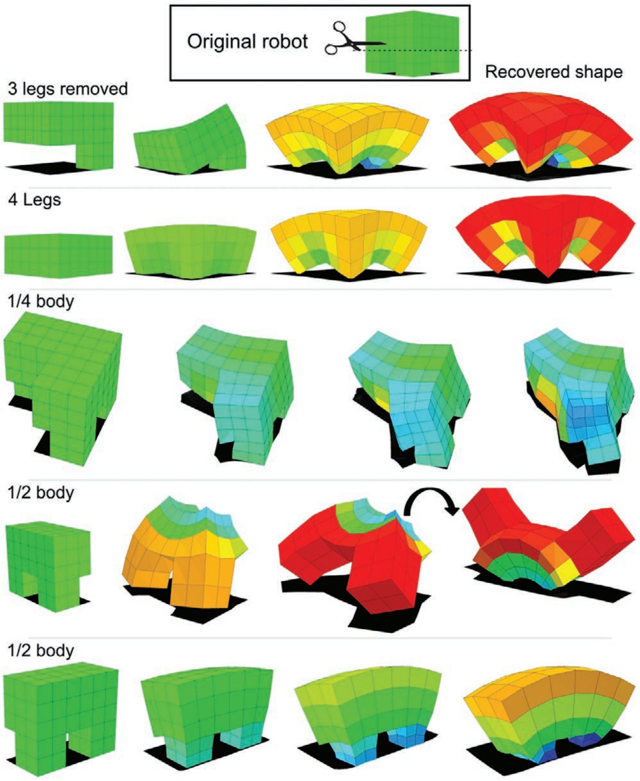

Figure 2. Simulations can automatically generate complex shape changing robots, including ones that recover from damage through shape change. The quadrupedal robot shown here discovered that, after being damaged, it was more advantageous to change its shape than adapt its control policy. Adapted with permission.[31] Copyright 2019, Sam Kriegman.

final, legged form of the robot—has been shown to speed the evolution of robust, adaptive behavior in simulated robots.[71] In other cases, evolved robots have rediscovered natural strategies on their own. For example, simulated soft robots evolved control policies that allowed them to squeeze their bodies through small apertures.[72] In another study, a simulated quadruped had all four of its legs simultaneously amputated; subsequently, evolution discovered that specific deformation to the resting shape could recover the robot's function more effectively than re-adapting its control policy for its new body (**Figure 2**),[31] which is analogous to biological regeneration, although using different mechanisms (mechanical deformation versus regrowth).

Computational design can also discover novel ideas not known to occur in nature. For example, regeneration was not the only successful adaptation strategy discovered by evolution in the experiments reported by Kriegman et al.[31] When the simulated robot was cut in half, evolution sometimes decreased the damaged robot's surface area by compressing the remaining limbs, and other times it expanded the robot's limbs, compressed its spine, and flipped over to recover an inverted locomotion strategy. Within and across nine different damage scenarios, the best shape-shifting strategies were diverse and creative: very few were a recapitulation of a familiar biological example. Thus, simulation can provide non-intuitive designs beyond those inspired by natural systems.

4. Shape Changing Robots

While biological and simulated systems alike indicate that even small shape adaptations can enable recovered or new functionalities, realizing shape changing robots in hardware presents its own set of unique challenges. However, we see immense potential in the convergence of multifunctional materials and soft robotics toward the goal of shape changing robots, and some promising examples already exist. Here, we focus on examples of physical robots that employ shape change to enhance, recover, or expand their capabilities.

Several robots have leveraged functional materials to change shape, to attain new gaits, and avoid obstacles, thereby solving problems that are traditionally in the realm of mechanics[73] and computer science.[74] For example, Shah et al. proposed a rolling soft robot that uses a cable-driven robotic skin to sculpt an inner clay body into a different morphology (**Figure 3**a).[30] Initially cylindrical, the robot could roll on flat ground; when it encountered an obstacle in its path, the robot changed into a dumbbell shape to roll over the obstacle without changing its gait or path. While the robot was designed with 20 independent degrees of freedom (DoFs) for shape changing, it was found that only a single DoF was necessary to perform the required obstacle avoidance. In another example, a caterpillar-inspired robot called GoQBot changed its shape to switch between controlled crawling and ballistic rolling gaits (Figure 3c).[75] Using shape memory alloy (SMA) coils to deform its silicone body in small arches, the robot could crawl forward. Upon rapid activation of the SMA actuators, the robot curled into a ball shape and initiated rolling in under 250 ms. Such a maneuver could be useful for escaping predation, rolling downhill in an energy-efficient manner, and increasing the robot's effective dimensions to enable it to easily overcome obstacles larger than its flattened shape. In yet another example, Lee et al. proposed a robot that folds fabric and sheets of poly(ethylene terephthalate) (PET) to enlarge its wheels and climb onto step-like platforms (Figure 3d).[28] The robot was then able to collapse its wheels to roll under narrow gaps, allowing the robot to operate over a wide range of terrains and environmental conditions. Despite being primarily made of flexible materials, the robot was able to use cleverly designed folding patterns to support a payload 400× the weight of its wheels. To adapt to changing flow conditions underwater, Ishida et al. developed a quadruped with a 4-DoF morphing top that could change its drag and lift coefficients to gain assistance from the current when the flow aligned with its direction of motion, and reduce drag when walking against the flow.[76] Similar to the rest of the robots in this category, only a few DoF for shape change were required to allow these robots to continue operation, without searching for complex control strategies to deal with changes in its environment.

Other soft robots have used shape change to switch between locomotion on land, in air, and/or in water. Baines et al. recently demonstrated a life-size turtle- and tortoise-inspired morphing limb that could change between flipper and leg shapes, as a step toward amphibious robots which can accomplish both aquatic and terrestrial locomotion (Figure 3f).[77,78] The transformation from flipper to leg occurred via coupled variable stiffness and actuation materials distributed along the length of the morphing limb. Initially in a flipper shape, fluidic actuators inflated, causing a change in limb cross-sectional geometry to transition to the load-bearing leg shape. The variable stiffness material, a thermoset polymer with embedded heaters, controllably softened and stiffened the limb to lock and unlock the geometries. Hawkes et al. designed an origami robot that could fold between shapes resembling a boat and a plane (Figure 3e).[79] Although these structures were not demonstrated moving through air or water, locomotion could potentially be achieved through integration of additional actuators. For example, other lightweight origami robots[80] attained controlled flight resembling the locomotion paths of insects.[81,82]

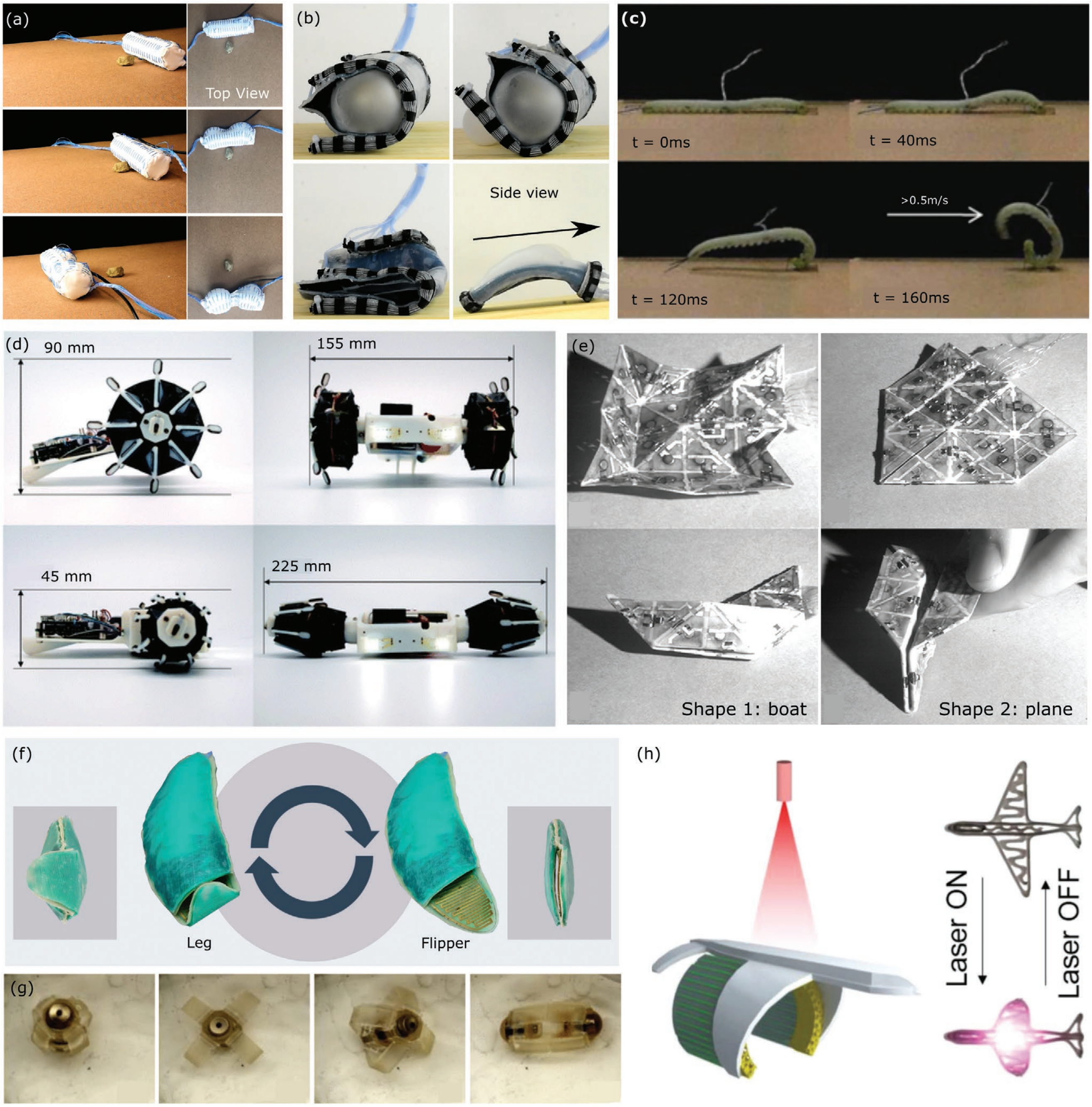

Figure 3. Shape changing soft robots. a) Cable-driven clay morphing robot changing shape to avoid an obstacle. Adapted with permission.[30] Copyright 2019, IEEE. b) Cylindrical rolling robot flattens to switch from a rolling gait to a crawling gait. Reproduced with permission.[87] Copyright 2020, The Authors. c) Caterpillar robot changing from inching to rolling. Adapted with permission.[75] Copyright 2011, IOP Publishing. d) Variable diameter origami wheel. Adapted with permission.[28] Copyright 2017, Mary Ann Liebert, Inc. e) Programmable origami robot transitioning between a "boat" and a "plane" shape. Adapted with permission.[79] Copyright 2010, National Academy of Sciences. f) Variable stiffness morphing limb for an amphibious legged robot. Adapted with permission.[78] Copyright 2020, IOP Publishing. g) Magnetically actuated soft capsule for drug delivery. Adapted with permission.[26] Copyright 2012, IEEE. h) Tissue engineered robot with light-activated morphing wings. Reproduced with permission.[83] Copyright 2019, Wiley-VCH.

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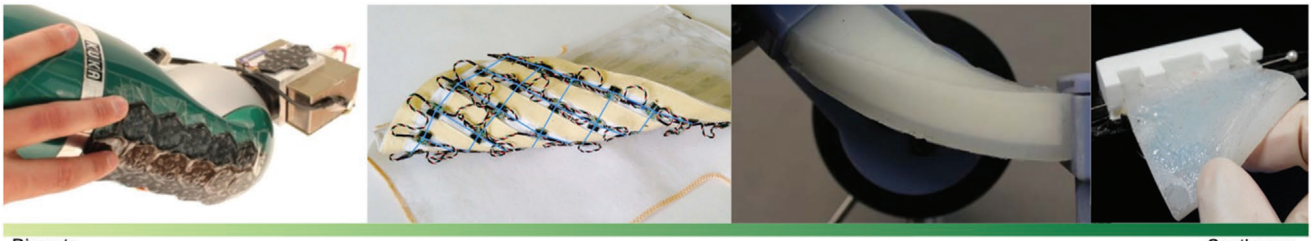

Figure 4. Sheets that can sense their 3D shape. Recent advances in shape-sensing e-skins use several sensing modalities, ranging from discrete to continuous approaches. Left to right: hexagonal PCBs with integrated accelerometers, sensor network with accelerometers and magnetometers, optical fibers in silicone foam, fiber Bragg gratings in silicone. Image for Hexagonal PCBs: Adapted with permission.[40] Copyright 2012, IEEE. Image for sensor network: Reproduced with permission.[37] Copyright 2012, IEEE. Image for opical fiber: Adapted with permission.[91] Copyright 2018, The Authors, published by American Association for the Advancement of Science. Image for fiber Bragg grating: Adapted with permission.[41] Copyright 2019, IEEE.

Shape change has also been used in human-centered applications. Yim and Sitti proposed a millimeter-scale, magnetically actuated capsule that can locomote and switch between a spherical and cylindrical shape (Figure 3g).[26,27] Although the robot could locomote in each shape, the robot used shape change to improve the precise positioning of its endpoints, and deliver simulated drugs inside of a synthetic stomach model. Another proposed millimeter-scale robot had oscillating cardiac muscle cells attached to the back of airplane-shaped "wings" to propel it across the surface of the liquid medium in a cell culture, simulating applications in targeted drug delivery in the human body (Figure 3h).[83] When the "wings" absorbed near-infrared radiation, heat spread to their attached temperature-sensitive hydrogel actuators to induce curling. The curled shape had a higher bending stiffness that prevented further swimming motions, allowing the robot to stop directly above a target location and release anticancer drugs onto cancer cells. Finally, researchers have demonstrated that shape change can alter our perception of robots during human–robot interactions,[84–86] thereby improving these exchanges and increasing the operational value of the robot.

Researchers have also explored the potential for automatically designing shape changing robots in simulation and transferring successful designs to reality. Kriegman et al. developed a scalable method to create physical shape changing voxel-based modular robots, and successfully transferred two strategies of shape change discovered in simulation to reality; however, functionality (locomotion) did not transfer.[31] Later, locomotion was transferred from simulation to reality using an improved version of the same system (silicone-based pneumatic voxels), however these locomoting physical robots did not change shape.[43] Another simulated shape changing robot used an inflatable core to transition between a cylindrical shape and a flattened sheet-like shape to adapt its locomotion to different environments.[87] Initially a rolling cylinder on flat terrain, the robot changed to the flattened shape with an inchworm gait to maintain efficient locomotion up an incline. This simulated robot design was successfully transferred to reality, thereby realizing a physical robot that utilizes shape change to gain access to additional environments (Figure 3b).

5. Grand Challenges

The examples given herein highlight how shape change can allow a robot to enhance or expand its functionality via adaptation or regeneration. However, to develop robots rivaling biological systems, several challenges need to be addressed. First, it is unclear how to optimally embed proprioception and intelligence into such machines to enable robots to sense their shape. Additionally, to design robots for tasks more complicated than can be solved through human intuition, it is imperative to automate the design of shape changing robots. Finally, transferring highly functional designs to reality requires functional materials that can be integrated into systems that can attain precise control over shape.

5.1. Shape Sensing

Next-generation shape changing robots will rely on proprioception to determine when a target morphology has been reached, optimize shape change through intermediate shapes, and decouple deformation-driven task performance from global shape change. During regeneration, an organisms' cells compare their body's current state to the target morphology, although the exact mechanisms for these processes are poorly understood.[4] Techniques exist for measuring the deformation of fixed-shape robots, which generally rely on a comparison to the reference body shape at rest. For example, continuum manipulator modeling relies upon assumptions about cross-sectional geometry,[88] while traditional robot kinematics assume each component is a rigid body.[89] However, if the reference body shape is changing, such an approach is no longer applicable. Thus, intrinsically (i.e., without external components) measuring the state of shape changing robots largely remains an unsolved problem.[90]

There have been several attempts to detect the shape of non-stretchable robot "skins" (**Figure 4**). Many studies treat the skin as an inextensible sheet of rigid elements joined by known axes of rotation (Figure 4, left). Hoshi and Shinoda arranged 24 printed circuit boards (PCBs) into a mesh and estimated inter-PCB rotations using accelerometers and magnetometers.[39] Building upon this work, Mittendorfer et al. developed rigid sensorized PCBs that could be connected and wrapped around robots.[40] Hermanis et al. then used a grid-like arrangement of accelerometers and gravitometers on a flexible fabric sheet.[37] In these studies, no attempt was made to estimate the true shape of the underlying object; the objective was to measure the location of the PCBs' centers with high precision.

Other proposed approaches leveraged techniques from machine learning and statistics to process sensor signals and

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extract a continuous estimate of the shape of the skins (Figure 4, right). Such an approach is more general, and could potentially lead to more accurate estimations of the state of shape changing soft robots. Rendl et al. used data from 16 piezoelectric bend sensors, which experience a potential difference on their electrodes during bending, on a PET sheet to estimate the sheet's shape as a combination of several shape primitives.[38] Another study used neural networks to estimate the shape of a silicone plate using inextensible optical fiber Bragg gratings strain sensors (coated with ORMOCER inorganic–organic hybrid polymers).[41] Van Meerbeek et al. embedded an array of optical fibers inside an open-celled elastomeric foam and used their output to predict the mode of deformation and angle of deformation of the foam, using machine learning algorithms.[91]

Several challenges emerge from inspection of these works. Some shortcomings arise from material limitations: none of the proposed approaches could accommodate or detect in-plane strains. There are solutions to making stretchable strain sensors[92–94] and stretchable circuits,[95,96] but is is unclear how to transfer these advances to sense a variety of dissimilar shapes. For instance, how many sensors, and what type of sensors, are needed to detect the shape of each robot in Figure 3? Biological organisms, such as humans, distribute multimodal sensing capabilities across their skin and at multiple depths,[97] and throughout their musculoskeletal system.[98] The efficiency of this approach is unclear, as evolution selects for survival, and biological constraints do not map perfectly to the constraints and cost–benefit relationships relevant in robotics. Additionally, how can sensors be developed to decouple large in-plane strains from transverse strain (pressure), at sufficiently high resolution? Some progress has been made toward independent multimodal sensing for robots with a fixed resting shape,[99] but these methods have yet to be tested in shape changing robots. Finally, the proprioceptive sensors used in shape changing robots should be simultaneously robust to repeated applications of external strain, able to withstand undesired local shear forces, and easy to manufacture at the densities needed to detect the complicated deformations experienced during typical operations.

Other challenges are algorithmic: each proposed sensing approach—broadly, what we classify as discrete versus continuous approaches—has drawbacks. The discrete method insufficiently handles continuously deformable surfaces, while the data-driven continuous approach only operates under limited deformation conditions. Solutions in this regard could involve applying techniques from differential geometry to fuse rotation and strain data to generate smooth surface estimates.[100–103] In the work by Stanko et al.,[100] a single algorithm was used to estimate the shape of objects as dissimilar as a mushroom, a chair, and a guitar. The only required input was distance estimates between successive orientation measurements. When paired with stretchable strain sensors[92–94] and stretchable circuits,[95,96] such algorithms could provide solutions to the overall problem of estimating the shape of a morphing robot.

5.2. Shape Finding

It is not obvious which shape a robot should assume in a given environment. While evolutionary robotics[35] may yield potential solutions, there are many unresolved fundamental questions in this area. For example: How will a robot know that its current shape is no longer optimal, and it should search for a new shape and behavioral policy? How should robot shapes and behaviors be generated given only environmental inputs? Here, we explore how the state-of-the-art could be improved to create automated pipelines for finding effective shapes and designing sophisticated shape changing robots.

The application of evolutionary algorithms to simulated robots has begun to address the questions above, but only within empirical studies with one or two objectives for the robots to solve.[31,87,104] Further, higher-level and/or trans-environmental tasks have been largely unexplored. Although evolved simulated robots have transitioned between terrestrial and aqueous environments,[64] no general understanding of how shape change can equip a machine to travel through air, water, or over land yet exists. Transitioning between shapes to solve widely varied tasks such as locomotion and grasping has not been considered, nor has changing shape in real time to avoid damage. To address these scenarios, the major challenges of catastrophic forgetting,[105] transferability,[106,107] simulation inaccuracies, system identification,[65] and the limited efficiency and sub-optimality of search algorithms likely need to be considered.

Most existing studies on simulated morphing ignored the costs of shape change. Although shape change is sometimes more computationally efficient than searching for control policies,[31,87] in hardware implementations, there is an energetic cost associated with changing shape. Energy must be expended to power actuators (e.g., SMAs and shape memory polymers,[108,109] dielectric elastomer actuators,[110] or various other soft actuators[111]) and materials may need to be replaced during regeneration or growth (e.g., via inflation,[31,112] additive manufacture,[113] etc.). Quantifying both the computational and energetic costs of shape change will be important to the realization of shape changing robots that operate in the real world.

Additionally, it is challenging to specify algorithmic constraints that guarantee that the shape and behavior solutions found are physically realizable. While it is possible to stretch any two homeomorphic shapes into each other, generating designs which are robust to simulator inaccuracies requires sufficiently realistic constraints, and algorithms that can navigate a constrained, likely highly non-convex, search space. Numerous methods to navigate the simulation–reality gap have been proposed, including injecting noise into the simulations[106] and estimating an assumed transferability function.[107] Other approaches for crossing the simulation–reality gap in soft robotics include reducing the robot to quasi-static motions[60] and simplifying the search space.[104] However, these simplifications dramatically reduce the range of capabilities that can be evolved and limit the scope of tasks that can be completed.

5.3. Shape Changing

Most morphing robots in the literature have been designed to attain a limited set of shapes as a proof-of-concept. Increasing the controllable degrees of freedom should generally improve the shape changing abilities of robots (**Figure 5**), but such

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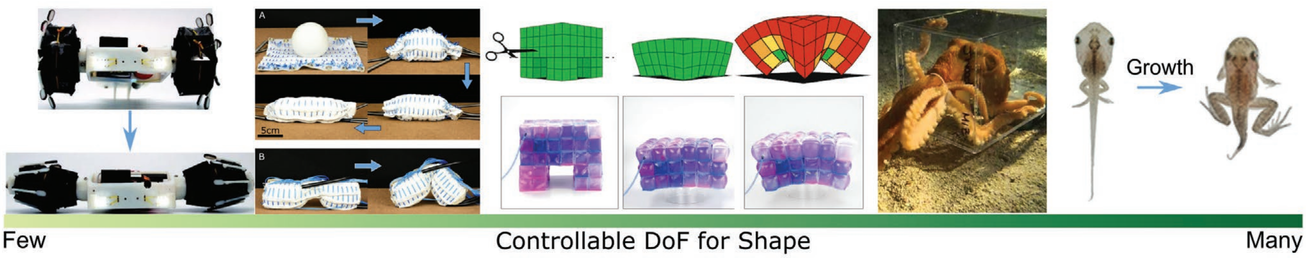

Figure 5. Additional controllable degrees of freedom will allow shape changing robots to approach the capabilities of biological systems. Current shape changing robots leverage relatively few controllable degrees of freedom (DoFs) to adapt, while some biological organisms leverage dozens of independent DoFs during normal motions, and growth allows organisms countless independent DoFs for changing their shape. Left to right: Morphing wheel; clay-sculpting morphing robot; voxel-based robots; octopus squeezing through a 1-inch diameter hole; tadpole-to-adult transition for a Microhyla fissipes frog. Image for morphing wheel: Adapted with permission.[28] Copyright 2017, Mary Ann Liebert, Inc. Image for morphing robots: Adapted with permission.[30] Copyright 2019, IEEE. Image for voxel-based robots: Adapted with permission.[31] Copyright 2019, Sam Kriegman. Octopus image: Reproduced with permission.[114] Copyright 2012, James B. Wood. Frog image: Reproduced under the terms of the CC-BY Creative Commons Attribution International License (https://creativecommons.org/licenses/by/4.0/).[142] Copyright 2019, The Authors, published by Frontiers.

complexity comes with trade-offs and limitations. For example, origami robots[80] are typically designed to attain a limited set of shapes by folding at discrete locations (Figure 5, left).[28] Additional shapes could be achieved by adding or utilizing additional folds, but would increase the system's complexity. The clay-sculpting robotic skins[30] were designed to stretch with their surface to attain a continuous range of shapes; however, they were restricted to shapes with circular cross-sections (Figure 5, second from left). Adding additional cables to this design, more complicated profiles could be attained, but the robot could not attain, for example, a quadrupedal shape. The field needs fundamentally new approaches to shape change, including novel actuators and growth mechanisms, paired with complementary technologies to control surface strain.

Typically, a robot's components are optimally placed for its morphology and target function. Yet, for a shape changing robot, optimal component placement will differ between morphologies. One solution to this problem is to increase the sensor and actuator component density throughout the robot to increase its controllable degrees of freedom. Potential ways to increase sensor and actuator density include multifunctional materials,[115–117] 3D circuits,[95] skins with tightly integrated sensing and actuation,[118] and multimodal sensing arrays.[97] However, numerous issues arise when increasing component density, including cross-talk, data processing, and complicated wiring schemes.[90] Communication protocols for large numbers of sensors or actuators is another challenge. Pneumatic robots, for example, usually require one three-state (inflate, hold, release) valve set per actuator. Although pneumatic multiplexing has been shown to independently control large arrays of actuators,[119] multiplexers often result in a lower attainable actuation frequency.

To further expand the range of shapes that morphing robots can attain, additional actuation modes need to be introduced. Many shape changing robots utilize a single actuation mode, for example, tension,[30] volumetric expansion,[120] origami folding,[28] or bending.[83] In contrast, many shape changing organisms exploit multiple actuation modes. For example, the tentacles of cephalopods and many species' tongues tightly integrate muscles with different orientations to achieve torsion, extension, and bending (Figure 5, second from right).[121,122] Integration of multiple actuation modes has largely been unexplored in the context of shape changing robots, and is a major unsolved challenge. Much can be learned from the field of microrobotics, where many robots have been built using stimuli-responsive polymers. Often these robots contain several actuation modes in addition to novel functionalities, such as camouflage.[123–126] Stimuli used in these micro-machines (magnetic fields,[123,125] chemical vapor,[124] light,[123] and solvent[126]) are usually less practical for larger-scale soft robots due to unfavorable strength-to-weight ratios at larger length scales. With additional advances in fundamental materials science, implementation of stimuli-responsive polymers in large-scale robots may become viable.

Combining novel actuators, robot-simulators, and shape-sensing technologies, robots could then utilize 3D "shape servoing," or closed-loop control of shape, to converge on a desired shape. In a 2D shape servoing application, an external vision system was paired with a robot arm to deform materials into a desired shape.[127] Building upon such extrinsic methods of shape control, it is conceivable that there will be optimal ways to use a robot's actuators to smoothly shift between desired shapes. Insight into how to efficiently change shape could come from observing how sculptors smoothly sculpt clay between many highly dissimilar shapes.[30] Formalizing intuition and observation into computationally tractable shape-control loops could come from mechanics-based modeling and solving an inverse problem (i.e., calculating the required control sequence to attain a desired shape), or using data-driven reinforcement learning models to solve problems in an automated, closed-loop fashion.

As a robot undergoes large changes in shape, the surface stress can often approach the maximum available actuator stress and restrict further motion. To overcome these limitations, one solution is to design robots that can reversibly undergo large deformations.[21,24] In contrast, many biological organisms experience large-scale, growth-driven shape change in response to numerous stimuli,[6,33] promoting long-term viability of the organism (Figure 5, right). It is hypothesized that control of these factors could eventually lead to synthetic organisms with programmable growth from varied initial states into target morphologies. Recent studies have proposed continuum robots that can grow along an arc-like path, using eversion[79] and tip-based additive manufacturing.[113] Progress is also being made in related fields, such as biohybrid robots,[128] expanding polymers[129] and hydrogels,[130] and simulating growing

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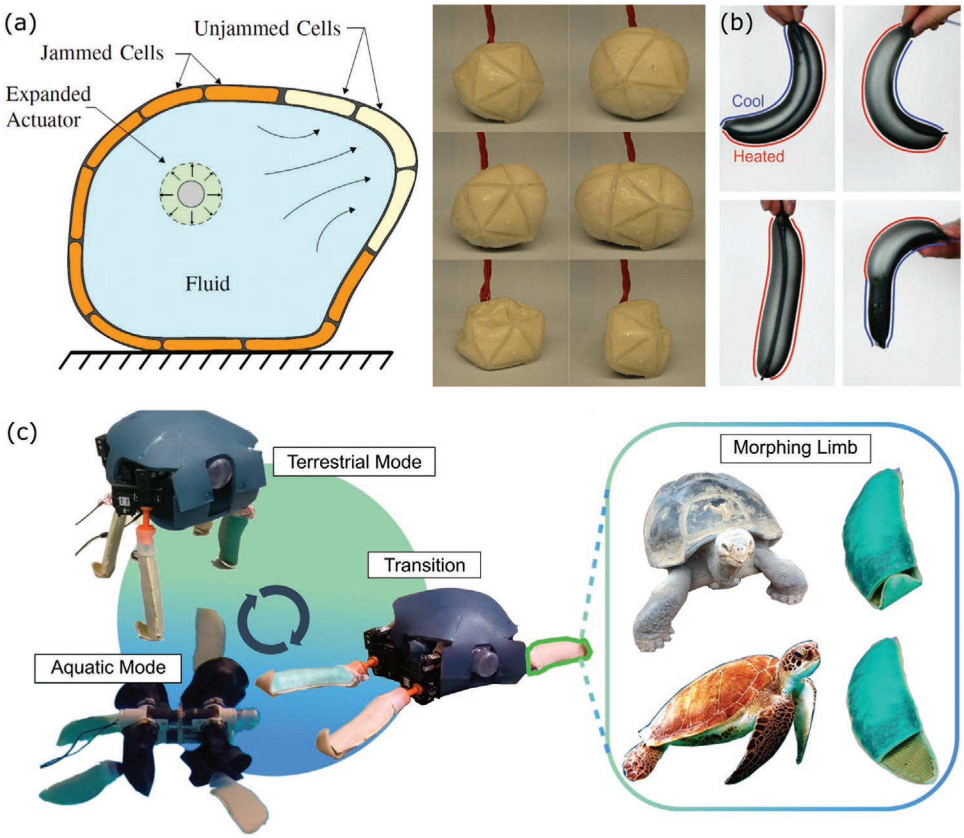

Figure 6. Variable modulus materials can allow robots to tune their morphing trajectories and selectively maintain desirable shapes. a) Granular jamming allowed an air-filled robot to selectively control its expansion (left) and generate a wide range of shapes (right) for locomotion. Adapted with permission.[132] Copyright 2009, IEEE. b) Low-melting-point-alloy inclusions in a silicone matrix allowed reversible morphing and shape memory in arbitrary geometries. The images show how the "switchable stretchability" material could tune the trajectory of a single inflatable actuator. Reproduced with permission.[136] Copyright 2019, Wiley-VCH. c) Variable stiffness material embedded in a morphing limb was used for softening during shape change, and stiffening to hold either a flipper or leg shape in aquatic and terrestrial environments, respectively. Tortoise and flipper images on the right: Adapted with permission.[78] Copyright 2020, IOP Publishing. The turtle image is from Pixabay.

robots.[34] However, the load-bearing capabilities of many of these systems are low, and the remaining systems have limited controllability and ability to grow into unplanned geometries.

Variable modulus materials (reviewed by Manti et al.[131]) can also potentially be used to control the deformation of sections during shape change, improve load-bearing capabilities, and reduce energy requirements. For example, one robot selectively stiffened sections of its outer membrane to direct deformation when the inner chamber was inflated, producing locomotion (**Figure 6**a).[132] Granular jamming, used in this example, is stretchable but generally has low tensile modulus relative to other state-of-the-art variable stiffness materials, including conductive epoxies[133] and laminar jamming.[134,135] Unfortunately, these alternative materials do not perform well over tensile strains larger than a few percent. Recent advances such as cutting serpentine patterns in layer jamming sheets to allow stretch in one direction,[18] and low-melting-point-alloy inclusions in a silicone matrix[136] (Figure 6b) have the potential to allow robots to control their stiffness while controlling large strains during shape change. By leveraging variable stiffness strategies such as layer jamming,[134,135] granular jamming,[8,18] or variable stiffness materials such as thermoset polymers,[133] robots could also increase their load-bearing capabilities in each attained shape, without requiring re-adaptation of control strategy. For example, in the turtle- and tortoise-inspired morphing limb proposed by Baines et al., the robot could hold a flipper-like shape for hydrodynamically efficient swimming, and switch to a load-bearing leg-like shape for walking using a softening/stiffening thermoset epoxy (Figure 6c).[77,78] Stiffening could also allow a robot to lock in its shape and disengage its morphing actuators, to reduce energy requirements. Researchers have shown this concept in various applications, including using a variable stiffness conductive epoxy composite to selectively soften and stiffen a gripper to maintain the position of its payload without additional energy input or control loops.[133] In other examples, researchers employed layer[137] and granular jamming[138] to selectively soften and stiffen continuum manipulators to hold a pose.

6. Conclusions and Outlook

We have surveyed the literature related to shape changing robots, from bioinspiration to simulation and hardware implementation. By actively morphing into different shapes,

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many state-of-the-art robots have been shown to expand their capabilities by gaining new locomotion modes,[28,75] avoiding obstacles,[30] or transitioning between body shapes suitable for swimming or walking.[77,78] Increased closed-loop control of morphology and material properties could eventually allow robots to rival the dynamic plasticity attained by natural systems. However, many open questions remain regarding when, how, and to what degree shape change is useful.

The phenomenon of shape change overlaps with considerations of adaptation at differing spatial and temporal scales. Spatially, for example, a rigid robot may experience local shape change at a joint, but none within the rigid segments from which it is comprised. In contrast, a soft robot may change its shape at all relevant length scales, globally and locally. Organisms[6] or robots[120] capable of physical developmental change may change their body plans slowly over their lifetimes, while faster, local deformations may occur at joints during specific behaviors. Consideration of how to seamlessly model and integrate such capabilities into the design of robots across length scales, while simultaneously balancing traditional design goals such as velocity, payload, and force output, remains a largely unsolved problem.

Much can be gained in future research by exploiting lessons of robustness from biology. A key component of biological embedded control is its multiscale goal-seeking nature.[139] Functional swarms—for example, termite colonies that maintain a shared nest—are made of individual bodies that each build and repair to their particular target morphology. This is done by organs that maintain specific physiological and functional specifications, and tissues which deform to maintain histological targets. These are, in turn, made of cells which optimize various parameters as they migrate, proliferate, and differentiate. Inside the cells are genetic and metabolic networks that also have degrees of memory, robustness, and homeostasis. The ability of each nested level to have its own local morphogenetic goals (in the cybernetic sense) contrasts with today's robots, which are largely made of unintelligent parts, although some early examples of embedded distributed computation and soft logic gates are emerging.[140,141]

As demonstrated by this progress report, innovations in multifunctional materials, soft robotics, and evolutionary robotics are converging to make shape changing robots more viable. Such shape changing robots should be viewed as important model systems for evolutionary biology and regenerative medicine,[10] providing simplified "bodies" in which to test theories of tissue computation, brain–body control, and regenerative algorithms, and in which to abstract the profound lessons of life-as-it-could-be from evolutionary contingencies.[33,34] Indeed, control of morphology is an unsolved problem in medicine—from fixing birth defects to traumatic injury repair, aging, and cancer. Thus, the question of shape and its dynamic control is an emerging new science at the intersection of evolution, biomedicine, machine learning, and robotics.

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Conflict of Interest

The authors declare no conflict of interest.

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anatomical homeostasis, evolutionary robotics, morphing robots, reconfigurable robots, regeneration, smart materials, soft robotics, synthetic morphogenesis

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