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Perspective

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Robots that evolve on demand

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Abstract

Now more than ever, researchers are rethinking the way robots are designed and controlled – from the algorithms that govern their actions to the very atomic structure of the materials they are made from. In this Perspective, we collect and comment on recent efforts towards multipurpose machines that use shape-morphing materials and components to adapt to changing environments. To frame our discussion, we point out biological adaptation strategies that have been adopted by robots across different sizes and timescales. This contextualization segways into the notion of adaptive morphogenesis, which is formally defined as a design strategy in which adaptive robot morphology and behaviours are realized through unified structural and actuation systems. However, since its introduction, the term has been more colloquially used to describe 'evolution on demand'. We set out by giving examples of current systems that exhibit adaptive morphogenesis. Then, outlining projected key application areas of adaptive morphogenesis helps to scope the challenges and possibilities on the road to realizing future systems. We conclude by proposing performance metrics for benchmarking this emerging field. With this Perspective, we hope to spur dialogue among materials scientists, roboticists and biologists, and provide an objective lens through which we can analyse progress towards robots with rapidly mutable features that eclipse what is possible in biological processes.

Sections

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Introduction

The capabilities of today's robots fall far short of those of biological organisms[1]. Across every conceivable performance metric – speed, efficiency, cognition, dexterity and mobility – biology reigns supreme[2–4]. A hallmark of biological organisms that makes them so good at what they do – one that has ultimately proven difficult to replicate in robotics – is their exceptional capacity to adapt to new contexts, tasks and environments. Organismic adaptations comprise physiological, behavioural and morphological changes that occur across levels of biological organization and at various timescales[5–7]. Moment-to-moment, organisms regulate their bodily properties through homoeostasis, adjust their movements, and harness the deformation of their body to interact in emergent ways with their surroundings[8–13]. On the order of one lifespan, organisms grow and exhibit phenotypic plasticity as a means of adapting traits in response to new environmental stresses, developing chemical resistance or gaining muscle mass, for example[14–17]. At even longer timescales, evolutionary selection interacts with the genetics of a species to innately adapt it to its niche. Selective pressures over time may lead to extreme morphological and physiological changes in organisms. In the case of the terrestrialization of vertebrates during the Paleozoic Era, for example, previously aquatic lineages radically deviated from fish-like forms, developing load-bearing appendages and respiratory systems commensurate with terrestrial habitation[18].

For decades, researchers have strived to emulate natural organisms' adaptations in bio-inspired robots, with increasing emphasis on fabricating bio-inspired hardware to achieve adjustable intrinsic properties, responsive movement patterns and mutable shapes[19–23]. Examples include artificial skin made from materials that readily change their properties in response to environmental stimuli[24–26], compliant materials that enhance locomotion in robots across modal implementations from legged to limb-less[27,28], and swarms of robots that can re-arrange themselves via mechanical or chemical interactions into different configurations[29–33]. As exhibited by these examples, hardware adaptations in robots are often engineered to occur at analogous timescales to the adaptations of their biological sources of inspiration[34]. This approach is perfectly reasonable when the identification of bio-inspired adaptive strategies is primarily based on observational studies[35–37], but it constrains transferable adaptation strategies to near real-time biological processes (on the order of seconds to hours). We posit that a wealth of bio-inspired robotic adaptations exists towards the extrema of natural processes: evolution.

Materials engineering has not only allowed researchers to robotify real-time adaptive strategies of organisms but has also presented an opportunity to embed and cycle between specialized adaptations that would only occur at long-to-evolutionary time horizons. We provisionally describe this idea as 'adaptive morphogenesis' (AM): adaptive robot morphology and behaviours realized through unified structural and actuation systems[38] (Fig. 1). The term adaptive morphogenesis arises in the biological literature as a way to explain how bacteria adjust their forms in response to environmental forces[39]. Our instantiation of the term conceptualizes similar phenomena in robotics: the body of a robot may contain 'adaptive' materials that undergo 'morphogenesis', or emergence of new form, based on the environment.

As in biology, morphological adaptations should improve the fitness, or performance, of the robot in terms of some metric (such as speed, cost of transport or maneuverability). However, unlike in biology, adaptations should occur on condensed timescales, be reversible processes, and entail no net change in mass (as with growth or amputation) or re-assembly of discrete components (as with modularism). In short, AM champions efficiency through use and re-purposing of a single piece of contiguous hardware. With this initial interpretation of the concept of AM in robotics, it is admittedly challenging to sort robots into distinct groups. Embracing the grey area surrounding the definition of an AM robot facilitates critical thinking about developments at the intersection of materials science and robotics, bringing different subdisciplines of the community together, which we believe will eventually lead towards a future of multi-functional machines capable of adjusting their shape and behaviour based on environmental context. AM can allow researchers to realize robots that accelerate what nature is capable of under the temporal constraints and inherent trade-offs of evolutionary selection[40,41]. Consequently, AM has colloquially become known as a sort of 'evolution on demand'[42].

In this Perspective, we investigate AM from new vantages. First, we catalogue existing examples of AM. Then, we contemplate the application space of AM, setting the stage for the identification of technological challenges and new avenues of research. We consider challenges along the entire robot development cycle from conceptualization to implementation, including screening the design space for adaptations, materials and mechanisms for evolving morphology, energetics or morphing, sensing of environment and robot, and control of shape and locomotion. In addition, we propose metrics for benchmarking robots developed with this emerging design strategy. A note on scope: this Perspective focuses on AM as it pertains to robotic locomotion. Of course, numerous evolutionary adaptations fall under the broader umbrella of adapting to 'tasks' (for example, the elongation of giraffe necks for enhanced predator surveillance)[43]. We forgo musing about synthetic counterparts to such a vast range of evolutionary adaptations, leaving it instead as an open discussion.

Case studies and examples

Although there is an abundance of robots built with adaptations inspired by biological processes occurring on short-to-intermediate timescales, there are far fewer robots that exhibit AM. We foresee instances of AM proliferating over the next decade as the need for robots expands outside of the factory floor and into scenarios wherein multi-environment adaptability and efficiency are tantamount to success[44–47]. Current examples still provide exposition for upcoming scientific challenges in the design of robots that evolve on demand.

Many AM robots to-date are quadrupedal and are capable of augmenting their locomotion mechanics and/or propulsor morphology to specialize across changing environments. Examples include quadruped robots that can melt and re-solidify thermo-plastic joints, restructuring movement kinematics on-demand[48] (Fig. 2a) or morph both body and leg shape to fit through tight and low spaces[49] (Fig. 2b). Another type of robot uses linear actuators to adjust its leg lengths for optimizing the cost of transport over different substrates[50] (Fig. 2c). In a case study of robot design informed by AM, we built an amphibious robotic turtle (ART) and assessed its utility for multi-environment locomotion[38]. Inspired by the bodily similarity but distinct propulsor shapes exhibited by terrestrial and aquatic turtle species[51,52], we designed ART with limbs that change between hydrodynamic flipper and load-bearing leg states. ART can swim in water, walk on land, and transition between water and land with comparable efficiency to unimodal robots (Fig. 2d). In another amphibious system, pouches distributed about the robot's body were inflated with an onboard pump to gain better traction on different substrates on land or increase hydrodynamic propulsion forces in water[53] (Fig. 2e). Beyond locomotion on land and in water, a shape-shifting quadcopter was designed with Field's metal,

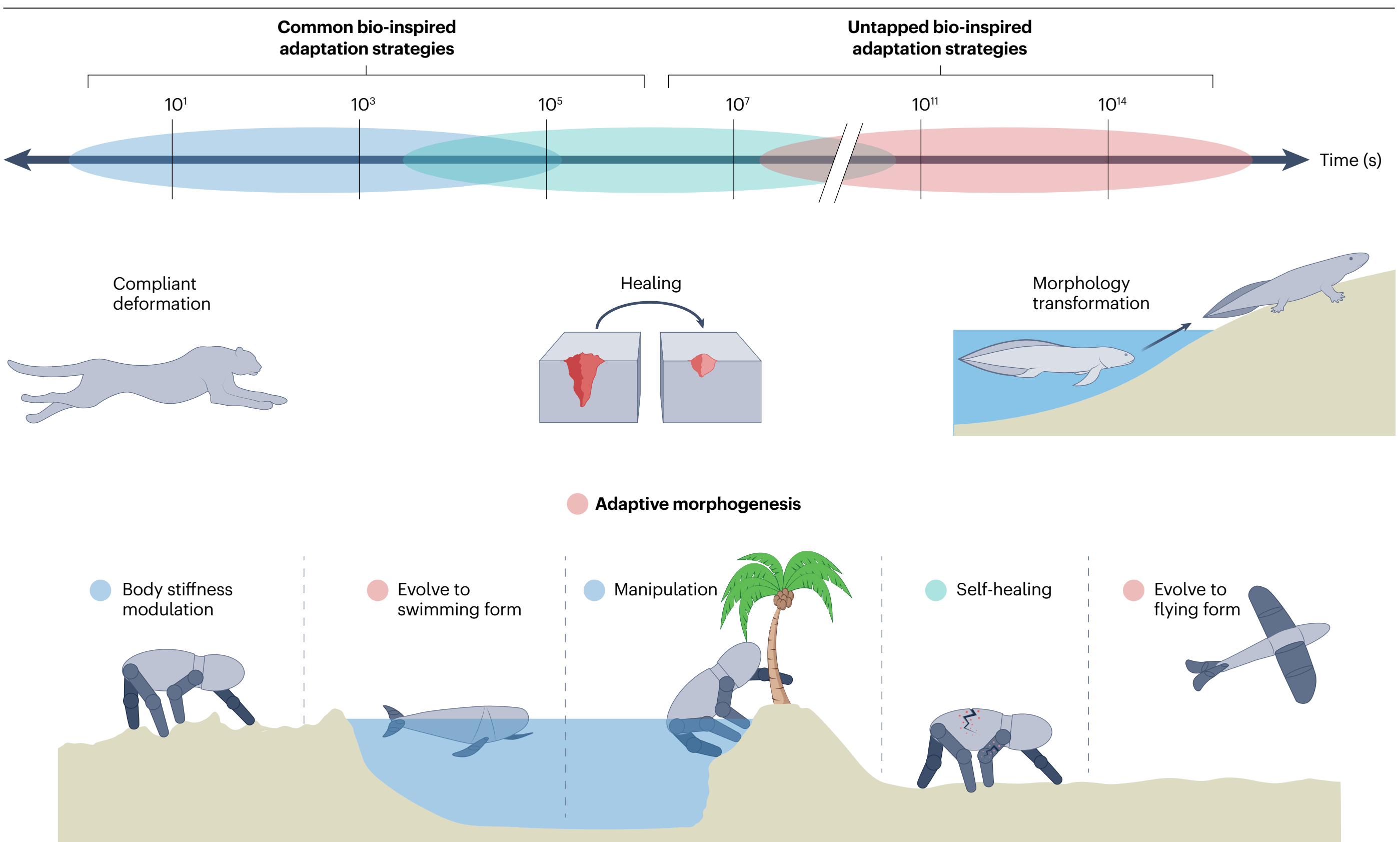

Fig. 1 | Adaptive morphogenesis, or 'evolution on demand', is a robot design strategy that synthesizes evolutionary adaptations for locomotion in different environments into a unified mechanism space. A hypothetical illustration is shown in which a robot navigates several environments, interacting with its surroundings, and using design strategies across the temporal spectrum of bio-inspired adaptations. Compliant mechanisms enable rough terrain traversal and manipulation. Novel materials enable self-healing over intermediate timescales, when the robot sustains damage. To access the radically changing environments it confronts, the robot is able to modify its morphology and locomotion modes via adaptive morphogenesis.

a low-melting-point metallic alloy, as its central structure. The Field's metal structure allowed the robot to switch between functional shapes for rotor-driven crawling and flying[54] (Fig. 2f). All of these robots benefit from AM by gaining new locomotion capabilities. However, because this line of research is still very much in development, there are many other untapped robot embodiments and applications to ponder.

Future applications of AM

In automated environmental monitoring, AM robots could alleviate the need to deploy separate robotic systems for each individual environment, permitting up-close inspection of multiple ecosystems with a single platform (Fig. 3a). The ability of AM robots to specialize their morphology and behavioural control policy to their environment can also improve locomotion efficiency. An efficient robot can operate out in the field for longer, addressing the pressing need for continuous streams of in situ data from critically endangered ecosystems[55–57].

The same concepts apply to mobile robot deployment for resource-constrained environments, such as space exploration (Fig. 3a). With lunar and Martian colonization and mining just on the horizon[58], a robotic explorer could benefit from the ability to adapt on-demand for locomotion within an assortment of environments — even those unlike anything on Earth — that it may encounter. Importantly, sending a general-purpose robot to space instead of several individual platforms (that would collectively weigh more and occupy more space) would diminish the monetary and environmental impacts of rocket launches[59,60].

Other promising applications are using AM robots as proxies to conduct studies on the development of the locomotor mechanics of species throughout their evolutionary history, and even to search over the phylogenetic tree of life to find species with similar morphological adaptations specialized for different environments (Fig. 3b). 'Artificial evolution' studies have previously been performed with simulated agents, but the generalizability of results is questionable owing to the discrepancies between simulated and physical systems[61,62]. Other studies have pursued embodied experiments, such as building a robot with fixed hardware to estimate the movement patterns of extinct species in the fossil record[63]. However, fixed hardware in the robot precludes studying the chronology of its physical adaptations without making dozens of separate platforms, each with slight design tweaks. With AM, a single embodied platform could serve as a template to explore different morphologies and behaviours within compressed timescales, granting unprecedented glimpses into the evolution of a species. Furthermore, with AM, it is possible to explore how a common ancestor can have descendants in different niches (such as for Darwin's finches), which generates a parameter space for shape adaptations. This

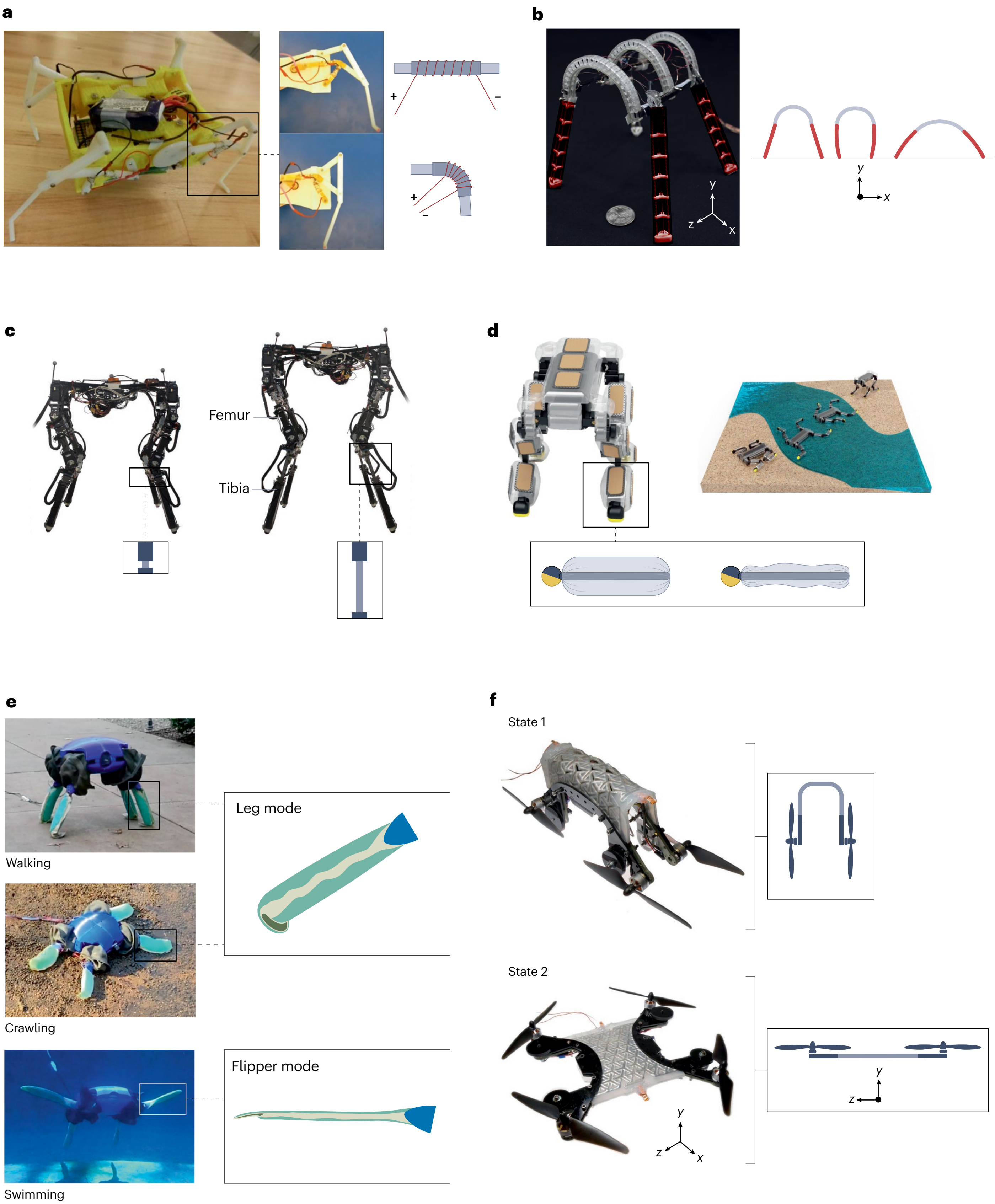
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Fig. 2 | Examples of robots that exhibit adaptive morphogenesis. **a**, Quadruped robot that reconfigures its joints to access new gaits for different terrain[48]. **b**, Quadruped robot that morphs body and leg shapes to overcome obstacles[49]. **c**, Quadruped robot that autonomously adjusts its leg lengths to improve efficiency on various substrates[50]. **d**, Quadruped robot that inflates parts of its body to change its swimming or terrestrial locomotion mechanics[53]. **e**, An amphibious robotic turtle that engages in walking, swimming and transition locomotion modes via morphing limbs and movement patterns[38]. **f**, Quadcopter that morphs its body between terrestrial and aerial propeller-driven locomotion modes[54]. Part **a** reprinted with permission from ref. 48, IEEE. Part **b** reprinted from ref. 49, CC BY 4.0. Part **c** reprinted from ref. 50, Springer Nature Limited. Part **d** reprinted from ref. 53, CC BY 4.0. Part **e** reprinted from ref. 38, Springer Nature Limited. Part **f** reprinted with permission from ref. 54, AAAS.

parameter space could inform the design of shape-morphing mechanisms in the AM robot and provide biological insight into physiological relationships between species.

Speculating about applications for the next generation of AM robots prompts questions about how adaptations are best selected from a seemingly endless realm of possibilities, the relevant performance trade-offs when designing shape-morphing mechanisms, whether energetic benefits gleaned from morphing shape actually outweigh the cost of morphing, and how to sense and control adaptations real-time. The efficacy of AM designs today, as well as the successful implementation of AM moving forward, lie amid interconnected questions such as these (Table 1).

From the nebulousness of robot conceptualization, down to the nuts and bolts of physical implementation, we believe that challenges surrounding AM are best studied through an interdisciplinary perspective. The following sections synthesize trends in robotics and adjacent fields such as computer science, biological engineering and nanotechnology. Collectively, these sections form a roadmap of future research directions and identify what technological hurdles must be overcome to realize robots that evolve on demand.

Screening the design space for adaptations

Inspiration for AM robots can be gleaned by observing the multitude of organisms that currently inhabit our planet and extinct organisms in the fossil record. Among the over two million catalogued species, diverse locomotion adaptations – ranging from the wings of birds to the pseudopodia of amoebas – present a vast array of choices. It thus remains unclear how to select evolutionary adaptations and incorporate them into machines[64]. Although natural evolution arises through mutations that alleviate organism-specific, niche-specific and era-specific pressures, these conditions are difficult to abstract and embody in AM robots. The design of AM robots has consequently remained a mostly ad hoc enterprise.

One approach to remove some of the heuristic basis from the realization of AM robots is through simulation. Simulation could theoretically be used throughout the AM robot design pipeline, helping to vet candidate materials, mechanisms, morphologies, and later on, shape and locomotion control policies. Artificial evolution using evolutionary algorithms, in particular, can search a vast space of possible robot shape mutations and vet the degree to which they confer functional advantages[65–67]. An evolutionary algorithm could take as input different robot designs and evaluate their 'fitness' (adherence to performance metric(s), such as locomotion efficiency). The parameters of top-performing designs would then be propagated to subsequent generations, and a degree of 'mutation' (randomness) injected to encourage exploration of the parameter space. As in nature, gradually and over many iterations, the evolutionary algorithm outputs a design that is optimized with respect to the designated performance metric(s). More recently, with the advent of differentiable physics engines, sample-efficient gradient-based search methods could one day discover promising AM strategies in only a handful of simulation attempts – many orders of magnitude faster than the comparatively plodding trial-and-error of evolutionary algorithms[68,69].

As is especially important to acknowledge in the case of AM robots, the physics of the real world are impossible to fully recapitulate in simulations. Simulators tend to exploit inaccuracies to achieve desired behaviours, resulting in the well-known simulation-to-reality (sim2real) gap[70]. There have been a number of efforts to mitigate the sim2real gap. One technique, domain randomization, injects noise into a simulator to account for mismatches between actual and simulated physics[71]. Concretely, this strategy might entail modifying the contact geometry and friction coefficient between a robot and its environment subtly at each simulation time step. The hope is that the simulation then converges on designs and control policies that handle the uncertainties of the real world. Other options that can help to close the sim2real gap involve supplementing or outright replacing the idealized physics models in simulators with experimentally collected data. For instance, augmenting simulation with stochastic neural networks can serve to correct the output of models such that they are more indicative of real beavior[72]. Alternatively, physics-informed neural networks can be trained directly on experimental data and used as proxies for dynamics equations derived from first principles[73].

A unique opportunity afforded by AM robots is to conduct self-experimentation to assess the efficacy of certain shape adaptations. This strategy could be particularly useful in cases wherein dynamics of the robot or environment are sufficiently complicated to elude reliable sim2real transfer. In seeking favourable morphological adaptations, a promising area of future research is thus to allow AM-capable robots to choose when to rely on sim2real and when to rely on direct physical self-experimentation. For example, certain body plans and behaviours, such as legs performing a quasi-static gait, are known to have effective sim2real transfer. Other body plans have less tendency to transfer well, such as those composed of soft materials with internal nonlinear dynamics and nonlinear dynamics between the robot and the environment. When deployed in a new environment, an AM robot could first elect to search in silico among body plans that have higher success rates of sim2real transfer. Then, when screening more complex morphologies, the robot could opt to rely on physical self-experimentation. Physically screening adaptations in real-time requires major innovations in terms of materials and mechanisms to realize evolving robot morphology.

Materials and mechanisms for evolving morphology

Imbuing a robot with the capability to fluidly adapt its shape requires compressing the gradual natural process of evolution into shape-morphing mechanisms that can operate in real time. The inherent challenges here revolve around mechanically programming these mechanisms to enable a high degree of shape change while simultaneously maintaining operational robustness across different environments.

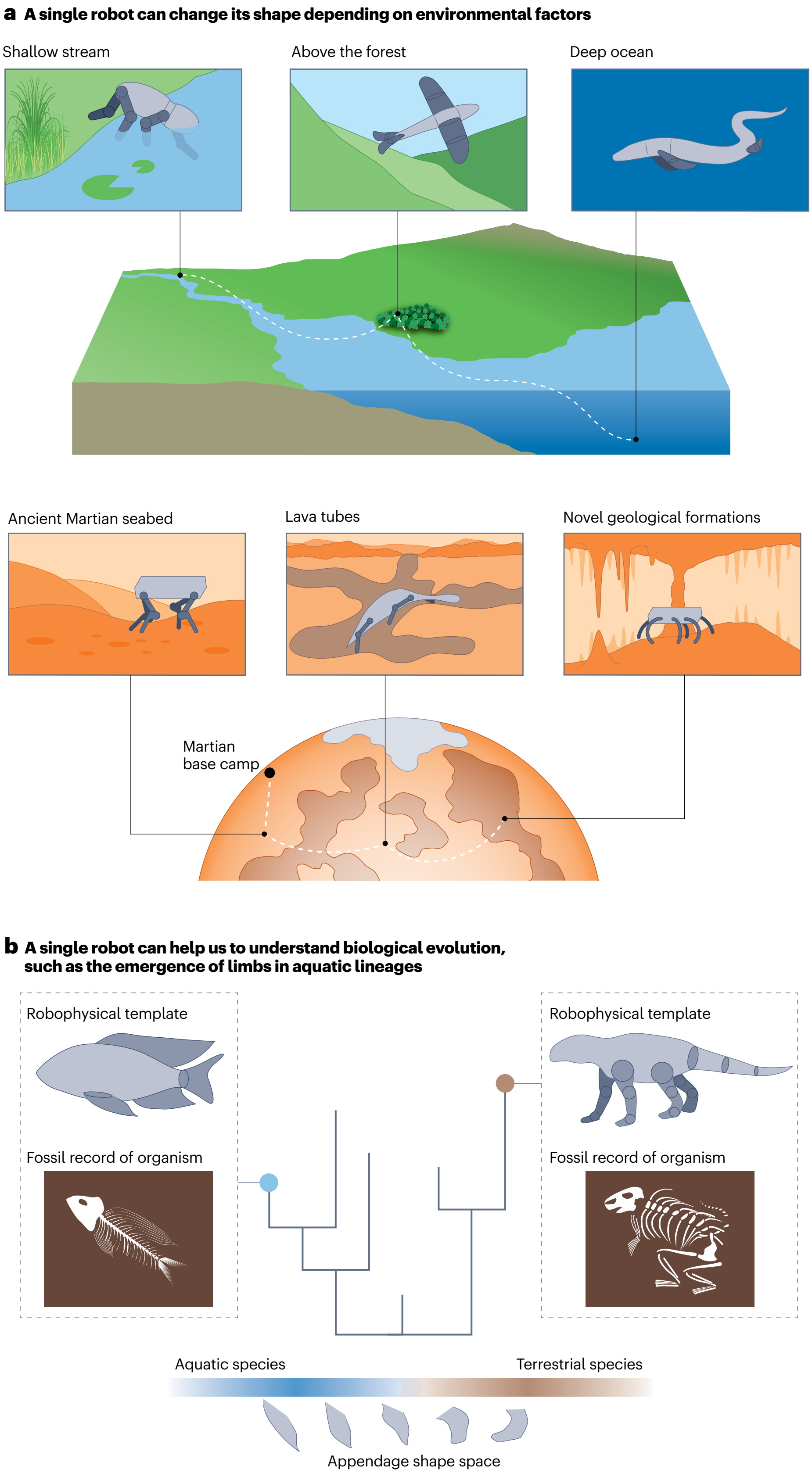

Fig. 3 | Future applications of AM robots. Adaptive morphogenesis (AM) robots can specialize on-demand for locomotion through different environments. This capability can be useful in all manner of applications. **a**, As one example, AM robots could serve as efficient and autonomous biomonitoring devices, providing continuous in situ data of endangered ecosystems that are necessary for their conservation (top). During missions in resource-constrained space environments, such as extraterrestrial planet surfaces, a single robot designed with AM could adapt for efficient locomotion through challenging geological features (bottom). **b**, AM could also be implemented to understand biological evolution, providing a single platform to study, for instance, the emergence of limbs in aquatic lineages. Traversing the phylogeny of animal morphologies reveals a shape parameterization space that may provide insights into how and why robots should change shape.

Before tackling these challenges, it is first necessary to decide if the shape-morphing mechanism will be passive or active.

Passive shape-morphing mechanisms

Passive mechanisms source their morphing impetus and the energy needed for the process directly from environmental stimuli, minimizing the reliance of AM robots on embedded electronics, sensors and external power sources. As such, passive mechanisms could be advantageous for resource-constrained applications or cases wherein automatic shape-morphing across environment thresholds is desired. Consider an ecological monitoring AM robot that needs to adapt its propulsor shape when transitioning between terrestrial and aquatic environments; in such a scenario, materials that morph upon being submerged in water might be a practical material choice[74,75]. As another hypothetical example, if a robot on Mars is intended to walk about the surface of the planet during daylight but then morph into an insulative shape when the sun sets to withstand temperature drops, light-responsive materials could passively mediate these diurnal transformations[76,77].

Despite their advantages, passive mechanisms sacrifice operational flexibility. AM robots using passive mechanisms would not be able to truly ‘evolve on demand’ unless the environment in which they operate is fully controlled. Indeed, techniques such as magnetically governed shape-morphing are made possible only with magnetic coils entirely surrounding the material, forming an artificial environment[78,79]; even diffusive process-based morphing is only successful if the exposure of the material to its driving stimuli is tightly regulated[80]. As structured and pre-known environmental transitions do not fully capture the diverse challenges that AM robots may encounter in real-world deployment, a viable alternative is to implement active shape-morphing mechanisms.

Active shape-morphing mechanisms

Active mechanisms require input signals generated by robotic hardware to initiate shape changes (the source of energy sustaining this morphing operation could come from the environment and/or onboard energy storage devices). Most AM robots built to date utilize active mechanisms (Fig. 2). Active mechanisms can be further categorized into two subclasses: those that require constant energy input to actuators to maintain a desired configuration (such as in Fig. 2c,d, wherein the robots need constant energy input to extend legs with metal linear actuators or inflate soft pneumatic pouches), and those that maintain configurations with no energy input. The latter subclass, ‘move-and-hold’ systems (Fig. 2a,b,e,f), includes actuators coupled to variable stiffness materials[81,82], multi-stable architectures[83–86], and plastically deforming materials such as clay[87].

From an energetic perspective, move-and-hold systems appear to be a superior choice for transitioning between functional configurations, especially when a robot needs to maintain a shape for an extended duration. However, it is critical that move-and-hold systems are designed such that environmental factors do not interfere with their trigger stimulus. Most move-and-hold robots (Fig. 2a,b,e,f) use thermally activated systems based on variable stiffness materials. Although thermally activated materials enable considerable stiffness modulations for radical and reversible morphological changes, they can become unreliable when subjected to extreme temperatures or forced convection boundary conditions[88–90]. In the specific case of ART (Fig. 2e), field testing on cold winter days made it difficult to morph the limbs at all. On especially hot summer days in the direct sunlight, the limbs would also begin to soften at undesired times. Unwanted environmental interference represents a large concern that impacts the ability of a robot to evolve on demand.

Materials for future AM robots

Various promising material candidates can be integrated into active shape-morphing mechanisms to achieve drastic and robust evolving robot morphology[91–94].

Swelling hyperelastic materials. One promising class of materials is swelling hyperelastic compounds, notably hydrogels and liquid crystal elastomers (LCEs). Programming desired shape changes into these materials usually entails engineering their emerging strain fields in response to driving stimuli. In the case of hydrogels, augmenting the crosslink density and locally varying the material thickness elicits anisotropic deformation[95–97]; for LCEs, shape change may be accomplished by reorienting mesogens with light or heat[98–100]. With advancements in 3D printing, it is becoming possible to co-extrude anisotropic fillers during the manufacture of such swelling materials, unlocking high-resolution shape programming approaching the sub-millimetre scale[101–104].

Future research should investigate how to embed functional vias for activation stimuli of these materials (such as hydration channels for hydrogels and conductive filler channels for Joule-heating LCEs), and protective coatings to shield them from unwanted environmental disturbances (a hydrophobic surface for hydrogels and an efficient heat exchange barrier for LCEs). To embed functional vias within these stimulus-responsive materials, advances in the processability of 3D-printed materials are required. New printing techniques, solvent treatments and optimal processing conditions, such as temperature and humidity control, must be developed to ensure that rheologies of materials are suitable for printing while exhibiting target post-print robustness and intrinsic properties (conductivity, moisture wicking and so on).

Jamming media. Another set of highly promising materials for active move-and-hold mechanisms are jamming media. These materials come in variety of form factors, such as granular, laminar and fibre, which may be realized through a number of material instantiations, such as

Table 1 | Challenges and key research avenues towards realizing future adaptive morphogenesis robots

Challenges	Key avenues	Examples
Searching the design space	Observational studies Differentiable physics simulation Simulation-to-reality gap mitigation	Domain randomization[73]
Materials design	Living and bio-hybrid materials Rapid, recoverable and temperature-independent morphing mechanisms	Jamming media[105]
Morphing energetics	Embodied energy Stretchable energy storage devices Environment-driven morphing	Solar-powered morphing[128]
State estimation	Minimal sensing Shape sensing Multimodal sensing	Robotic skins[137]
Control	Machine learning and simulations Bio-inspired actuation methods Physical intelligence	Recurrent neural networks models[156]

coffee grounds, paper and natural thread. Move-and-hold mechanisms composed of jamming media harness compaction of the constituent materials to increase kinematic and frictional interactions, often by vacuum pressure. For AM robots, jamming media offers stark stiffness differentials that are largely unaffected by temperature changes, and recovery capacity after being subjected to loads that would otherwise induce mechanical failure in other variable stiffness materials[105,106].

Jamming media have previously found applications in shape-morphing continuum manipulators[107] and dynamic legged robots to modulate ground contact friction while navigating diverse terrains[108,109]. For effective implementation in AM robots, there needs to be further understanding of how to program jamming media into desired target shapes, either by coupling them to other actuators that coerce programmed curvatures, or merely understanding how they equilibrate to a minimum-energy jammed configuration. Research must quantify the interplay of external forces, bounding membrane geometry and granular, fibrous and laminar constituent form factors to develop design tools for the shape of move-and-hold jamming systems.

Living materials. A relatively untapped class of substances for active shape-morphing mechanisms are living materials – ranging from microscopic bacteria to multicellular organisms. Living materials can serve as actuators across orders of magnitude in scale and programmatically transform into complex shapes[110,111]. For example, brewer's yeast (*Saccharomyces cerevisiae*) diffused in a polyacrylamide hydrogel elicited twisting and dilation, replicating the quality of shape morphing accomplished by a purely synthetic swelling materials[112]. Another study has achieved similar deformation modes by fabricating a hygromorphic composite composed of pollen with edible ink patterned on its surface[113]. Beyond demonstrating excellent shape-changing potential, living materials can automatically recover after damage[114] and survive the harshest of environmental conditions[115] – qualities that make them suited to AM robot encountering unstructured multi-environments.

A promising research direction is in combining synthetic materials with living ones to create bio-hybrids with the native multifunctionality of biology yet accelerated shape-changing capacity of synthetic mechanisms[116]. To do so, we must enlist the expertise of bioengineers. A deeper understanding of how to appropriately maintain the functionality of living tissues when extracted from their native environment is needed. Moreover, research on seamless physical integration and communication between synthetic and living components will be imperative.

Morphing energetics

Evolution in nature requires vast amounts of energy fuelled by fire, flesh, sunlight, oxygen and geochemical sources[117,118]. Machines additionally have access to synthetic high-density energy storage devices, such as electrochemical batteries and supercapacitors. AM robots definitively use very little energy compared to what nature requires to produce derived biological lineages, though existing examples still rely on power-hungry morphing mechanisms. Most existing AM robots need to be tethered to an external source of energy to morph, whether to an external power supply (Fig. 2a–c), both pressure and power supplies (Fig. 2e), or a designated morphing docking station (Fig. 2f). Being tethered ultimately curbs the autonomy and versatility of robots during AM.

To morph or not to morph

When considering the energetics of AM, the cost of changing shape should be minimized relative to the benefits provided by the adaptation. For example, if using a fish-like shape to swim a given distance (under specific conditions) allows a robot to save 30 J of energy, ideally, morphing to the fish-like shape should cost less than 30 J. If the energetic benefits gleaned from morphing do not surpass its cost, the adaptation is not energetically advantageous.

The question of whether to morph has no fixed solution and depends closely on the characteristics of the environmental transitions a robot must accomplish. In cases wherein a robot only briefly encounters a new environment, it might be more energetically favourable to remain non-optimized rather than investing energy in a new adaptation. Conversely, it could also be favourable for a robot to adapt to reach superior performance in another metric, such as speed, even if it is not necessarily energetically advantageous in the short term. A biological analogy for this is an animal escaping predation: rapid escape maneuvers are costly, but the animal survives. However, just as they do in nature, episodes of high energy expenditure could have negative ramifications for the long-term stability and performance of AM robots. Systematic analyses of the trade-off between morphing energy and locomotion performance for AM robots are, therefore, needed moving forward. Overall, energetic considerations point back to strategies when engineering the material composition of the robot.

Energetic materials for AM robots

One promising approach to economize the energetics of AM systems is following the principle of embodied energy, which encourages integrating power systems closely with robot structure so they serve multiple purposes (for example, a battery could also provide structural support)[119]. If the body of a robot can morph its shape, so too must its sources of embodied energy. Ongoing research into energy storage devices that can accommodate high stretches and curvatures holds promise in this domain. Much of this research focuses on tuning intrinsic properties of carbon-based or metal-based nanomaterials, embedding them into stretchable elastomeric substrates to render supercapacitors and batteries. Here, geometry has a key role in performance. Kirigami-inspired cuts in supercapacitors made from various base materials resulted in reliable electrochemical function up to a remarkable 400% strain[120]. Other geometric modifications, such as coercing pre-buckling, engineering special high-strain microstructures, and forming materials into fibres, can impart similar levels of stretchability into energy storage devices while preserving their electrochemical performances[121].

Harvesting energy from the environment to facilitate morphing is another viable approach to make AM efficient. As previously mentioned, passive morphers can directly convert energy from environmental stimuli such as mechanical vibrations, heat, light, humidity and chemical gradients into morphing energy with no intermediate storage step[122–126]. Conversely, for active morphers, harvesting systems could charge onboard storage devices or build up mechanical energy for subsequent triggered morphing operations[99,127,128]. Morphology, control policy and environmental stimuli all influence each other, governing the efficacy of energy systems in a robot[129] and motivating the need for AM robots to possess a means of continuous self-assessments and contextual assessments.

Environment state estimation and sensing

When evolving on demand, a robot can benefit from continually evaluating its own state (proprioception) and the state of its environment (exteroception) to decide if further adaptation is energetically expedient or even necessary.

Proprioception

Some AM systems have no sensing integrated into their morphing mechanisms, relying instead on open-loop processes (Fig. 2a,e,f). Others use resistance measurements of actuators dually as sensors (Fig. 2b), motor encoders (Fig. 2c) or pressure sensors to approximate the shape state (Fig. 2d). A primary challenge surrounding proprioception is what type of sensors to use to reconstruct the shape of a robot.

Shape changes may be parameterized in a number of ways, based on measurements such as a distribution of normals across a surface area[87], principal and Gaussian curvatures[130,131], or distance between individual material points on a body[132]. Quantities of interest when sensing shape may, thus, include localized strain, relative position and orientation. Devising architectures that sense these quantities to obtain meaningful estimates of shape state is an active field of research[133–136]. Particularly promising candidates for application to AM systems are shape-sensing robotic skins that conform to the body of a robot, accommodating high degrees of stretching and bending[137,138].

Deciding where to actually put sensors on a robot is another important challenge of proprioception. AM robots may be characterized by a continuum state space that is impossible to reconstruct with a finite number of discrete sensors. Simulated agents have been used to decide the optimal sensor placement when accomplishing dynamic locomotion for generic morphologies[139]. However, this work only addresses robots moving through one environment, so the question of sensor placement for multiple locomotion modes with a single set of hardware remains open.

Exteroception

Examples of exteroceptive AM include robots that perceives the terrain immediately in front of it with a camera (Fig. 2c) and robots that can sense environmental forces via cutaneous sensors (Fig. 2d). A primary consideration with exteroceptive sensing is deciding what environmental information is actually relevant to initiate adaptations. For a given system, there may be a baseline of exteroceptive sensing infrastructure that provides sufficient information; exceeding this baseline may only yield marginal performance gains.

For instance, the robot in Fig. 2c used a camera to classify terrains and adapt its leg lengths, but had it also been equipped with a moisture sensor, perhaps it could have made marginally better decisions about leg lengths when traversing terrain. However, the additional sensor might bog down the robot with additional mass and power requirements and render it more fragile. The trade-off between the exteroceptive information density and functional utility of an AM robot thus represents an exciting area for research. Work investigating minimal sensing architectures is predominately confined to theoretical case studies in 2D environments[140,141] and could benefit from an extension to studies on hardware platforms with real (and noisy) sensors[142].

Multimodal sensing

In practice, AM blurs the lines between proprioception and exteroception by inexorably linking a robot and its morphology to its environment[143]. This observation motivates the use of a single sensor for both proprioceptive and exteroceptive state information. An integrated strategy would reduce the number of independent sensors that necessitate power and communication lines, boosting efficiency and diminishing the space in the robot body dedicated to just sensing. As an illustration, an onboard camera could both track the shape of a morphing component within its field of view and ascertain environmental conditions such as substrate quality.

Following this idea, robots could benefit from advances in multimodal sensors that discern and decouple multiple stimuli[144]. Ongoing research on multimodal sensing has resulted in material architectures capable of discerning and decoupling multiple deformation modes[145–147]. As a canonical example, an elastomeric substrate was embedded with a deformable array of copper-polyamide sensing elements to facilitate capacitive sensing of shear, strain and pressure[148]. Prevalent issues with multimodal sensor designs are their large number of components and difficulty of manufacture, which render them mechanically fragile and muddles interpretations of their signal output. It is, thus, desirable to innovate compact, mechanically simplified sensing architectures to perceive multiple stimuli. More work is also still needed to reliably expand multimodal sensors to perceive other physical quantities beyond proprioceptive measures of shape, including environmental factors that may influence morphing, such as temperature, pressure, humidity and pH. Once equipped with appropriate self-sensing and environment-sensing capabilities, the question remains on how an AM robot should use the state feedback to evolve and move intelligently through its surroundings.

Control

AM robots could require control policies more sophisticated than those of traditional robots. Not only must they decide when and how to change shape, but once they arrive in a configuration, they must coordinate movements of propulsors for locomotion through diverse environments.

Passive shape control

The fact that current and future AM robots may be built from passive shape-morphing soft materials, although a challenge in one sense, simultaneously provides a unique shape control opportunity: The environment can passively deform the physical shape of a robot in such a way as to facilitate its expression of desired behaviour. This concept was aptly demonstrated with the advent of granular jamming grippers[149]. The control effort needed for a jamming gripper to grasp an object reduces markedly because the gripper passively adopts stable grasp configurations on contact with that object. In a similar manner, passive bodily adaptation could be exploited in future AM machines such that the environment 'suggests' which form is most appropriate for a given environment. Consider a non-spherical rolling soft robot. Local surface protrusions will suffer impact forces more often than indentations; if these protrusions are soft, they will gradually be compressed, yielding a more spherical robot without recourse to active control. A more spherical shape will, in turn, facilitate energy-efficient rolling.

Passive, environment-mediated transitions in form and function of AM robots could serve as a new class of morphological computation[150,151] or physical intelligence[24], providing a new avenue for exploring issues of adaptive control that have been under investigation for decades. One such issue is that of ultrastability[152]: how organisms inherently 'know' how to recover homoeostasis when pushed by novel events far beyond the limits of normal operation. AM may be a solution to ultrastability. Rather than changing into a new form actively, being literally pushed into a new form by the environment may provide previously impossible recovery routes back to homoeostasis.

Active shape control

If an AM robot utilizes active shape-morphing mechanisms, then it may be necessary to control the shape of that robot based on embedded sensor feedback. Traditional linear control strategies, such as proportional-integral-derivative controllers, may have trouble retaining stability given the nonlinear material properties and environment-dependent dynamics of shape-morphing mechanisms. Much work is needed to step towards effective model-based controllers, including new constitutive laws of emerging shape-morphing materials that track their dynamics in response to different environmental stimuli and loading conditions.

Physics-informed machine learning[153,154] may have a crucial role in AM robot control because it can serve to compress the complex dynamic equations of a system into minimal, more tractable forms. For example, researchers have used autoencoder architectures to reduce the model order of a spring–mass–damper network while retaining comparable behaviour to the complete dynamics[155].

Other advances in machine learning techniques, such as recurrent neural networks and model predictive control, are beginning to enable closed-loop control of shape-changing soft robotic continua by effectively handling nonlinear dynamics and time-dependent responses[156–158]. For instance, with less than 5 min of data collected from testing on a physical system, researchers demonstrated a versatile Koopman operator-based control scheme capable of maintaining accurate control over high deflections and accelerations of a soft continuum arm[159]. Moving forward, researchers should seek to validate the generalizability of these emerging techniques across different shape-morphing robot embodiments.

Control of locomotion

Locomotion control solutions depend on the actuators that an AM robot uses for propulsion, whether they are traditional direct current motors, soft actuators or other active shape-changing mechanisms. Traditional motors are common in existing AM robots, probably owing to the relative ease of implementing established control techniques. The majority of gaits in these AM robots are based on pre-programmed position-based controllers.

Moving forward, bio-inspired strategies, such as central pattern generators (CPGs), could be used for more sophisticated locomotion capability. On the basis of the central nervous systems of animals, CPGs generate repeated motor commands with short limit cycles. They are mostly deployed in an open-loop manner and have seen implementation in many walking and swimming robots[160]. The primary advantages of CPGs for AM robots are their simplicity, stability in the presence of perturbations, and amenability to scaling to systems with many degrees of freedom[161]. However, CPGs have limited capacity to deviate from prescribed movement patterns. Additionally, as the state of the environment is an important determinant of the shape and gait of a robot, completely open-loop strategies (as many CPGs are) might fall short. For AM robots to traverse difficult environments, more adaptive locomotion policies are necessary, perhaps ones that additionally consider performance metrics such as robot efficiency, speed and stability.

Locomotion control policies derived from reinforcement learning (RL) of simulated environments and agents have achieved tremendous success in the past 5 years. For quadruped systems represented by rigid body dynamics simulations and placed within RL frameworks, zero-shot transfer of controllers to actual robots has been demonstrated in previously insurmountably complex and unstructured outdoor terrains[162,163]. We believe that an RL-based locomotion policy approach holds promise for AM robots. However, to screen thousands of policies for robots whose bodies or propulsive mechanisms may be composed of soft, stimulus-responsive materials, advances are necessary to simulate the dynamics of the robots faster than real-time.

If all of the previous challenges are addressed, and a controller is successfully trained on an AM robot for locomotion in one configuration, it would need to be re-trained, or trigger a switch to another policy, for all emerging robot configurations. In the limit of many different adaptations, such procedures scale poorly. AM thus mandates more generalized control frameworks that can accommodate gait control in the context of spontaneous development of entirely new bodily features. Transformer neural networks offer substantial promise in this regard. For example, a single learned policy can effectively operate a variety of unseen robot morphologies with different numbers of appendages, configurations and sizes[164,165]. However, because transformer networks require sets of known robot shape parameterizations for training data, truly new morphologies that are beyond simple interpolations of training data have no guarantees of controllability. In addition, moving forward, these generalized control methods should be tested not only in simulations but also on embodied platforms.

Performance metrics

Systematically evaluating robots that exhibit AM is, unto itself, a challenge. It may be difficult to compare the efficacy of AM across multiple embodiments if focusing on outcome-oriented performance metrics, such as peak force or top speed. Instead, we propose metrics for the process of shape adaptation itself, hoping that these generalize across various instantiations of AM robots. Adaptation quantifiers (AQs) can serve to evaluate and compare systems that undergo shape-morphing operations, setting necessary benchmarks for the field (Box 1).

Box 1 | Example AQs for a robot that exhibits AM

We provide concrete examples of adaptation quantifiers (AQs) for an existing adaptive morphogenesis (AM) robot: the amphibious robotic turtle (ART) platform[38] (Fig. 2e). The table below includes the values obtained for the AQs. To obtain AQ1, we used a direct current power supply (Korad KA3005P) to sustain the morphing operations of ART and used a plug-in power recorder (Zhurui PR10). We then converted the power to electrical energy by multiplying it by the time elapsed. For AQ2, we used a change in diameter (the primary deformation dimension during morphing) as a shape metric and discerned the change from high-definition camera images. We determined AQ3 by timing the transformations that occurred while measuring AQ2. We assessed cyclic transformations of one of the limbs of ART for AQ4, but we did not test it to its failure point. Lastly, as ART uses only actively driven shape-morphing mechanisms, the passive component of AQ5 is 0.

AQ	Result for the ART platform
Cost of adaptation (AQ1)	10,360 J (flipper to leg), 10,290 J (leg to flipper)
Magnitude of adaptation (AQ2)	2.8× diameter change (from 21.5 mm flipper to 60.2 mm leg) AQ3: 0.014 mm s^{-1} (flipper to leg), 0.774 mm s^{-1} (leg to flipper)
Repeatability factor (AQ4)	50 (max tested)
Reliance on passive versus active adaptation (AQ5)	0:1

Cost of adaptation (AQ1)
This metric is the total energy input to the robot to facilitate the completion of an adaptive process. For example, if considering a shape-morphing robot utilizing Joule-heated thermoplastic materials coupled to pneumatic actuators to change shape (as is the case for ART)[38], the cost of adaptation would be the sum of the energy input to the Joule heaters plus the energy required for inflation. Note that morphing between certain configurations may require different subsystems and therefore different amounts of energy expenditure. When reporting, a description of the assumptions involved in calculating the energetics should include the equation used to calculate energy, and whether that energy comes from mechanical, electrical or chemical processes. Combined with an application-specific metric, such as cost of transport, the energetic cost of adaptation contextualizes the performance gains of the adaptation.

Magnitude of adaptation (AQ2)
This metric aims to measure the disparity between the initial and final shapes of the robot. As mentioned earlier, the adaptations of AM robots may draw inspiration from morphologies spanning various organism phylogenies, wherein the interrelations among species on this phylogenetic tree describe a vast physiological parameter space. Beyond biological notions of shape similarity as discerned through phylogenic proximity, there are myriad ways proposed in the literature to quantify shape[166]. Admittedly, the best choice for calculating AQ2 will depend on the embodiment of a particular robot and the available sensing infrastructure to reconstruct some notion of shape.

For 3D morphers, the Hausdorff distance could be useful in that it computes disparity between collections of points — one collection being the 'before change' and the other being the 'after change' point cloud reconstructions of a robot, for example — and does not require a one-to-one mapping between points[167]. Another relevant term that arises in continuum mechanics is the right stretch tensor in the polar decomposition of the deformation gradient[168]. The right stretch tensor excludes rigid body translation and rotation from its notion of shape change, which can be useful in differentiating the routine kinematic motions of a robot from explicit morphological transformation.

Yet another way to quantify shape change, particularly concrete in the context of AM systems, is the 'Earth Mover's Distance'. This metric calculates dissimilarity between two distributions by assuming that the distributions have mass and that energy is consumed by physically moving the mass from one distribution to another over a specific distance to re-shape it[169]. For approximately 2D morphers, such as a robotic skin[170], the metric tensor from differential geometry seems like a good choice to describe shape, as it has been extensively used to model morphing sheet-like systems[84,171].

Overall, we suggest that researchers report the simplest metric that captures meaningful information about the shape of a robot. For robots whose shape-morphing mechanisms only exhibit a single degree-of-freedom (DOF), it would make sense for AQ2 to be a measure of this one dimension. As illustration, the robot in Fig. 2c uses linear actuators, each with a single DOF. An AQ2 that quantifies extended leg distance might make sense for this robot. Conversely, the robot in Fig. 2b exhibits nearly infinite DOF owing to its continuum appendages. An AQ2 that quantifies the space curve configuration of its appendages relative to some rest geometry, such as the Frechet distance[172], might make sense for this robot. It may also be desired to report the magnitude of adaptation in terms of ratios, such as surface area-to-volume ratio, or dimensionless quantities normalized by the rest geometry of the robot, to capture variations across scale.

Glossary

Autoencoder
A type of neural network that compresses input data into a lower-dimensional representation and then reconstructs the original data from that compressed form.

Behavioural control policy
The way a robot moves and adapts its body to accomplish a task.

Central pattern generators
(CPGs). Robot control schemes modelled on animals' spinal cords that generate rhythmic and repeated actuation signals.

Darwin's finches
A group of bird species with diverse beak shapes and functions; classical example of how organisms adapt over time to their environments.

Differentiable physics engines
Simulations in which all physical variables may be differentiated, enabling use of gradient-based machine learning techniques.

Functional vias
Vasculature in a robot facilitating sensing, actuation, control or power, through transport and distribution of material(s).

Hygromorphic
Swelling in response to humidity changes (as does wood, for example).

Phenotypic plasticity
The ability of organisms to adapt their body properties in response to changing environmental conditions (an example of which is the development of muscle with repeated exercise).

Pseudopodia
An offshoot from the body of a eukaryotic cell formed to facilitate movement or to ensnare food.

Reinforcement learning
(RL). Machine learning approach to teach an agent how to take actions in an environment to maximize a reward.

Simulation-to-reality (sim2real) gap
The disparity in performance between an agent in simulation and an agent physically deployed in the real world.

Transformer neural networks
A type of neural network that uses an attention mechanism to efficiently process sequential data.

Ultrastability
The ability of a system to maintain function, in spite of environmental changes, by modifying the dynamics between itself and its surroundings.

Zero-shot transfer
Direct sim2real transfer without any tuning or iteration.

Rate of adaptation (AQ3)
Going hand-in-hand with AQ2 is the notion of rate of adaptation: the change in a physical quantity that is being adapted divided by the time elapsed between the start and finish of an adaptive process. Assume a robot develops a new arm, changing from a surface area of 100 mm^2 to 200 mm^2 in 10 s. Its rate of adaptation is, therefore, 10 $mm^2\,s^{-1}$. This metric could elucidate temporal coupling between multiple integrated adaptive processes. It could also grant insight into the efficacy of classes of mechanisms used for shape-morphing. For instance, adaptations leveraging mechanical instabilities may result in a high rate of adaptation, whereas those relying on diffusive processes could take orders of magnitude longer.

Repeatability factor (AQ4)

This metric indicates the number of adaptation cycles that a robot could complete. In the case of a shape-morphing robot that transforms between flying and aquatic form factors, one full cycle is given as state transitions flying form → aquatic form → flying form. An adaptation that is not reversible (that is, a one-way transition) has a repeatability factor of 0. This metric additionally helps to compare morphing materials and mechanisms used for AM, getting at what underlying material choices and fabrication strategies tend to maximize repeatability.

Reliance on passive versus active adaptations (AQ5)

This metric tallies adaptations in a robot that occur passively through a material response to external stimuli to those that are actively initiated by computation. As an illustration, a robot that transforms as a function of light exposure and also utilizes programmable logic controllers to trigger actuators that transform other body parts has one passive and one active adaptation, resulting in an AQ5 of 1:1. Standalone, this metric encodes some notion of the reliance of a robot on computational hardware versus physical intelligence. When considered in tandem with the other AQs, such as AQ1, this metric can serve as a guideline to realize robots synthesizing several to dozens of adaptations. For instance, the distribution of passive versus active adaptations in a robot could correlate to its cost of adaptation.

Conclusion

Bio-inspired adaptive strategies have changed the landscape of robotics. The proficiency of organisms across multiple tasks, ranging from manipulation to locomotion, has compelled researchers to devise new materials and mechanisms in hopes of capturing some of what makes biology effective. An emerging robot design strategy, AM, champions the integration of bio-inspired adaptive strategies that normally would occur at evolutionary timescales into a unified mechanism space. AM has the potential to yield robots that optimize over multiple performance metrics during locomotion, in a sense exceeding what is feasible in natural systems. Although the field is nascent, there is compelling evidence to suggest that AM is a viable design strategy for all manner of robot applications wherein morphological adaptability is requisite to success. Technological barriers spanning adaptation selection, shape-morphing mechanism design, energy, sensing and control continue to stand in the way of truly multi-purpose robots. The brimming nexus of materials science, biology and artificial intelligence poises the field for rapid developments over the next decade, stepping ever closer to robots that rapidly and efficiently evolve on demand.

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