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Materializing Autonomy in Soft Robots across Scales

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The impressive capabilities of living organisms arise from the way autonomy is materialized by their bodies. Across scales, living beings couple computational or cognitive intelligence with physical intelligence through body morphology, material multifunctionality, and mechanical compliance. While soft robotics has advanced the design and fabrication of physically intelligent bodies, the integration of information-processing capabilities for computational intelligence remains a challenge. Consequently, perception and control limitations have constrained how soft robots are built today. Progress toward untethered autonomy will require deliberate convergence in how the field codevelops new materials, fabrication methods, and control strategies for soft robots. Here, a new perspective is put forward: that researchers should use tasks alone to impose material and information constraints on soft robot design. A conceptual framework is proposed for a task-first design paradigm that sidesteps limitations imposed by control strategies. This framework allows emergent synergies between material and information processing properties of soft matter to be readily exploited for task-capable agents. Particular attention is paid to the scale dependence of solutions. Finally, an outlook is presented on emerging research opportunities for achieving autonomy in future soft robots as large as elephant trunks and as small as paramecia.

1. Motivation

Biological organisms and their extraordinary capabilities have been a persistent source of inspiration in robotics. Across scales, the autonomy of living organisms is enabled by their very bodies and tissues—not just their cognitive abilities. The multifunctionality of these soft and compliant tissues provides a passive adaptability and robustness that engineers struggle to replicate in autonomous robots today.[1,2] For example, even single-celled organisms such as slime molds are capable of complex navigational tasks like localization[3] and planning.[4] These tiny organisms can use their soft bodies to simultaneously facilitate locomotion,[5] persistent memory,[6] and computation.[7,8] This pattern persists in larger organisms as well: by leveraging the mechanics of their musculoskeletal systems, vertebrates can also achieve a kind of physical intelligence[9,10] that frees up cognitive resources for higher-level reasoning.[1,11] Soft robotics was founded with the explicit purpose of designing agents capable of similarly leveraging this bodily, physical intelligence to simplify their environmental interactions and lessen their computational burdens in a life-like manner.[12] Yet, in spite of much progress translating advances in soft matter engineering into bioinspired functionalities, the integration of such materials into soft robots with truly bioinspired autonomy remains largely unrealized.

At the heart of this roadblock lies soft robot control. Soft robotics has chiefly focused on the fabrication[13,14] and actuation[15,16] of functional, deformable materials,[17–19] driving substantial innovations in each of these areas. By comparison, there have been fewer developments in soft robot perception,[20,21] learning,[22,23] and control.[24–26] Technical challenges arising from the underactuated, nonlinear, and hysteretic nature of soft robot dynamics, as well as the intensive sensory and computational demands of modern control architectures, have produced an information-processing bottleneck in soft robotics. Similar trends have emerged for small-scale soft robot design, with advances focusing on novel materials[27,28] and actuation mechanisms.[29] Moreover, at decreasing length scales soft robots and active matter systems can be too small to host standard circuitry and power sources, making any onboard computation prohibitively challenging.[30–32] Despite these fundamental engineering challenges, the integration of information-processing within physically intelligent material substrates is crucial to realizing autonomy in soft robots at all scales.[33–36]

To make matters worse, soft robotic control strategies do not—and will likely never—generalize in the same way as traditional robot control. To be physically intelligent, soft bodies must be well-adapted to their environmental niches, requiring their control strategies to adapt in kind. This is to say that different kinds of soft robots will need different control approaches. While some researchers do not attempt to overcome current information-processing bottlenecks, others have faced the

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The ORCID identification number(s) for the author(s) of this article can be found under https://doi.org/10.1002/aisy.202300111.

DOI: 10.1002/aisy.202300111

challenge of soft robotic control head-on. However, these researchers have tended to limit themselves to only building soft robots that they already know how to control. This approach, which we term *control-first design*, entails restricting the design of robot bodies to those controllable through well-known means, such as those characterizable by analytical models (e.g., piecewise constant or polynomial curvatures[37–39]) or tractable with finite element analyses.[40–42] Control-first design has led to the production of soft robots with limited usefulness and task-capability. Thus, the stringent information-processing constraints of soft robots have sparked contentious discussions in the field: how do we best proceed with developing new soft robotic control schemes?

To help guide the field toward the development of useful soft agents, this Perspective presents a conceptual framework for a *task-first design paradigm* for soft robotics. At its core, our Perspective advocates for this task-first approach to highlight that the challenges of soft robot control are directly tied to the soft robot bodies we can actually build. Our framework preempts imposing unnecessarily restrictive conditions on soft robots and their capabilities by starting the design process first with task specification rather than controller design. In this sense, our approach seeks to address the potential consequences of adhering to current trends in soft robot design that have led the field toward information-processing bottlenecks. Our framework is intentionally adaptable and system agnostic to guide the design of any soft robot at any scale, from walking soft robots to bioinspired active matter systems. We also provide soft robot designers generalized considerations for control approaches at large (1 cm–1 m) and small (1 cm–1 μm) length scales once a task-capable robot body has been built. We intend for researchers to use this framework not as an instruction manual or methodology, but as a guide when starting new projects or conceiving new research directions in soft robotics.

To motivate the adoption of our proposed framework, we first discuss in Section 2 how tasks naturally impose material-based and information-based requirements on soft robots that vary by scale. To support our claim, we provide examples of the scale-dependent consequences of control-first soft robot design in Section 2.1. In Section 2.2, we discuss how a task-first approach to autonomous soft robots is naturally supported when morphology informs controller design. From task requirements, we suggest promising research directions to facilitate the exploration of soft robot designs in Section 3. We believe this will enable the discovery of agents that can be fabricated to exploit emergent synergies between body dynamics and control architectures, thereby surpassing individual subsystem limitations to achieve greater task-capability. Overall, we hope this Perspective serves as a call to action for soft robotics researchers to begin creating agents with truly autonomous behaviors by placing task specifications at the forefront of the design process.

2. Tasks as the Starting Point for Design

The root of the problem with control-first design is that it imposes ad-hoc limitations on robot bodies. By envisioning a space of possible robot designs, as in **Figure 1**, we can picture how designing a body to meet a priori control demands needlessly shrinks the design space of task-capable robots. Control-first design does this by first selecting one of a few well-established soft robot control strategies. By necessity, these control strategies must make assumptions about the morphologies of soft robots that they can be deployed on. Then, these assumptions restrict the space of soft robot designs to a small subset

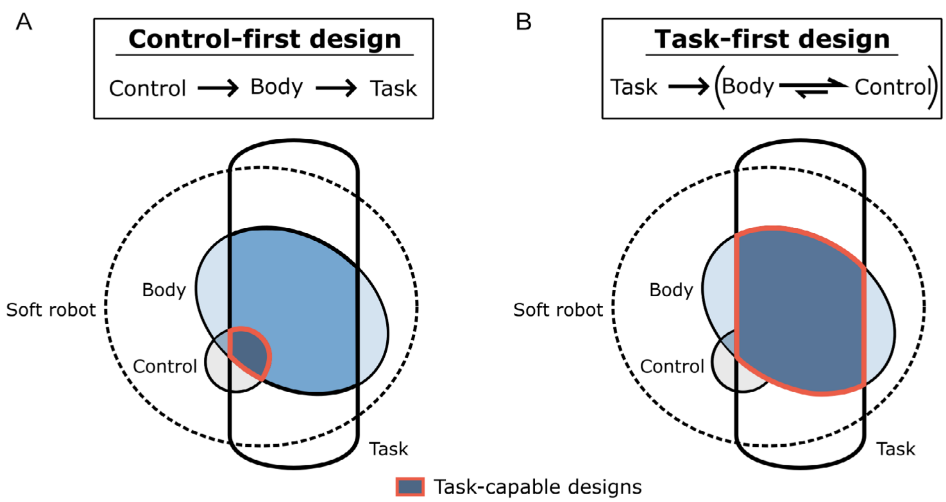

Figure 1. Designing autonomous, task-capable soft robots across scales. The diagrams illustrate the impact of control-first and task-first design in soft robotics. A) Control-first design shrinks the space of viable task-capable soft robots by imposing information-processing constraints on the design of soft robot bodies. These constraints lead to the fabrication of soft robots whose morphologies adhere to the assumptions of existing soft control architectures (see region outlined in red). B) By prioritizing task requirements from the start, task-first design leads to a greater set of task-capable soft robots (see region outlined in red). Task-first design relieves roboticists from constraining designs a priori, while facilitating the design of soft robots that exploit synergies between material and information-processing properties to achieve their task. While valid controllers may not always be available for every possible combination of task and body, this approach relies on the suggestion that designing a bespoke controller for a particular application is typically more feasible than developing novel materials and fabrication methods to make robot bodies that suit the assumptions of a given control strategy.

(see the red outlined region in Figure 1A). Additionally, these morphological restrictions limit materials and fabrication methods to those compatible with the control strategy and its associated assumptions. From the set of designs compatible with the chosen control and fabrication strategies, candidate robot designs are selected with respect to their task-capability. This design approach leads to an overly-conservative filtration of viable designs (see Figure 1A). In doing so, we remove from consideration many designs with potential for task-capability that take advantage of synergies between physical and computational design elements. If we were to start by selecting a task and distilling its requirements, we could avoid imposing unnecessary restrictions on the design process and ensure that resulting soft robots are task-capable from the very beginning (see Figure 1B). This is precisely what task-first design seeks to achieve.

To demonstrate this idea and the trade-offs of control-first versus task-first design, we consider designing a prototypical soft robotic arm in **Figure 2** as an illustrative example. Continuum arms like these have emerged as a popular testbed for developing soft robot controllers. Suppose we define the task for this soft robot as reaching into an opaque paper bag and grasping an object inside (Figure 2A). A task-first designer may conclude that the task requires dexterous maneuverability of the manipulator and proprioceptive tactile sensors distributed throughout the soft robot. In the absence of co-design technologies (see Section 3.1), the task-first design process proceeds sequentially with actuator selection, as actuation is a key determinant of task-capability. Suitable sensing methods to meet the task's information requirements would then be selected. The actuators and sensors would then be integrated into a design to give a soft robot its morphology. The designer would finally develop a suitable controller to complete the task. In contrast, starting the design process with a controller restricts the selection and actuators and sensors to those that best meet the control strategy's needs (Figure 2B). For example, feedback for a piecewise-constant curvature (PCC) controller, a popular option for continuum arms, is more easily provided by motion capture than integrated sensors. Not only is the soft robot constrained to a controlled environment equipped with cameras in this scenario, but also, additionally, the task of grabbing an object out of a bag is now made more difficult since the task requires a loss of line-of-sight to camera fiducials on the robot. As a result, while choosing an exteroceptive sensing strategy met the needs of the controller, it produced a task-incapable design. This is just one illustration of how controllers do not tend to make a good starting point for soft robot design.

Since all of robotics is concerned with the ways in which energy and information exchanges between machines and their environments can be leveraged toward tasks,[43] it is therefore sensible to design autonomous, task-capable robots by beginning with the task itself (see Figure 1B and 2A). While one may imagine many different approaches to soft robot design, our proposed methodology seeks to directly address the shortcomings of control-first design. Task specifications establish requirements that define the desired operational properties of a soft agent. These requirements may capture appropriate device length scales,[44] on-board power needs,[45] operating temperatures,[46–50] sensing modalities,[51] compatible chemistries,[52,53] ranges of actuation,[54] and more. These requirements reflect environmental

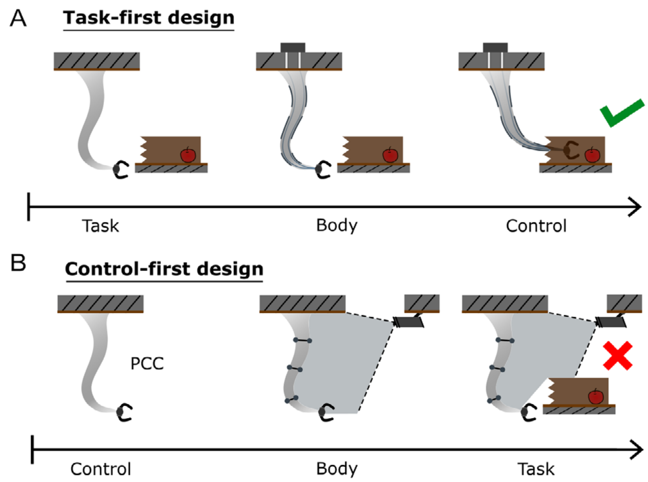

Figure 2. Control-first versus task-first design. The example here considers continuum soft robot arms because of their prevalence across application domains in the field. A) Illustration of a typical task-first design process. In all cases, the task is to grasp an apple resting inside of an opaque paper bag. Actuation and sensing strategies are designed to meet task requirements. The result is a task-capable robot. B) Illustration of a typical control-first design process. Independently of the task, the soft robot is designed for use with a piecewise-constant curvature (PCC) controller. Feedback for the controller is provided by exteroceptively with cameras, and the actuators are designed to meet the controller's requirements. The soft robot is not task-capable, as its sensing and maneuverability were not designed to meet task needs.

and functional needs that inform subsequent design choices. They also set bounds for the selection of appropriate materials and manufacturing methods capable of incorporating the necessary components for mediating exchanges of energy, information, and physical interactions. Finally, tasks assign clear success criteria for specifying machine behavior.

Once task requirements are identified, we suggest that everything downstream of the task ought to be flexible. This is to say that only the task itself may act as a filter on the space of possible designs, and no prior choice of controller or robot morphology should further restrict task-capability (see Figure 1B). This expands the space of viable designs—as illustrated by the relative sizes of red outlined regions in Figure 1—and clears the way for robots capable of exploiting emergent synergies between closely integrated physical and computational design elements. Hence, an agent's morphological makeup and its information-processing capabilities should be jointly designed to best accomplish the task.[55–60] It is important to note that for a given choice of task and body plan, one is not always guaranteed to find a valid controller. In this sense, a task-first approach presumes that designing an application-specific controller is typically more feasible than devising novel materials and fabrication methods to suit the morphological requirements of a given control strategy. We illustrate this fact in the sequence of Figure 2A and in the differently-sized arrows of Figure 1B, which indicate the relative challenge of having morphology influence control strategies and vice versa. Methods allowing robot bodies and controllers to be simultaneously co-designed with respect to a task present a promising path forward to resolving this issue.[61–63] However, as we discuss in Section 3, these remain early in their development with candidate solutions implemented in bespoke software packages.[64,65]

In this Perspective, we classify task requirements into two broad categories: material-based and information-based requirements. Requirements corresponding to explicit demands on the physical makeup of the agent, such as force or speed generation[66] or operational geometric constraints,[67] are material-based, while those based on their information-processing capabilities, such as proprioceptive shape estimation[68] or ability to compute model-predictive control,[69] are information-based. These distinctions are not meant as rigid boundaries but rather as useful guidelines for thinking about soft robot design problems. Importantly, control-first design approaches will likely limit a soft robot's ability to fulfill information-based task requirements. Without co-design,[62] task-first design starts from either material or information considerations and iterates toward solutions that satisfy each set of requirements. To this end, materials and fabrication processes should inform the development of suitable sensing and control, and computational processes should ideally inform the development of more capable robot morphologies (see Figure 1B and 2A). We explore the ways in which control-first design and task-first design affect the task-capabilities of resulting agents, highlighting the scale dependence of both approaches in the following sections.

2.1. Control-First Robot Morphologies

Control-first design has a substantial impact on robot task-capabilities because information-processing imposes stringent constraints on soft robot bodies. For soft robots to satisfy the assumptions of popular soft robotic control architectures, their morphologies often need to adhere to strict guidelines that may limit their usefulness (see Figure 1A and 2B). In large soft robots at sizes ranging from 1 cm to 1 m, current limitations in soft robotic materials and manufacturing methods typically prevent appropriate sensors and computing hardware to be integrated into soft bodies to meet control needs. This is also the case for most microscopic systems at length scales of 1 μm to 1 cm, where traditional integrated circuitry experiences scaling challenges.[44,70,71] Much less, building small-scale soft robots is difficult enough without having a control strategy impose design constraints on the robot's body and morphology. For these and many other reasons, satisfying the demands of particular control schemes is not an optimal way to start designing a soft robot. We provide examples of control-first robot design and explore its diverse consequences across scales below. At large scales, we choose to focus on soft devices based on continuum appendages, as these constitute what we consider to be the most canonical examples of control-first design. At small scales, we highlight recent examples from the microrobotics and active matter literature.

2.1.1. From 1 cm to 1 m: Soft Digits to Soft Walkers

Of the few control approaches derived with soft robots in mind, those based on PCC models are widely used for soft robotic digits and appendages. They are arguably the most emblematic of control-first design and its shortcomings as well, making for a particularly insightful class of systems to serve as a case study. Originally developed for continuum arms mimicking octopus tentacles and elephant trunks, PCC-based approaches model continuously deformable arms as collections of linked arcs of constant curvature and with homogeneous material properties.[72–74] These assumptions simplify an otherwise infinite-dimensional control problem into an analytically tractable finite-dimensional one by collapsing the hyperredundancy of continuum devices into a few degrees of freedom.[75] Nonetheless, these simplifications come at the cost of constraining the capabilities of soft robots to those admissible by the PCC formalism. The burden of these constraints on the resulting agent can be quite high when compared to an alternative task-first design—especially in light of the increased access to computation at these length scales (see **Figure 3**).

While PCC models have been successful in multiple application domains, they provide the implicit template of control-first soft robot design. According to this template, a practitioner would explicitly design a soft robot body to be controllable by a PCC-derived method and then attempt to solve a task. The functionality of PCC-compatible soft robots depends on the serial integration of multisegment deformable arms with actuation embedded within segments, whose deformations must satisfy the constant curvature hypothesis.[37,38] PCC-based control also requires an understanding of the locations, velocities, and accelerations of each segment's ends. Though recent work has used intertial measurement units (IMUs) to provide this information,[76,77] most controllers depend on exogenous sensors like motion capture to acquire it.[38,78] Thus, the PCC approach immediately places fabrication, materials selection, and sensing constraints on a robot that can be nontrivial to manufacture, functionalize with sensors, and use in situations where contact is required.[79–81] There are many examples of such soft robotic arms capable of 2D and 3D motion designed in a task-agnostic manner to satisfy PCC assumptions, as shown in Figure 3v (see also refs. [78,82,83]), thereby sacrificing task-capability in favor of a well-understood control strategy.[78,84]

Even when the assumptions of PCC-based methods are compatible with a given task, control architectures designed around PCC are not necessarily optimal.[85,86] PCC-based control can be adapted to account for a soft robot's interactions with the environment (e.g., being loaded when picking up or interacting with an external object, or during walking as shown in Figure 3vii).[87] But, the modified controllers are only valid for contrived conditions and narrow regimes of deviation from free, unloaded motion. For example, in the study of Onal and Rus,[88] the authors designed a limbless soft robot for a bioinspired crawling locomotion task using a PCC model. However, limbless animals in nature (e.g., snakes and worms) often bend and buckle in ways that are incompatible with the constant curvature hypothesis—explicitly making use of these movements in ways that are known to provide an advantage during locomotion.[89] If the task under consideration is snake-like locomotion, there exists a broad literature analyzing and controlling such systems from which to draw inspiration, without prespecifying the ways in which the robot is allowed to move and interact with its environment.[90–92]

Similar control-first designs based on other control architectures exist as well.[42,93] In particular, Cosserat rod theory is a popular alternative to PCC control strategies.[94–97] Rather than working with the PCC assumption, these methods typically make

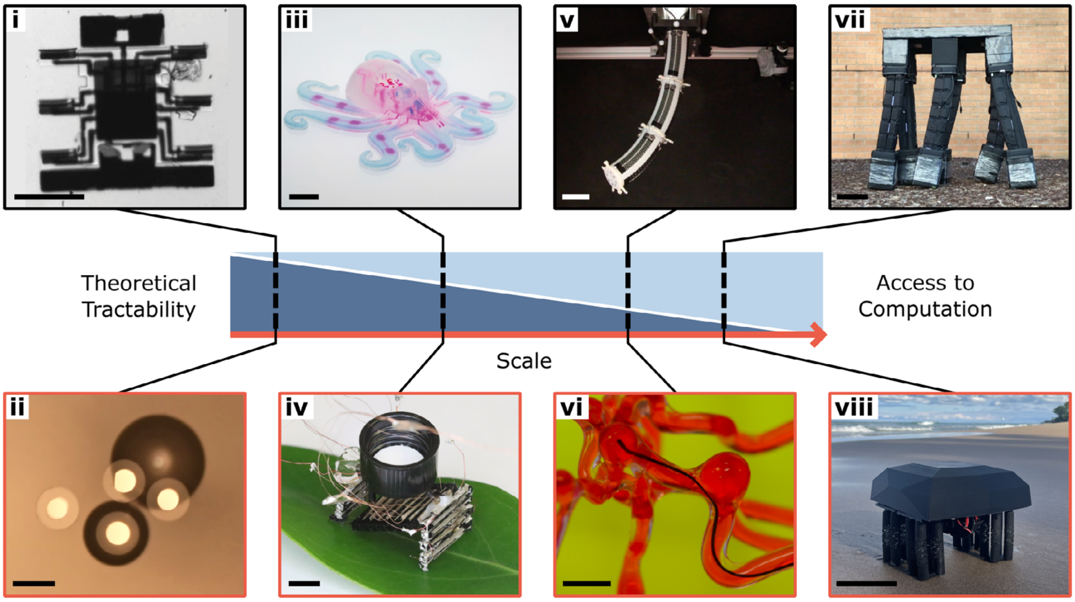

Figure 3. Soft robotic systems of varying degrees of theoretical tractability and access to computation across scales. Odd numbered systems were designed via a control-first approach, and even-numbered systems were according to a task-first approach. The systems are: i) Locomoting microrobot, scale-bar 100 μm (Reproduced with permission.[110] Copyright 2022, AAAS); ii) Colloidal microrobotic generators,[142] scale-bar 250 μm (Photo provided by T. A. Berrueta, Northwestern University); iii) Entirely soft octobot,[115] scale-bar 10 mm (Photo provided by L. K. Sanders, Harvard University); iv) Untethered metamaterial robot,[155] scale-bar 4 mm (Photo provided by X. Zheng, University of California, Berkeley); v) Proprioceptive PCC soft arm,[79] scale-bar 5 cm (Photo provided by R. L. Truby, Northwestern University); vi) Soft ferromagnetic catheter, scale-bar 1 cm (Reproduced with permission.[122] Copyright 2022, AAAS); vii) Meter-scale PCC walker,[187] scale-bar 15 cm (Photo provided by S. Li, Massachusetts Institute of Technology, Tsinghua University); viii) Motorized, untethered, soft auxetic walker,[126] scale-bar 10 cm (Photo provided by R. L. Truby, Northwestern University).

a piecewise constant strain assumption that can similarly constrain the space of soft robot designs.[98] For example, in the study of Boyer et al.,[94] the authors designed an eel-like swimming robot for a Cosserat-based control architecture. However, once again, the constant or piecewise-constant strain hypothesis does not match the behavior of eels in nature, whose dynamic control over internal strains is precisely what enables their deft maneuverability.[99,100]

Overall, each of the examples we have highlighted above illustrates how imposing controller-specific constraints on the soft robot prior to the specification of a task collapses the space of admissible soft robot designs, limiting the task-capability of the final agent. Each example also shows a general trend for macroscopic systems: as soft robot bodies become increasingly complex, the theoretical tractability of their control and design diminishes. This can make a first-principles understanding of their dynamics and interactions with the environment prohibitively challenging. This observation alone highlights why control-first design in soft robotics is both extremely difficult and restrictive of soft robots' task-capabilities. As we discuss more below, macroscopic soft robots should consider embracing modern computational tools that are available at these scales, such as data-driven control,[101] to become truly autonomous.

2.1.2. From 1 cm to 1 μm: Microrobots to Active Matter

Surprisingly, designing microscopic soft robots and active matter with respect to their information requirements is not as limiting as it is for their macroscopic counterparts. The task-capability of soft robots tend to become increasingly limited and access to computation becomes more restricted as we build soft robots at smaller scales. Thus, as illustrated in Figure 3, the performance gap between agents designed around computational elements and those designed around tasks is not as wide as it is for larger soft robots. The increased tractability of theoretical control methods with decreasing scale is another factor shrinking this performance gap. For microscopic devices, analytical characterization of the relationship between environmental stimuli, material properties, and their resulting behavior is often more feasible than for larger soft robots.[102–106] Given such an analytical understanding, the space of soft robot designs can be navigated in terms of intuitive parametrizations based on system phenomenology, resulting in more capable designs, regardless of control approach.

Of the many fields benefiting from increased theoretical tractability at small scales, the field of microrobotics has recently experienced several impactful advances.[44,107–109] In the study of Reynolds et al.,[110] the authors reported the design of an integrated circuit for on-board digital control, as well as a novel process for integrating their devices with microactuators, which were previously developed.[108] To illustrate their results, the authors constructed the first electronically-integrated microrobots on the scale of paramecia capable of untethered actuator-driven locomotion via on-board control (see Figure 3i). By design, much of the microrobot's form and function is directly determined by its control considerations. First, fabrication methods and materials were selected to be compatible with traditional silicon-based control circuitry that has been modified to satisfy the footprint and power needs of the microrobot. Then, taking into account the energy limitations of the control circuitry, surface electrochemical actuators (SEAs) were designed to bend through a single-species adsorption mechanism when a voltage is applied. Finally, the control circuitry was programmed to produce low-frequency electrical oscillations to drive the actuators and produce a locomoting gait. As we can see, many elements of the microrobot were designed by following the template of control-first design. However, underlying this advance is a tightly integrated theory that explains the relationship between SEA material properties (e.g., thickness, free energy of adsorption, etc.), the control circuit's capabilities (i.e., max output voltage), and the resulting behavior of the SEAs (i.e., radius of curvature), as captured by the first equation of Miskin et al.'s paper.[108] Theoretical developments of this kind enable roboticists to navigate design spaces with relative ease, suffering little drawbacks from taking a control-first approach (see Figure 3i). However, as we will see in Section 2.2.2, there are still some downsides to this approach in general.

When we consider microsystems on the scale of active matter particles, the dividing line between what constitutes control and material blurs beyond recognition, but the role of theory continues to be central toward realizing any nontrivial functionality. Active matter systems are typically comprised of particles whose dynamics are either self-phoretic or externally driven by fields and forces, such as thermal gradients or electromagnetic fields, leading to diverse self-organized behaviors that may be harnessed toward tasks.[111] While in some applications the external forcing fields themselves act as a source of coarse-grained control, in many settings this is not the case. In such field-free systems, what one considers as control is often the material properties of the particles themselves and the ways in which these shape their behaviors. For example, in the study of Brooks et al.,[112] the authors provided a theoretical framework from which to "program" the behavior of active colloidal particles through the design of their 3D shape. In this case, each particle's morphology very literally is determined by the choice of control strategy. However, because of the scale-dependent impact of control-first design, as well as the theory's elucidation of the tight coupling between control, morphology, and resulting behavior, the authors have been able to design and manipulate the dynamics of experimental active matter systems with this approach.[113,114]

As we step back and consider larger scales, control-first design begins to produce diminishing returns once again. At mesoscopic scales, soft robot design can be very challenging because systems may be simultaneously too large and complex for analytical characterization, and too small and power-constrained to have access to sophisticated computation. For these reasons, designing mesoscopic soft agents around their information-processing constraints can negatively impact their task-capability. For example, in the study of Wehner et al.,[115] the authors developed an entirely soft untethered octopus-like robot capable of cyclically actuating its tentacles (see Figure 3iii). By using a soft microfluidic control architecture without a task that demands it, the downstream capabilities of the agent suffer as a result. The microfluidic oscillator responsible for controlling the actuation of the agent's tentacles is limited by the fuel's flow rate, and this limits the amount of energy that can be transduced into mechanical actuation. Though the soft robot produced 0.04 N of force per actuator, this was insufficient for locomotion or performing other tasks. Despite exploring 30 different robot designs, the lack of theoretical tractability or automated design tools prevented the authors from finding designs with greater performance for a practical task.

As we have illustrated throughout the last sections, control-first design can have severe consequences on the capabilities of soft robots. Moreover, we have shown that this impact is strongly scale-dependent and mediated by the interplay of two primary forces influencing the design process: the tractability of theoretical analysis and ease of access to computation. Since theoretical tractability and access to computation are themselves highly scale-dependent properties (see Figure 3), their interplay characterizes the degree of design difficulty—having the most severe impact at mesoscopic scales where neither theory nor computation is widely available.

2.2. Task-First Robot Morphologies

A task-first approach encourages solutions to soft robot design that integrate morphological and computational design elements by prioritizing the development of task-capabilities by any means necessary (see Figure 2A). By starting with actuator selection, a soft robot's task-capability can be more easily ensured up front. For example, if a task requires displacing an object a given distance, then an actuator can be selected early on that generates the necessary forces to do so.[116] Subsequently, sensing and control elements should be integrated without sacrificing task-capability. As we consider smaller and smaller scales, the availability of actuation mechanisms diminishes, and their compatible environmental chemistries narrow.[107,117–121] Moreover, choosing an actuator can have a large impact on downstream design decisions by determining compatible energy sources and fabrication strategies.[15,60] These will further dictate the material components that can be added to the soft robot for distributed perception and integrated control. To this end, we believe task-first soft robot design most naturally prioritizes the selection of materials, actuators, and fabrication strategies needed to achieve material-based task requirements and body morphology at appropriate length scales. This then enables information-based requirements to be subsequently met, as illustrated in Figure 2. We highlight several soft robots below as examples of systems that follow a task-first design process. Each possesses a body with tightly integrated sensing and control capabilities.

2.2.1. From 1 cm to 1 m: Soft Digits to Soft Walkers

Throughout much of Section 2.1.1, we highlighted examples of soft robots whose morphologies were forced to meet the constraints of control architectures like those based on PCC or Cosserat rod models. Rather than taking a control-first approach, we can allow the task requirements themselves to define the role of perception and control in a robot's design. As we show through the examples below, a task-first design approach opens opportunities to push both material and information-processing advances without introducing ad-hoc restrictions that only limit an agent's task-capability.

The most fundamental opportunity that task-first design opens up is allowing roboticists to freely explore material properties and robot morphologies prior to committing themselves to a controller and its demands. For example, in the study of Kim et al.,[122] the authors design a soft ferromagnetic microcatheter to assist with minimally invasive endovascular surgeries (see Figure 3vi). Providing robotic assistance during neurosurgery is no trivial task: it demands dexterous maneuverability in geometrically constrained and safety-critical environments where the ability to make sharp turns is essential to navigation performance. The researchers used theoretical models and genetic algorithms to maximize their design's maneuverability—a task requirement—by altering its material properties.[123] While the material requirements of a surgical robotic microcatheter are stringent, its information requirements are more relaxed because in stationary systems of this scale, perception, and control can often be entirely off-boarded onto external hardware. By designing their control systems in service of the material requirements of the task, the researchers were able to accelerate real-world neurosurgical procedures by over 30% on average.[67] With the introduction of sophisticated machine learning-based and image-guided planning and control, these technologies have the potential for completely autonomous surgical operation, where soft robotic catheters safely and gently move within the body in a way that is currently intractable with model-based control.[124]

Untethered operation remains a central challenge in soft robotics. Whether a soft robot can operate without tethers depends sensitively on its on-board energy storage capacity, the force output of its actuators, and the energy efficiency of its actuators and control elements. While new forms of energy storage require fundamental progress in battery systems,[125] task-first design can facilitate the development of energy-efficient soft robots. In the study of Kaarthik et al., [126] the authors introduce a soft robotic quadruped for an untethered locomotion task (see Figure 3viii). Untethered locomotion requires actuators that are simultaneously strong enough to bear loads and efficient enough to handle extended operations. To this end, the authors architected their robot's soft legs out of assemblies of handed shearing auxetics (HSAs), which are capable of high-force output.[127,128] Taking advantage of their robot's load-bearing capacity (up to 1.5 kg), the authors motorized their HSA legs using off-the-shelf servomotors and coordinated their gaits using a battery-powered microcontroller.[126] Conventional servomotors are remarkably robust and energy efficient despite their rigidity, which facilitates untethered operation of the authors' soft robot for over 65 min. Rather than opting for an entirely-soft control solution, the authors took advantage of the freedom afforded to them by their task's requirements and integrated traditional motor control elements into their soft robot design. The use of on-board computation offers great opportunities for soft robot autonomy when the task permits it. Modern control paradigms like active learning[129–134] can be deployed on microcontroller hardware to provide morphology-aware adaptation to a robot's sensing and control strategies. We believe that such integration of physical and computational intelligence aboard soft robotic hardware is essential to realizing truly bioinspired autonomy.

Despite the importance of material and actuator selection in task-first design, information-processing elements can still play a pivotal role. In fact, certain classes of soft robotic systems may require sophisticated control to achieve any task-capability at all. However, such control architectures must be able to adapt to and be informed by the agent's morphology to avoid design restrictions. In macroscopic systems, adaptation of this kind largely comes through the integration of machine learning.[22] Large soft robots are capable of housing nontrivial computational elements that enable system identification,[135,136] sensor characterization,[130,137] and adaptive control[96,129] (see Figure 3). For example, in the study of Bruder et al.,[69] the authors made use of data-driven Koopman operators to identify the dynamics of a continuum manipulator and provide morphology-independent adaptive control.[138,139] Additionally, Han et al.[140] used recurrent neural networks to extract pressure information from soft microfluidic sensor arrays that are otherwise hard to interpret due to their nonlinearity and hysteresis. Despite much interest in machine learning methods, the field is yet to widely implement them in the task-first fashion that we suggest.

2.2.2. From 1 cm to 1 μm: Microrobots to Active Matter

We highlighted above the role that analytical characterization of small-scale soft robots can have on their design. Theoretical models can greatly reduce the drawbacks of control-first design at microscopic scales by facilitating the exploration of design spaces through intuitive phenomenological parameters. Still, there is room for improvement in small-scale soft robot performance through task-first design.

As a first example, we consider the task of cyclically actuating microrobotic arms—a precursor to the more complex task of producing locomoting gaits. This task's primary requirement is the production of low-frequency electrical oscillations needed to drive arm movements, which are surprisingly challenging to engineer in microrobotic systems.[141] In fact, the production of low-frequency electrical oscillations is the central control function that the circuitry of the microrobot in the study of Reynolds et al.[110] achieves, as discussed in Section 2.1.2. However, to produce these oscillations they required sophisticated microfabrication strategies and circuits comprised of over one thousand transistors. In contrast, Yang and Berrueta et al.[142] achieve this same feat without the need for complex integrated electronics or elaborate mechanical assemblies by exploiting the self-organized dynamics of a simple collective of colloidal microparticles (see Figure 3ii). Here, the authors satisfy the task's requirements by first modifying their system's material properties to reliably generate mechanical oscillations. Then, through the use of an electrochemical fuel cell they can transduce the system's mechanical oscillations into oscillating currents that power the same SEA-based microrobot arms as in the study of Reynolds et al.[110] To determine the necessary parameters to achieve self-organized low-frequency oscillations, the authors derived an analytical model of their system based on the statistical mechanics of active collectives.[143–145] In this way, the authors explore the design space and devise a task-first control solution that is entirely emergent from the morphological properties of the system.[146] Hence, while the theoretical tractability of microsystems can reduce the impact of control-first design, a task-first approach can still lead to simpler solutions.

At scales smaller than those of microrobots, system capabilities tend to be so limited that task-first design does not necessarily produce improved outcomes. However, as progress in dynamical self-assembly[147,148] and dissipative adaptation[145,149,150] continues to evolve, active particle systems may be able to exhibit emergent task-capabilities collectively. Thus, while we do not expect noticeable differences at the level of individual particles and simple systems, sufficiently complex supramolecular assemblies may eventually benefit from task-first design. These assemblies often exhibit exotic emergent behaviors with potential for task-capability, as in the self-organized movement of so-called living crystals.[151] For example, Martinet et al.[152] designed active colloidal metamachines capable of exploiting their self-organized dynamics toward work production. Leveraging theory and experiments from previous studies,[153,154] the authors assembled collections of particles into gears and cogwheels with controllable direction and angular momentum. By focusing on a cargo transport task, the authors design a colloidal metamachine based on these cogwheels that can pick up, direct, and release a passive chemical load. As active matter systems and their properties become increasingly complex, we posit that task-first approaches may play a role in achieving more sophisticated behaviors, such as those illustrated in our examples.

Rational principles that can guide designs toward satisfying material requirements are crucial to overcoming the challenges associated with the mesoscale. Intuitive theoretical models, efficient numerical simulations, and versatile fabrication strategies all provide effective ways to navigate system design parameters in a task-first manner. Cui et al.[155] made use of all three approaches to design a metamaterial-based milli-robot capable of sophisticated sensing and control (see Figure 3iv). Unlike conventional materials, metamaterials are architected from complex building blocks that are often each capable of deforming, rotating, buckling, and more.[156] These can be designed to exhibit programmable properties[157] or even robotic functionalities through the integration of actuation elements.[158] Along these lines, Cui et al.[155] introduced a class of sensorized, piezoelectric robotic metamaterials capable of controllable multi-degree of freedom actuation. They develop a theoretical framework that generalizes piezoelectric strain tensors to architected metamaterials, as well as provide finite element modeling techniques and new multimaterial additive fabrication strategies to facilitate the design of task-capable soft systems based on their material platform. In validating their approach, they developed an untethered mesoscale soft robot that is capable of autonomously steering and obstacle avoidance. In accordance with task-first design, they used their theory to determine the strain modes needed to enable directed planar movements using architected piezoelectrics. Then, they designed and fabricated a self-sensing piezoelectric lattice capable of generating those modes of actuation through its metamaterial properties. Finally, by exploiting the system's strain tensor-based sensing and actuation, they implemented a simple algorithm aboard a microcontroller that enables sophisticated autonomous functionalities. This work exemplifies the potential that can be realized when tasks drive the design process toward systems that tightly integrate morphological and computational components.

Task-first design, as illustrated by our examples, provides opportunities for roboticists to exploit the integration of physical and computational intelligence. Taking advantage of computation and theory when they are respectively available (see Figure 3) can lead to the design of soft robots capable of overcoming subsystem limitations through the emergence of synergies between body dynamics and control architectures. For this reason, it is crucial to continue developing computational tools and facile fabrication techniques that can facilitate the exploration of design spaces in the absence of theory, as we discuss in the following section.

3. Navigating the Design Spaces of Soft Robotics

Ideally, soft robot design would be the result of an automated process where a task is specified, its material and information requirements are distilled, and a candidate design is produced. Some version of this vision is already emerging for traditional robots. For example, model-predictive control and graph heuristic optimization methods have successfully co-designed robot control architectures and body morphologies.[159] Robot rigidity allows controller and body design to be decoupled and optimized. But for soft robots, the tight coupling of actuation, sensing, morphology, and control hampers any straightforward application of similar techniques. Overcoming this hurdle will require progress across a broad range of distinct research areas, from optimization-based co-design to multimaterial 3D printing. In the following subsections, we highlight computational and material research domains that are positioned to play an important role in facilitating the task-first design of soft autonomous agents across scales.

3.1. Design Automation Tools

Throughout Section 2, we highlighted the ways in which theoretical models can facilitate the design of autonomous soft robots. By easing the navigation of soft robot design spaces, new theories allow roboticists to discover better-performing designs through the modulation of physically relevant system parameters. However, as Figure 3 highlights, the theoretical tractability of soft robots is strongly scale-dependent. Without guidance from theory, how exactly can one determine the best way to integrate material components to achieve a specific task? This is precisely where automated design tools and methodologies stand to have an impact.[160] Soft roboticists typically build soft robots by hand through a prototype-driven, trial-and-error process that is both time-consuming and inefficient.[26] However, the space of soft robot designs is prohibitively large. It spans combinatorially many agent morphologies, each potentially involving different materials with distinct functional properties and particular information-processing affordances depending on the fabrication method(s) used. Exhaustive design is intractable at most scales. Hence, tools to intelligently and efficiently navigate this space and facilitate rational design are crucial to the future of soft robotics (see **Figure 4**).[161]

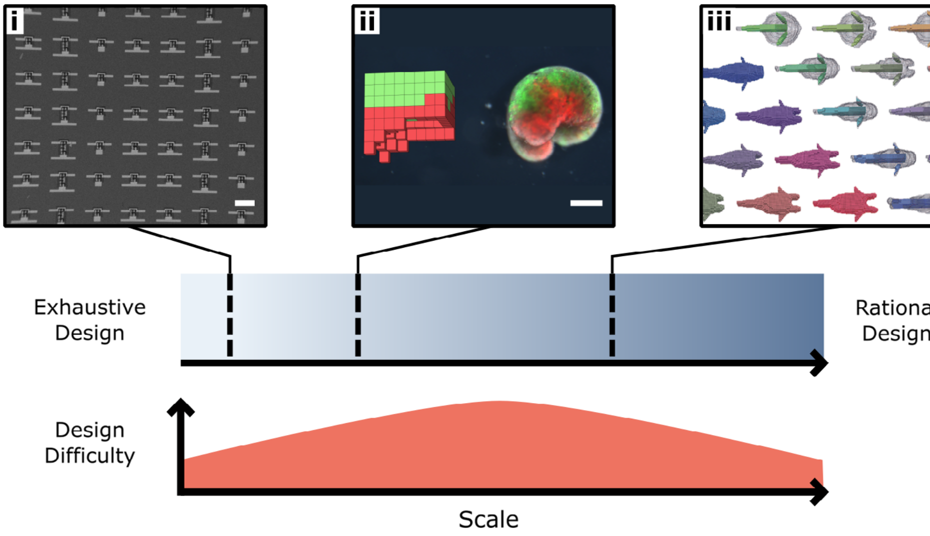

Figure 4. Available design approaches and difficulty of designing for task requirements across scales. At microscopic scales, access to massively parallelized fabrication strategies can make exhaustive trial-and-error design approaches fruitful. At larger scales, the fidelity of model-based design optimizations can enable rational design approaches. Mesoscopic scales face the greatest challenges because neither exhaustive nor rational approaches provide an obvious solution to design challenges. The example systems shown are: i) Lithography-enabled microrobots, scale-bar 100 μm (Reproduced with permission.[108] Copyright 2020, Springer Nature); ii) Xenobot designed by evolutionary algorithm, scale-bar 500 μm (Reproduced with permission.[194] Copyright 2020, National Academy of Sciences); iii) Aquatic soft robots co-designed via differentiable simulation (Reproduced with permission.[187] Copyright 2021, Association for Computing Machinery).

3.1.1. Optimization-Based Co-Design

Autonomous design of soft robots requires methods capable of exploring and optimizing robot morphologies, sensing, and control strategies simultaneously. In this sense, co-design methods will be central to the future of soft robot design. Formal co-design problems are typically framed as optimizations subject to interdependent constraints. As a simple example, consider optimizing the performance of an actuator that is tasked with bearing a given load, and whose power demands require a battery of a given output. Since the battery weighs down the actuator and its size determines the power output, the system's load-bearing and power constraints are coupled. Co-design techniques have been developed to handle problems such as these, which are ubiquitous in soft robotics, yet standard optimization methods are not suited to solve. While much work toward a mathematical theory of co-design has emerged over the past decade,[61–63,162,163] its application in robotics has met some challenges. Namely, its been proven that there exist no computationally efficient algorithms to optimize robot designs subject to task considerations,[164,165] which limits the applicability of any naive implementation of these methods. That being said, recent work has focused on developing techniques to circumvent the practical limitations of co-design, as we discuss in this section.

In the absence of formal co-design solutions, assistive tools and heuristic approaches should nonetheless be developed to help partially close the loop or at least provide feedback on the design process. Importantly, we note that some solutions will be better suited for the challenges of certain scales than others, as shown in Figure 4 and discussed in Section 2.1.2. At the smallest scales, fabrication processes can often be parallelized to achieve massive throughput efficiently, which can lessen the drawbacks of trial-and-error design approaches.[108,166] In such settings, exhaustive design can be used effectively to explore candidate robot designs (see Figure 4i). In contrast, rational design tools may be necessary in larger devices to capture the complex multiscale physics at play through model-based design optimizations (see Figure 4iii). More broadly, as we consider the many scale-dependent factors that affect task-first soft robot design—diversity of available materials, abundance of fabrication methods, theoretical tractability, simulation fidelity, and access to computation—we find that mesoscopic length-scales pose the greatest challenges (see Figure 4). At these scales, systems can exhibit phenomena that are simultaneously too complex for mechanistic first-principles study, and too detail-dependent for coarse-grained or continuum models to reproduce, which makes both theoretical and computational characterization challenging.[167]

3.1.2. Machine Learning-Assisted Co-Design

Despite its formal properties, researchers have managed to circumvent the practical limitations of co-design by taking advantage of approximate solutions, simplifying assumptions, and heuristics. One area that has been particularly fruitful is the use of machine learning for approximating otherwise intractable co-design and combinatorial optimization problems.[168] For example, researchers have been able to automate the design of silicon chip floorplans through the use of reinforcement learning, where the algorithm can search for approximately optimal designs with the help of neural representations of the chip's elements and functionalities.[169] Reinforcement learning as an approach is broadly amenable to task-first design because it is explicitly concerned with how agents can learn to solve tasks through modifications to their behavior or system parameters.[170] However, its stringent data requirements can pose issues in settings where high-fidelity system simulations are not available, as is the case in many robotics applications.[171] Beyond reinforcement learning, soft roboticists have made use of other machine learning techniques to solve design problems, using neural representations of task requirements to find approximate solutions to body and control co-design problems.[64,172–174] Spielberg et al.[172] used machine learning to find approximate solutions to several sensor placement and control co-design tasks with simulated soft robots. Their algorithm optimizes soft robot morphologies with respect to a given task by learning sensor locations and control policies that are useful toward completing the task. By similarly taking advantage of machine learning-based co-design, we posit that researchers will make substantial progress toward task-first co-design of soft robots.

3.1.3. Evolutionary Co-Design

Another field with a long history of contributing to applied co-design methodology is embodied intelligence and artificial life.[175–177] Rather than use neuroscience-inspired methods like neural networks, the artificial life community has favored machine learning techniques inspired by biological evolution and heredity, making use of evolutionary algorithms as well as differentiable simulations to tackle co-design problems. Much like our own proposal, the artificial life community seeks to design autonomous agents whose material and cognitive make-up are well-adapted to their environmental niche.[178–180] However, our task-first design proposal differs in aim and scope from merely realizing embodied intelligence. Whereas artificial life researchers are interested in a design's evolution and environmental adaptation as an object of study in itself,[181–183] here we see it as a means to an end—that is, the completion of a given task. Nonetheless, the methods developed by the embodied intelligence and artificial life communities are well-suited to task-first soft robot design, presenting opportunities for researchers at the interface of these fields.

One such method is differentiable simulation, which makes use of simplifying assumptions to enable computationally efficient optimization-based co-design. Differentiable simulations model parametric dependencies between the behavior of material substrates and their physical properties as differentiable functions, which substantially simplifies the underlying optimization problem.[57] As a result, complex co-design problems can be efficiently tackled purely through gradient descent on the simulation's parameters. However, because many physical phenomena and design elements introduce nonsmoothness, the fidelity of solutions generated by differentiable simulations can vary. Nonetheless, many such approaches have been successful, designing robot morphologies, sensors, controllers, and actuators jointly.[184–186] For example, Ma et al.,[187] used differentiable functions to encode and simulate a robot's shape, which they jointly optimized along with a neural network controller via gradient descent to enable efficient co-design of underwater soft robots (see Figure 4iii).

When nonsmooth elements are of crucial importance to soft robot design, evolutionary algorithms offer a gradient-free alternative.[55,58,188,189] These do not depend on design parameter gradients, relying instead on fitness heuristics to guide an evolutionary search process (see Figure 4ii). Evolutionary algorithms work by evaluating the fitness of an initial pool of candidate designs, the most fit of which are used as a starting point for subsequent generations of candidate designs. Although these methods are computationally expensive, they have been shown to work in many complex co-design problems, resulting in soft agents that can operate in real-world environments across scales.[190–193] In recent work, Kriegman et al.[194] made use of evolutionary algorithms to design soft robot morphologies in simulation for a locomotion task. These simulated soft robots were then realized in vivo by assembling frog stem cells into configurations that match their in silico designs—thereby creating synthetic, task-capable, living organisms co-designed by an evolutionary algorithm. While much progress remains to be made in soft robot design automation, practical co-design techniques like the ones highlighted will play an important role.

3.2. Materials and Fabrication Methods

In the previous section, we discussed the ways that automated design tools can facilitate task-first design, playing a similar role to that of theoretical models in easing navigation of soft robot design spaces. If novel theories and automated design technologies ease the process of navigating a design space, then fabrication and material innovations extend its boundaries (i.e., they expand the set of possible bodies illustrated in Figure 1), giving practitioners more flexibility in how they choose to maneuver in this space. Of the countless ways in which progress in materials and fabrication technologies can impact soft robot design, here, we highlight a few areas with particular near-term potential. We choose to focus on areas positioned to improve integration of information-processing within soft robots.

3.2.1. Additive and Digital Manufacturing

While sophisticated software can propose myriad intricate designs, soft roboticists are fundamentally constrained by what they can actually manufacture. Hence, materials and fabrication innovations straightforwardly enrich a soft roboticist's design palette. Of these tools, 3D printing's ease of rapid prototyping is well-suited to task-first design.[13,14,195] Additionally, simultaneous fabrication of robot bodies, control elements, and embedded sensors is increasingly possible thanks to advances in multimaterial 3D printing.[196–202] Heterogeneous integration of soft materials with programmable mechanical, electrical, or optical properties is a key step toward improving information-processing in soft robots. As a result, advances in areas such as multimaterial direct ink writing,[203] embedded 3D printing,[204] and digital projection lithography[205] will be instrumental. Improvements to printable materials, printhead design, accessible length scales of fabrication, programmability of material properties, and more will facilitate task-first soft robot design.[196–202]

3.2.2. Soft Sensorization

Advances in soft robot sensorization will also be key to overcoming the information-processing bottlenecks holding back soft robot autonomy. However, the integration and distribution of sensors in soft robots remains underexplored due to challenges in fabrication, signal interpretability, as well as morphology-dependent sensor performance.[79,140,206–209] Progress in this area also depends on advances in multimaterial fabrication methods like those discussed in the previous section.[51,55,195,197,210] For example, Truby et al.[211] used embedded 3D printing to make somatosensitive actuators with distributed tactile proprioception out of elastomer-ionogel composites. Multimaterial printing and patterning with ionic inks such as these is a promising avenue for soft sensorization because it allows sensors to interface with devices such as microcontrollers that can enable sophisticated state estimation and feedback control.[212] Electronically integrated sensing is important because soft sensor signals can be highly complex and hard to interpret. As discussed in Section 2.2.1, machine learning techniques such as recurrent neural networks can be used to learn input-output maps to make complex sensor array signals more interpretable.[140] However, this is as of yet only possible aboard a robot when sensory information can be extracted and analyzed electronically. In addition to black box machine learning techniques, progress in computational and theoretical multiphysics modeling would help improve soft sensor characterization.[213–215] Thus, we see soft sensing as a crucial component of task-first soft autonomy, and believe that there are diverse opportunities in fabrication, electronic integration, and modeling to advance the field in the near-term.

3.2.3. Electronically-Addressable Actuation

Despite recent progress in electronics-free soft robot designs,[115,216–219] the capabilities of nonelectronic, soft robotic controllers will remain outpaced by those of electronic computing architectures. Hence, by working instead with electronically-addressable components, the computational advantages and advanced techniques developed for traditional electronics can be readily exploited within soft robots. Thus, electrically driven soft actuators are needed to integrate with electronic information-processing elements within soft robots without sacrificing task-capability.[21,79,220] There are three primary modes of electrical actuation: thermomechanical, electrostatic, and electrochemical.[221] In each of these modes, the role of the electric current or voltage as input is to elicit a mechanical response from the material. Already, electrically controllable actuators are being designed for soft robots[221] and related systems such as shape-morphing robotic surfaces.[222–224] For example, in thermomechanical actuators like liquid crystal elastomers (LCEs),[225–227] passing currents produce shape changes in conductive materials via Joule heating. Joule-heated LCEs have been integrated into load-bearing, shape-morphing surfaces[222] and with multifunctional liquid metal heaters for closed-loop actuation of artificial muscle fibers.[226] Extending the available suite of efficient, electronic actuation mechanisms, the materials these are compatible with, and the sophistication of their resulting behaviors is an important research thrust in support of soft robot autonomy. Through the lens of task-first design, we see the effect of both electronically-addressable sensing and actuation innovations as increasing the overlap between the space of possible bodies and the space of available control strategies (see Figure 1). Thus, we believe that these areas will be of particular importance toward seamlessly incorporating physical and computational intelligence in soft material substrates.

4. Outlook

The introduction of soft matter as a set of building materials for robot bodies has irreversibly changed the field of robotics by bringing physical intelligence to machines. However, even as the field of soft robotics has grown, autonomy in soft robots is still out of reach. The methods the field has introduced for building physically intelligent robots remain limited in their ability to distribute and integrate information-processing elements like sensors and controllers within these new robots. As a result, the field now faces information-processing bottlenecks that fundamentally limit the usefulness of the robots it produces. Thus, the challenge of coupling perception, learning, and control with physically intelligent systems remains as much a robotics challenge as a materials one.

Here, we have encouraged the field to achieve soft robot autonomy by first focusing on task-capability before considering controller designs. We have argued that the field's current control-first focus severely limits the potential of resulting soft robots. Much of the problem is rooted in the fact that, unlike traditional systems, there exists no systems science for soft matter systems—there are neither tests for well-posedness, nor automated synthesis, nor universal guidelines for design. Due to the complexity of soft matter engineering, this should not come as a surprise. As we have highlighted in the previous section, progress in several areas is needed before off-the-shelf rational design of soft robots and robotic materials becomes practical. A soft matter systems science will not look like the control-first systems science of the past century. A task-first systems science will provide analysis and synthesis tools for soft robots as a function of task specifications—with the seamless integration of physical and computational intelligence as a primary goal—providing a path forward for engineering the complex systems of the future.[228]

In this Perspective, we identify guiding principles that can help engineers materialize autonomy in soft robots across all scales. We reference examples of recent works to support our positions and suggest that a task-first approach to soft robot design may yield yet undiscovered affordances and capabilities in soft robots. These affordances will play an important role as automated soft robot design tools continue to mature. These design tools will then facilitate navigating the expansive space of soft robot designs, and form the basis for the kind of truly bioinspired autonomy that motivated the development of soft material systems in the first place.

Acknowledgements

This research was supported by the Air Force Office of Scientific Research (AFOSR, grant no. FA9550-22-1-0218, R.L.T.), the Office of Naval Research (ONR, grant no. N00014-22-1-2447, R.L.T.), and a US Army Research Office grant W911NF-22-1-0286 (T.A.B. and T.D.M.). T.A.B. is supported by the Northwestern University Presidential Fellowship.

Conflict of Interest

The authors declare no conflict of interest.

Keywords

autonomous robots, microrobotics, robotic materials, soft robotics, task-first design

Received: February 28, 2023
Revised: July 11, 2023
Published online: August 28, 2023

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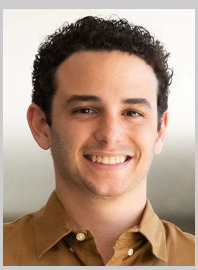

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