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Perspectives on Intelligence in Soft Robotics

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Engineers frequently aim to streamline environmental factors to facilitate the effective operation of robots. However, in nature, environmental considerations play a crucial role in shaping the embodiment of organisms. To comply robots with the complexity of real-world environments, embedding similar intelligence is key. In the field of soft robotics, various approaches offer insight into how intelligence can be integrated into artificial agents. A discussed topic is the intricate relationship between the brain and the body at the core of intelligence in robots. The goal of this article is, therefore, to unravel the strategies to implement different types of intelligence currently adopted in soft robots. A classification is made by making a distinction between agents that adapt to their environment by 1) their adaptive shape, 2) their adaptive functionality, and 3) their adaptive mechanics. Additionally, the perspectives on intelligence based on their computational approach are distinguished: centralized computation, decentralized computation, or embedded computation. It is concluded that a tailored robotic design approach attuned to specific environmental demands is needed. To unlock the full potential of soft robots, a fresh perspective on embodied intelligence is described, so-called mechanical intelligence, emphasizing the robot's responsiveness to changing external conditions of a real-world environment.

1. Introduction

The remarkable adaptability and versatility found in various organisms in nature have long captivated the scientific community. Examples include the hyper-redundant arms of cephalopods enabling multimodal locomotion, the soft bodies of snakes that allow for navigating through tight spaces, and the design of the human hand that allows for precise grasping capabilities. The properties of these natural systems, combining soft and rigid materials, enable them to respond effectively to environmental changes solely through physical interactions.

In contrast, conventional man-made robots typically display limited adaptability due to their rigid design and construction from materials like stainless steel, aluminum, or titanium, with Young's moduli in the order of 10^9–10^{12} Pascal.[1,2] As a result, conventional rigid robots are generally suitable to perform predefined tasks in controlled and known environments and are generally optimized to perform repetitive tasks. To design robots that are able to perform well in a real-world environment, which is unknown and highly dynamic, the classic approach of robot design should be adapted.

In recent years, a new class of robots started to emerge that incorporate soft materials similar to what is found in nature.[3] Soft robots are typically made of hyperelastic materials, such as silicone rubbers, with Young's moduli in the range of 10^4–10^9 Pascal.[2] Soft robots typically inherent the ability to execute tasks in unknown, dynamic, and unpredictable environments. Just like organisms in nature, they exploit their material properties and shape to passively interact with the environment.[2,4] Researchers have also made significant progress in developing soft robots that possess the unique ability to heal their body structure, akin to the self-recovery mechanisms observed in natural organisms.[5,6] This makes soft robots suitable for a wide range of applications, from infrastructure inspection to space applications and deep-sea exploration (**Figure 1**).[3,7] Moreover, the material properties of soft robots considerably reduce the risk of harm made during impact,[2] which makes them especially suitable for human–machine interaction or interaction with delicate objects, in medical applications or the agrofood industry.[2]

Unlike their inspiration sources from nature, soft robots encounter challenges that are inherently associated with their material properties. These challenges currently inhibit their full implementation in real-world applications. Generally, the main challenges these robots encounter are related to their lack of output forces[8] and their unpredictable behavior. The former is mainly related to the properties of the soft actuators embedded in soft robots, which generally generate only low contact forces. The latter is caused by the highly nonlinear behavior of soft robots and their complex contact situations, both a result of their

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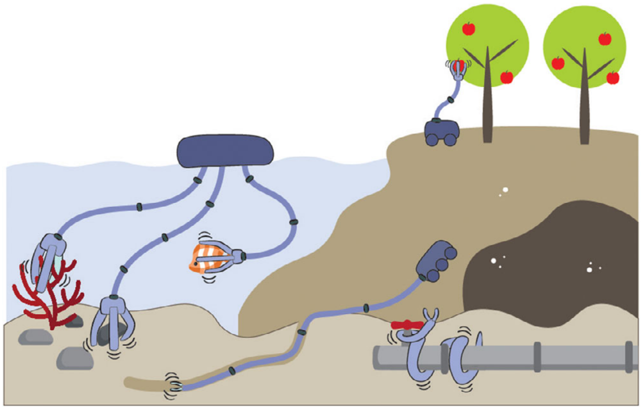

Figure 1. Soft robots for deep-sea exploration and terrestrial applications passively adapting to the changing circumstances of the challenging environment.

soft material properties. The theoretically unlimited degrees of freedom make standard control methods for rigid robots not applicable, which challenges precise control.[7] Again, the adaptive properties that facilitate the soft robot's intelligent adaptive behavior simultaneously impede their actual use in real-world applications. Currently, compromises are being made by, for instance, applying moderate softness or only local soft properties, resulting in moderate contact forces or moderate adaptive features.

The ability to integrate intelligence into soft robots without compromising their functionality emerges as a concern. Legg and Hutter[9] define intelligence as *the ability of an agent to achieve goals in a wide range of environments*. The adaptive properties of soft robots make them promising candidates for incorporating intelligence, as they can readily respond to a wide range of environmental conditions. By designing soft actuators,[10] soft sensors,[11] and even soft logic[12,13] and memory,[14,15] the trend is to develop one monolithic soft structure as an all-in-one system,[16,17] which opens up opportunities for fully autonomous soft robots. Nevertheless, the full realization of this potential depends upon overcoming the existing challenges associated with their soft and highly nonlinear material properties.

In the field of soft robotics, various approaches offer insights into how intelligence can be integrated into artificial agents. A topic of debate is the intricate relationship between the brain and the body at the core of intelligence in robots. **Figure 2** presents a visual representation of diverse perspectives concerning intelligence embedded within artificial bodies, each emphasizing varying degrees of consideration for the role of the body in the process of incorporating intelligence into robots. These perspectives are defined as follows. 1) Artificial intelligence: *A cognitivist view on intelligence with the focus on brain and central processing*.[18] 2) Embodied Intelligence: *The investigation of the tight coupling between an agent's body and brain*.[19] 3) Morphological Intelligence: *The reduction of computational cost for the brain (or controller) resulting from the exploitation of the morphology and its interaction with the environment*.[8] 4) Physical Intelligence: *Physically encoding sensing, actuation, control, memory, logic, computation, adaptation, learning, and decision-making into the body of an agent*.[19] 5) Mechanical Intelligence: *An artificial agent's degree of responsiveness to changing external conditions encoded by the programmed states of its body*.

The multidisciplinary landscape of this field of incorporating intelligence in agents led to the adoption of a wide range of technologies. Other reviews describe advances in perceptive intelligence in soft robotics,[20] machine learning methods for soft robotics,[21] the bioinspired evolution in soft robotics,[22] or summarize the research of (modeling) embodied intelligence in soft robotics.[23–25] This review paper stands out by incorporating and comparing all the major perspectives on intelligence in soft robotics. It not only discusses and compares these perspectives, but also categorizes the strategies typically employed by soft robots. The goal of this article is, therefore, to unravel the strategies to implement different types of intelligence currently adopted in soft robots. We uniquely center our attention on the design of robots tailored for intricate environments through embodied intelligence. By doing so, we aim to offer valuable insights into state-of-the-art developments and pave the way for future development in this rapidly evolving multidisciplinary field.

The structure of this review is organized as follows. Section 2 delves into the various layers of intelligence depicted in Figure 2 and listed above, moving from the outermost to the innermost layers. Section 2.1 through 2.3 concentrate on the official definitions of the different perspectives, clarified with examples. Section 2.4 provides a comparative analysis of the computational systems used to embed intelligence in soft robotics. In Section 3, we describe a fresh perspective on intelligence, called mechanical intelligence, which emphasizes responsiveness to environmental requirements, see Figure 2.

2. Peeling the Layers of Intelligence

2.1. Artificial Intelligence

Artificial intelligence (AI) mainly focuses on the computational engine of the robot.[18] This approach is also known as computational intelligence, the classic approach of intelligence, good old-fashioned AI, or the symbol processing approach.[26] In this approach, the robot's body is usually considered a source of noise that needs to be compensated by its software, whereas the hardware of the robot is usually perceived as the facilitation of the software.[18] Robots based on AI are generally successful in factory environments with controlled conditions, such as situations involving stable movement, constant geometries, constant orientation, or known terrain.[18] Examples are industrial robotic arms[27] or humanoid robots such as the humanoid Asimo developed by Honda.[4,28] Current advancements in AI demonstrate robots that can handle unstructured terrain by, for example, reinforced learning. However, these robots are associated with high computational costs and lack the flexibility to perform different autonomous functionalities in unknown environments.[29]

2.2. Embodied Intelligence

A more modern approach to intelligence was introduced in the mid-1980s, called embodied intelligence or embodied AI. This

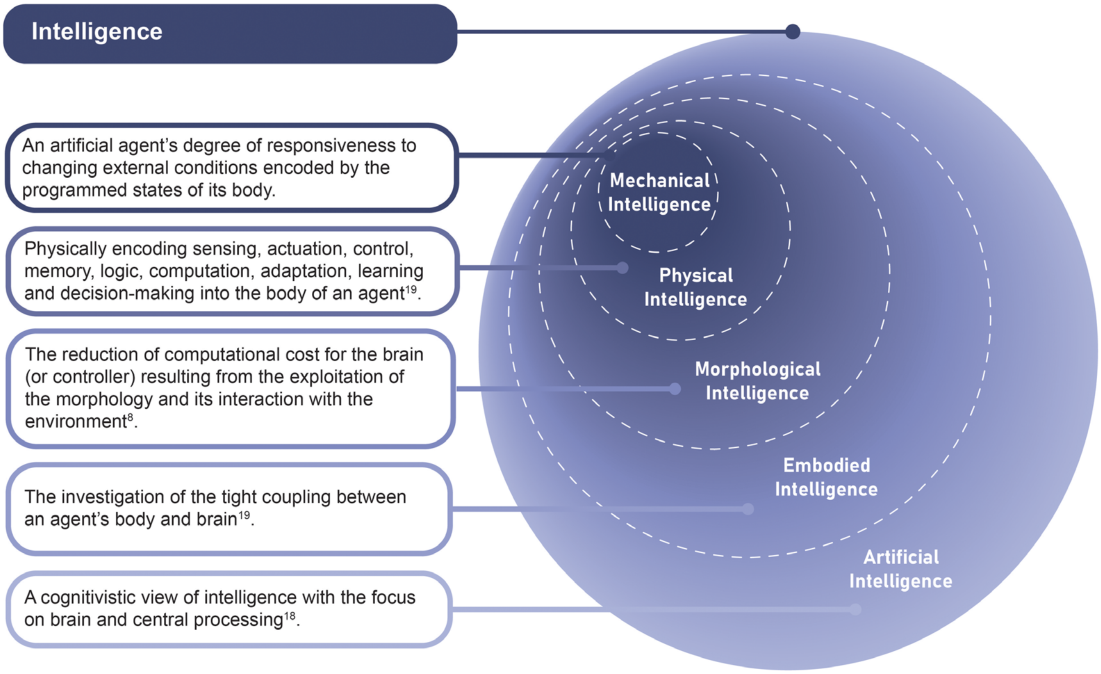

Figure 2. Schematic overview of the different perspectives of intelligence in artificial agents. At the left, the official definitions of the different concepts of intelligence are stated. As the core, the concept of mechanical intelligence is presented, which is a fresh perspective on intelligence emphasizing the robot's responsiveness to changing external conditions of a real-world environment. The layers transition from an emphasis on central processing (outermost) to a focus on embedded processing (innermost).

approach provides a new perspective on intelligence focused on the complex interaction between the robot's embodiment and environment.[18] In this perspective, the robot's physical body is designed in such a way that it eases its internal processing when interacting with the environment. In other words, the robot's control system is mediated by the mechanical properties and geometry of its embodiment.[30] Robots incorporating embodied intelligence are typically more resilient in real-world applications.

Noticeably, organisms in nature master embodied intelligence to respond to real-world situations. Their development is the result of a long evolutionary process. Similarly, the embodied approach emphasizes that the development of robots should focus on their brain–body coevolution, where the brain and body should evolve together. The embodied artificial evolution describes that robots might evolve out of a large pool of genotypes considering materials, components, and robot systems.[31] This would result in powerful robots with their material and morphological composition properly exploited for their task-environment performance.[31,32] Morphological computation is a central concept in the field of embodied intelligence,[33] of which Pfeifer et al. gave the following definition: *morphological computation is based on the processes conducted by the body, that otherwise would be performed by the brain.*[4,18] However, the concept of embodied intelligence can be drawn further as, in essence, its focus lies in investigating the tight coupling between an agent body and brain.[19]

We identified two approaches for incorporating embodied intelligence into an agent: 1) employing either a decentralized computational system or 2) employing an embedded computational system. The latter approach is particularly widespread in soft robots. To guide new researchers in the field of embedded computation, we identified three primary strategies currently used to apply embedded computation in soft robots, which will be further discussed below.

2.2.1. Decentralized Computation

A way to incorporate embodied intelligence in an agent is by applying decentralized computation, which is in contrast with the centralized computation approach related to AI. Agents using decentralized computation embed conventional controllers locally within their embodiment. A decentralized control system gathers information from local feedback and control signals, with less emphasis on the centralized global state of the agent.[34] An example of an agent that integrates a decentralized control and feedback system is the octopus. The octopus would be burdened with a highly complex system to control its hyper-redundant arms when its processing would only be performed centrally. The specially arranged anatomy of the octopus' nervous system shows that the majority of its nerve cells are located at the periphery, which is close to the motor and sensory information flow from the arms[35] (**Figure 3**A). This means that the processing of the arm's motor control is partially off-loaded from the central nervous system toward the peripheral nervous system,[35] as the neuromuscular system of the arm is able to autonomously execute motor programs.[36] This is emphasized by the octopus' arm which, after being amputated, remains capable of activating motor programs by feedback control due tactile sensory stimulation.[37] In summary, the decentralization of the arm's control system off-loads the octopus' overall central control system.

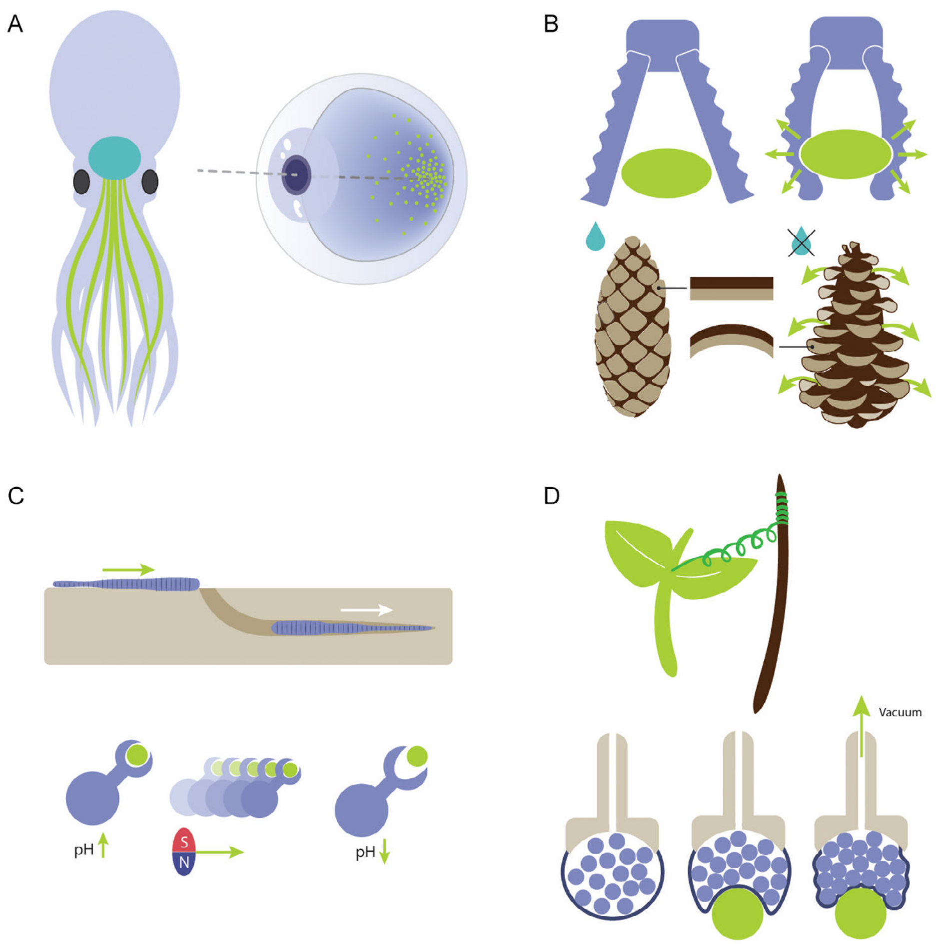

Figure 3. Illustration of embodied intelligent agents. A) Left: The decentralized control system of the octopus, in which the central brain and optical lobes are visualized in blue and the peripheral nerve system in green. Right: The decentralized sensing system of the eye, in which the decentral arranged photoreceptors are visualized in green. B) Illustration of embodied intelligence through adaptive shape. Top: The passively adaptive grip of a soft gripper that adapts to different target objects. Bottom: A pine cone opens its scales due to the humidity of the environment. C) Illustration of embodied intelligence through adaptive functionality. Top: Earthworm adapting its shape to optimize its functionality during locomotion in air and locomotion in soil. It has been shown that earthworms only locomote using the first segments in soil. Bottom: Soft microrobot adapting its functionality due to its embedded magnetic particles and pH-sensitive materials. D) Illustration of embodied intelligence through adaptive mechanics. Top: Tendril coil serving as a spring-damper system to support the plant. Bottom: Variable stiffness soft gripper which adapts its stiffness when vacuum is applied.

Next to these complex control systems, decentralized computation can also be observed in simple reflexes, such as the patellar reflex. Reflexes showcase a local network of sensory neurons and motor neurons that facilitates a fast response to a stimulus. In the case of the patellar reflex, the stretch of the patellar tendon results in an automatic contraction of the quadriceps muscle. This mechanism, responsible for maintaining balance during walking, functions without interference from the central brain. Reflexes are often useful in situations that require rapid and autonomous responses, for instance, during emergencies.

Moreover, a decentralized arrangement of sensory structures could enhance the performance of the feedback system. For example, the nonhomogeneous arrangement of the light-sensitive cells in the compound eyes of house flies compensates for the phenomenon of motion parallax.[38,39] In plants, command centers operate at the level of apexes. This arrangement serves as inspiration for robots that perform lateral motion detection. Another example of space-efficient imaging can be found in the human retina, in which the density of photoreceptors is highest at the center and gradually decreases toward the periphery of the visual field[40] (Figure 3A). This results in an optimal balance between resolution and required computational power. By focusing the high-resolution region toward the point of interest, this arrangement ensures an optimal visual information flow.[40]

In addition to using decentralized computation, embodied intelligence can be achieved by embedding computation directly into the body of an agent, a process we define as embedded computation. Unlike decentralized computation, which involves integrating conventional controllers or central computation into the embodiment, embedded computation involves embedding intelligence in the embodiment itself. We made a classification of the main strategies that are currently employed to apply embedded computation in soft robots. These soft robots are divided into three distinct groups.

Adaptive Shape: Agents in this category embed the ability to adapt their physical configuration in response to environmental cues. Their functionality is facilitated or improved by these adaptive properties.

Adaptive Functionality: Agents in this category dynamically adjust their functionality depending on situational demands, which results in multifunctional agents.

Adaptive Mechanics: Agents in this category embed the ability to adapt their mechanical properties to the conditions of a new environment.

It must be noted that the groups are not mutually exclusive, as certain agents can exhibit characteristics or features that align with multiple categories concurrently. In such cases, these agents possess attributes or features that place them within the scope of more than one category, indicating an overlap or intersection between the defined groups, such as a variable stiff soft gripper that both adopts an adaptive shape and adaptive mechanics or an earthworm that both adopts adaptive shape and adaptive functionality, as explained in more detail below. The goal of these groups is not primarily to establish a distinct categorization, but rather to provide inspiration and enhance clarity of the different intelligent approaches found in nature and artificial agents.

2.2.2. Embedded Computation by Adaptive Shape

Generally, soft robots are associated with embodied intelligence due to their soft material properties that adapt to the environment. Soft pneumatic multifingered grippers are typical examples of robots that show a control system with embedded computation by passively adapting their shape to the environment. These grippers' behavior is defined by the interaction between their body and the target object. The compliant properties of the individual pneumatic fingers shape the gripper passively around the pressure points of the targeted object, which results in a universal underactuated gripper[8,41] (Figure 3B). An example of such a gripper making use of contact-driven deformation is the soft gripper developed by Ilievski et al.[42] which is able to lift various shaped objects, such as a raw egg and a mouse. Other examples are the multifingered robot hand developed by Suzomori et al.[43] or the soft pneumatic gripper for delicate surgical manipulation developed by Low et al.[44] These soft pneumatic fingers are also known as fluidic elastomer actuators, PneuFlex actuators, or Pneumatic Networks (PneuNets).[41] Next to pneumatic actuation, these soft manipulators can be actuated by tendons, shape-memory materials and other active materials such as hydrogels, or they can be fully contact-driven.[41,45] Their soft material properties make them passively adaptive to their environment, easing their internal processing. Embedded feedback control is shown in the soft pneumatic fingers developed by Joshi and Paik.[46] These pneumatic fingers estimate their output force and displacement without additional sensors, but by the use of their intrinsic sensing capabilities. Due to their compliant properties, the generated output force and finger displacement result in internal pressure and volume change.[46] This means that the internal properties of the pressure and volume provide feedback regarding the state of the soft pneumatic finger, so the state can be adapted to grasp an object safely. Another example of a soft gripper that incorporates a feedback system with embedded computation is developed by Gossweiler et al.[47] Due to the embedded mechanochronic polymer, this gripper reacts to stress by changing its color. The color of mechanochronic polymer changes depending on the gripper's level of bending. This enables easy assessment of whether the gripper is currently in a gripping state or a releasing state.

In nature, plants offer a wide variety of inspiration for the integration of embodied intelligence in soft bodies, as plants show intelligent behavior within a brainless body, which means centralized computation is not available.[48,49] There are a large variety of plants that react to environmental stimuli by a shape change.[49] An example is the Venus flytrap, which reacts to an external force, for example, the touch of an insect, by closing its trap due to its bistable joint.[50] This mechanism has served as inspiration for a variety of soft robots, such as the compliant shading device Flectofold developed by Korner et al.[51] the magnetically actuated bistable robot developed by Zhang et al.[52] the temperature-actuated snapping hydrogel sheet developed by Fan et al.[53] the hygroscopic bilayer structure developed by Lunni et al.[54] or the pneumatically actuated bistable gripper developed by Pal et al.[55] For a systematic overview of artificial Venus flytraps, we would like to refer to the study of Esser et al.[56] Many plants deform passively by taking up water from the environment to swell their hygroscopic cells.[49] Depending on the architecture of these hygroscopic cells in combination with nonswelling cells, bilayered structures are created that show specific deforming behavior. Examples of plants stimulated by humidity are pine cones, which seed scales close when subjected to a humid environment and open when subjected to a dry environment[49] (Figure 3B). The direction of deformation of the scales is encoded in the embedded fibers. Nonliving agents, such as pine cones or plant seeds,[57] are of particular interest as their behavior is completely dependent on their embedded computation. This phenomenon served as inspiration for the development of autonomous soft robots, such as the 4D-printed flap structures that autonomously deform due to changes in environmental humidity.[58] Climbing plants exhibit a similarly remarkable manifestation of embodied intelligence, as they effectively determine their growth direction and attachment points despite the absence of a central nervous system. Similarly, in the apex region of plant roots, the roots display an ability to "decide" their growth direction. The embedded nature of these decision-making processes, especially in the case of roots lacking visual perception, highlights the intricate and distributed mechanisms at play.

2.2.3. Embedded Computation by Adaptive Functionality

Soft robots possess the unique ability to deform their bodies due to their material properties, enabling them to function differently in varying environments. This principle finds parallels in nature, where certain organisms showcase the capability to deform their bodies to achieve adaptive functionalities. For instance, consider the earthworm, which exhibits remarkable deformable body patterns depending on the desired function, whether it is locomotion or burrowing (Figure 3C). When locomoting, the earthworm extends its head while shortening its bottom to avoid slipping.[59] During burrowing, the earthworm anchors its bottom while extending and creating space for its head.[60] These intricate movements are achieved through localized radial extensions or elongations of its body. By strategically contracting its muscles in various wavelike patterns, it can achieve specific deformations that suit the intended functionality. This principle served as inspiration for the earthworm-inspired soft robot developed by Ozkan-Aydin et al.[61] This robot can alternate between anchoring and locomotion by respectively undulating its bottom or peristaltically deforming its full body. An even more drastic example from nature that shows embodied intelligence by adaptive functionality is the caterpillar-to-butterfly metamorphosis, in which a transition is made from locomotion on land to locomotion in the air.[62]

An example of a field in which multifunctional bodies proved to be useful is the field of microrobots, as multifunctionality allows for miniaturization. These microrobots respond to different environmental stimuli to actuate different functionalities. Xin et al.[63] developed a microrobot for localized cancer cell treatment that opens its gripper in a low-pH environment, closes the gripper in a higher-pH environment, and locomotes using a magnetic field (Figure 3C). The robot's response to its environment mediates its control system, which makes the actuation of different functional modes less demanding. Also, the embedded stimuli-responsive materials mediate the robot's feedback system, making the robot independent of an external power source. An example of a multifunctional soft sensor is the fingerprint-inspired e-skin system for sliding detection developed by Chen et al.[64] Four embedded spiral electrodes are patterned in such a way that the amount of skin deformation provides information about both the sliding direction and the displacement and speed. Embedding such a multifunctional sensor in the feedback system would allow a soft robot for further miniaturization.

Other examples showing embodied intelligence by adaptive functionality are the mechanical creatures called "Strandbeesten" by Theo Jansen. These kinetic machines are designed in such a way that they walk independently powered by the wind. They autonomously change their direction depending on the environment. Some creatures can even change their locomotion mode from walking to flying. These machines' embodiment takes over their control, switching the locomotion mode, embedding an embodied intelligence.[19] They work in cooperation with the environment, instead of working against the disturbances associated with the environment.

2.2.4. Embedded Computation by Adaptive Mechanics

The third category of soft robots that show embedded computation by their adaptive mechanics consists of a group of soft robots that make use of their adaptive properties to adapt the way forces act on their body or are generated by their body in different environments. Nature shows the same principle in, for example, the tendril coils that some plants use to support their weight. These tendrils reach out to detect potential support structures in a straight shape and deform into a coiled shape when they reach the support[65] (Figure 3D). The coiled tendril serves as a spring-like and energy-damping structure supporting the plant.[49] This mechanism serves as inspiration for coiling soft robots, which are often built from bilayered structures with a strain mismatch whose equilibrium state is controlled by certain stimuli, for example, heat,[65,66] current,[67] or pneumatics.[68]

Another example found in nature showing embedded computation by its adaptive mechanics is the self-stabilizing feature of the muscle–tendon system in the leg. The elastic properties of the tendon and muscle passively adapt the angulation of the knee during impact with the ground, corresponding to the irregularities of the terrain.[18] The intrinsic dynamics of a body are exploited to reduce the complexity of its control system.[69] This feature of incorporating self-stabilizing behavior is also referred to as *intelligence by mechanics*.[70] Holmes et al.[71] even hypothesized a feedforward control loop of the muscle activation for legged animal motion by preflexes. An artificial example showing embodied intelligence by self-stabilizing properties is the hexapedal robot developed by Cham et al.[72] This hexapedal robot makes use of the mechanical reflexes of its complaint knee joints to adapt its posture passively to the terrain. This reduces the computational load related to the positioning of the robot's legs.

Soft robots embedding variable stiffness also show embodied intelligence by adaptive mechanics. A classic example is the jammed-based coffee balloon gripper.[73] The gripper deforms passively around the target object in its soft state, adopting embedded computation by an adaptive shape. After the application of a vacuum, the coffee particles get packed and the gripper transitions toward its stiffened state (Figure 3D). The initial compliant properties of the gripper are exploited to reduce the gripper's controlling load, whereas the stiff properties of the gripper are needed to create sufficient contact forces. Here, the contribution of the gripper's geometry and materials is dominant in reducing its computational load.[4] Another soft robot making use of variable stiffness in a more localized manner is the soft robot arm inspired by the octopus developed by Laschi et al.[74] Similarly to the octopus arm, the arm is divided into muscles, where longitudinal muscles are represented by cables and transversal muscles are represented by shape memory alloys (SMA). Locally activating the SMA actuators and pulling the longitudinal cables result in a local increase in stiffness.[74] The soft properties of the arm provide it with an adaptive shape corresponding to the environment, which is counterbalanced by its local stiffening that increases the output force locally.[30] This is, among others, useful in gripping applications. Cianchetti et al.[75] demonstrated that this principle also applies on a smaller scale. They demonstrate a soft arm with dimensions applicable for minimally invasive surgery, incorporating variable stiffness by granular jamming. In the soft state, the arm is able to move around obstacles, but when needed, the arm transitions into its jammed state to increase its payload. Next to reducing the computational load of an agent, variable stiffness can be used to improve the performance of the feedback system. For example, Yue et al.[76] developed a multi-degrees-of-freedom force sensor in which the sensor sensibility can be adjusted by changing the stiffness of its pneumatically actuated variable stiff structure. With this intrinsic range of sensing, the sensor is suitable for a wide range of applications.

An often-cited example of a robot incorporating embodied intelligence is the passive dynamic walker.[18,77,78] This two-legged robot walks down a predetermined slope without the need for any control. The mechanical construction of the robot is designed in such a way that the walking behavior is fueled only by gravity. This robot makes optimal use of morphological computation by eliminating the need for any internal processing. There is an ongoing debate surrounding the passive dynamic walker's actual capability to perform morphological computation or whether it is simply a passive mechanical process.[79] To avoid the discussion of the interpretation of the term *computation*, Ghazi-Zahedi[77] proposed an alternative term for morphological computation, which is *morphological intelligence*, defined as *the reduction of computational cost for the brain (or controller) resulting from the exploitation of the morphology and its interaction with the environment*.[77] The term *computational cost* is applicable in a larger context compared to the definition of embodied computation. It refers not only to the amount of computation encoded in the body but also to the energetic cost.[77] In nature, this kind of intelligent behavior is, for example, shown by fish swimming behind obstacles to optimize their energy expense by resonating upcoming vortices in their body.[80] The vortices excite vibration modes which trigger resonance and motion. They use the dynamics of their flexible body to reduce the energetic cost of swimming, therefore embedding a morphological intelligence in their body. Other examples are V-shaped falling paper systems, whose shape can be optimized to minimize the falling speed.[81] The design of a simple piece of paper can impact its interaction with the environment by adapting the drag force generation. This unique quality allows the paper to showcase a form of embedded intelligence resulting from its morphology.[81]

2.3. Physical Intelligence

An approach closely related to embodied intelligence is physical intelligence.[19] Physical intelligence describes the understanding of how a body creates intelligence physically while interacting with the environment. Physical intelligence is defined by Sitti et al.[19] as *physically encoding sensing, actuation, control, memory, logic, computation, adaptation, learning and decision-making into the body of an agent*. Physical intelligence differs from embodied intelligence by essentially focusing on the intelligence encoded in the body, whereas embodied intelligence focuses on the tight coupling between an agent's body and brain.[19]

A physically intelligent example from nature showing improved functionality through its embodiment is the foot of a gecko. The contact surface of the foot is covered by hierarchical microstructures, which gives the gecko the ability to climb vertically[79] (**Figure** 4A). The microstructure creates tight contact between the feet and the underlying terrain, as it adapts to the irregularities of the terrain.[79] This results in sufficiently powerful van der Waals adhesion to walk on vertical surfaces.[82] Geckos would not be able to exhibit this climbing functionality without their specialized morphology, hierarchical arrangement of the setae, orientation of the air, and distributed forces (among others), which means that the gecko's foot morphology embeds physical intelligence. Examples of physically intelligent soft robots inspired by the gecko are, for instance, the soft unidirectional robot developed by Wang et al.[83] the soft adhesive pads developed by Aksak et al.[84] or the multifinger gripper with gecko-inspired adhesives developed by Ruotolo et al.[85] Physical intelligence can also appear among agents if their collective physical interactions create intelligent behavior. In nature, this

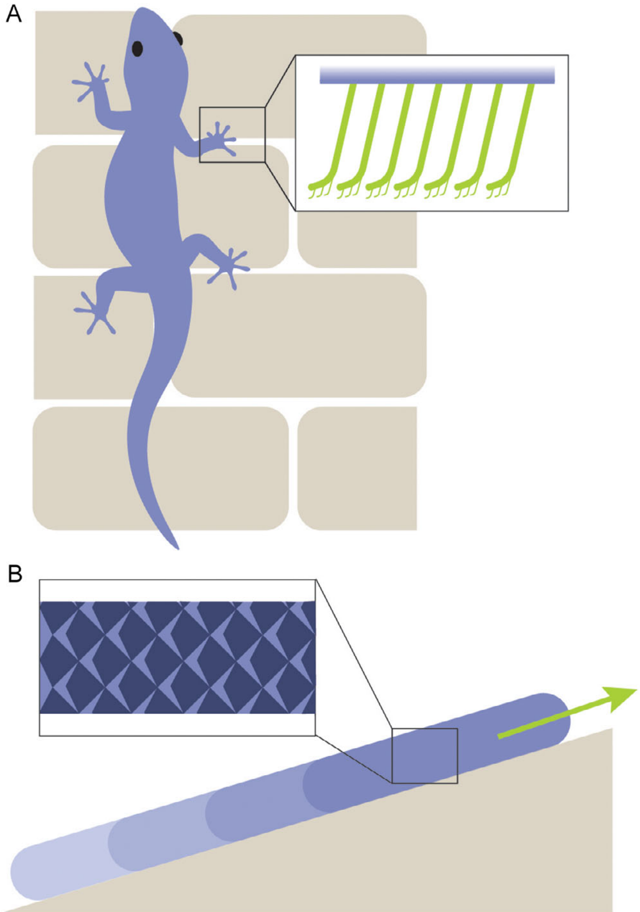

Figure 4. Illustration of physical intelligent agents. A) The hierarchical structures consisting of setal arrays, containing setae which terminate in spatulae on the feet of geckos give them the ability to climb vertically. B) The Kirigami soft robot developed by Rafsanjani et al.[88] can climb hills due to its kirigami skin.

appears as result of the swarm behavior of ducklings. Here, the ducklings use the vortices generated by the other ducklings to lower the metabolic rate per individual duckling. Examples of soft robots showing physical intelligence through swarm behavior are the microrobots developed by Dekanovsky et al.[86,87] Their local interaction with each other results in the weaving of spider-like webs that adsorb hormonal pollutants from aqueous environments.[76]

An example of a soft robot showing physical intelligence through functionality facilitated by its morphology is the soft kirigami crawling robot developed by Rafsanjani et al.[88] The skin of this snake-inspired robot contains kirigami cuts, which provides directional frictional properties to the outer surface of the robot (Figure 4B) and results in efficient crawling gaits.[88,89] Without these integrated kirigami structures, the robot could not perform this crawling locomotion mode, which means that the functionality is encoded in the design of the robot's body. These artificially designed structures that show unique properties through their design are also called metastructures.[19] Other unique properties they could include are, for instance, vibration attenuation, electromagnetic behavior, photonic behavior, or a negative poison ratio. Embedding metastructures in soft robots provides the body with additional functionalities that it originally would not contain, resulting in a physically intelligent body.

Soft robots could also embed physical intelligence by encoding logic, memory, or control in their embodiment. Examples of the former are the circuits developed by Preston et al.[12] which exist out of soft pneumatic digital logic gates. By making use of a bistable valve to encode NOT, AND, and OR digital logic, these logic gates have the potential to serve as the base for completely soft autonomous robots. These soft robots could even display their stored memory on a soft bubble display.[14] Other examples of soft robots embedding, logic, memory, and control are the soft robots with integrated fluidic circuits developed by Mahon et al.[15]

2.4. Intelligence by Different Computational Systems

The overlap and differences between the different perspectives on intelligence can best be understood by their control system architecture. With control or computation, we mean an executive operation that has some steady state and once the initial or boundary conditions change then an algorithm is executed leading to a calculated output based on predetermined rules. A distinction categorizes agents based on the following computational approaches.

2.4.1. Centralized Computation

In this approach, the control process is centralized, involving a single controller that sends input signals to a corresponding actuator. In a closed-loop system, feedback is provided by a single-output signal toward a separate sensor. Centralized computation is associated with the AI layer in Figure 2.

2.4.2. Decentralized Computation

An agent that involves decentralized computation distributes some computational load of the central control system across multiple separate controllers. In closed-loop configurations, the feedback system is enhanced by replacing a centralized sensing unit with multiple distributed sensing units. This arrangement can lead to improved agent control, an improved sensory information flow, and faster response times. The example of the octopus was given, in which the motor control of the arms is partially offloaded from the central nervous system toward the peripheral nervous system. Decentralized computation is associated with the embodied intelligence layer in Figure 2.

2.4.3. Embedded Computation

Agents employing embedded computation integrate either their control process in the actuator, their sensing mechanism in the actuator, or they embed both within the actuator itself. An agent can incorporate embedded computation by providing the embodiment with an adaptive shape, adaptive functionality, and/or adaptive mechanics. Agents are empowered to function autonomously and the opportunity is provided to eliminate the need for an external power source. For this reason, embedded computation is the only computational system that is adopted by nonliving organisms that still show adaptive behavior. The example of a pine cone was given, in which both the sensing of the environmental humidity and the control of its bending behavior are embedded in the material of its scales. It must be noted, however, that the cellulose in the scale is not a standalone sensor. Embedded computation is associated with the embodied intelligence layer, the morphological intelligence layer, and the physical intelligence layer in Figure 2.

Figure 5 shows control schemes associated with the different computational systems. Each computational system contributes to various levels of autonomy and control efficiency. It also presents how the types of intelligence shown in Figure 2 relate to each other. AI is the only type of intelligence associated with centralized computation whereas the other types of intelligence are associated with embedded computation or decentralized computation. The primary difference between embodied intelligence, morphological intelligence, and physical intelligence lies in their emphasis on how embodiment reduces the central processing load. All three perspectives involve embedded computation, integrating control or sensing within the embodiment. However, an embodied intelligent agent also enhances the coupling between its control system and embodiment by distributing the computational load across multiple locations within the embodiment. This approach offloads the central system or improves the feedback system, aligning with decentralized computation.

3. Environmental Responsive Intelligence

3.1. Intelligence of Soft Robots

Soft robots present an interesting case as they are framed as examples that embody both embodied intelligence and physical intelligence. This is often explained by their soft material properties that facilitate embedded computation that makes them suitable for navigating unpredictable and dynamic environments. However, in reality, these soft properties sometimes show inherent challenges to the robot's overall functionality. A typical pneumatically driven soft gripper can be taken as an illustration, which excels in its ability to shape passively to a diverse variety of objects. Although soft grippers demonstrate adaptability, a significant limitation arises in balancing between maintaining sufficient gripping forces and preserving their soft and gentle nature. It can be stated that a balance should be found wherein an intelligent soft robot should not only demonstrate an adaptive behavior but also effectively perform its core functionalities. A soft gripper should possess the capability to respond to changes in the shape of the targeted object while ensuring it sustains sufficient gripping forces. This would, for instance, mean that a soft gripper not only conforms its shape to the targeted object but also modulates its stiffness to maintain optimal load forces under a wide range of conditions.

Environmental considerations play a crucial role in shaping structural adaptations. Fully soft bodies, such as those observed in octopuses, exhibit optimal functionality within aquatic environments where arm density is equivalent to water, which

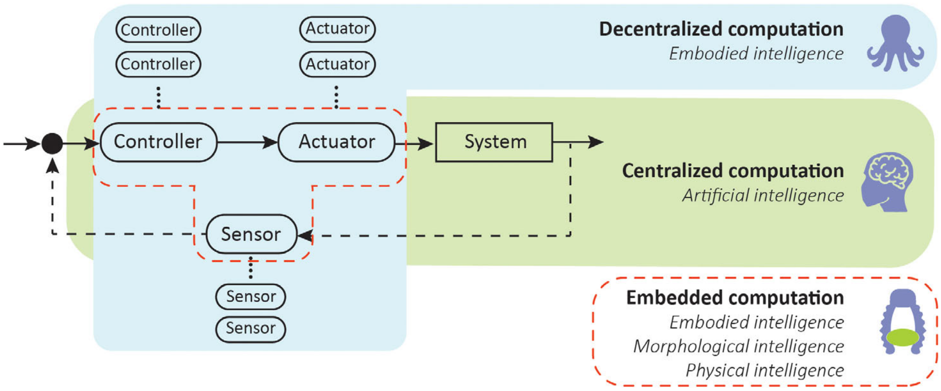

Figure 5. Schematic of computational system architectures. Green: Centralized computation associated with an artificial intelligent agent. Blue: Decentralized computation associated with an embodied intelligent agent, distributing computational load of the central control system across multiple separate controllers or a local controller. Red: Embedded computation associated with embodied intelligent, morphological intelligent, or physical intelligent agents, driven by an integrated control and/or sensing system into the body of the agent.

minimizes energy expenditure. Conversely, in terrestrial settings, rigid skeletal frameworks are indispensable for structural integrity, highlighting the environment-specific requirements in robotic design. Notably, the scale of a robot is contingent upon its environment; fully soft designs, operational in terrestrial environments, adopt smaller sizes to mitigate gravitational impact. The nuanced interplay between structural rigidity, environmental context, and efficiency advocates for tailored robotic designs attuned to specific environmental demands.

As of now, engineers often seek to streamline environmental factors to facilitate the effective operation of robots. Historically, the simplification of environmental factors was necessitated by the prevailing technologies. However, contemporary advancements in technology present a landscape wherein opportunities have emerged to integrate environmental complexity into the robot design process, which becomes imperative when targeting real-world applications. To develop robots capable of thriving in such diverse and challenging settings, the adoption of embodied intelligence is paramount. This entails the meticulous design of the robot's physical form to harmonize it with its specific operational environment. Consequently, engineers must possess foreknowledge regarding the robot's intended responses to the environment.

3.2. Mechanical Intelligence

To achieve responsive behavior, soft robots would need to incorporate so-called mechanical intelligence. We define this term as *an artificial agent's degree of responsiveness to changing external conditions encoded by the programmed states of its body*. Here, the term *external conditions* refers to the set of requirements linked to the agent's working environment for maintaining its functionality. As the working environment changes, the agent needs to adjust and meet new corresponding requirements. In other words, responsive agents can adapt to suit different working environments, ensuring they continue to operate effectively. These adaptations might involve changes in body mechanics, shape, or even functionality. Responsive behavior is embedded in the design of the agent, meaning that various responsive states are intentionally programmed during its design process. This can also be referred to as *control by design*. The term *programmed states* refers to the agent being designed to respond in predetermined ways to new sets of requirements, ensuring its functionality remains unimpeded. In essence, the agent's degree of responsiveness is encoded through these programmed states. A higher number of states embodying different responses would indicate greater mechanical intelligence in the agent, as it can achieve its goal in a wider range of environments. This perspective on soft robots' responsiveness differs from the embodied intelligence, morphological intelligence, and physical intelligence approach, as it primarily focuses on the degree of the agent's responsiveness to the environment and accompanying external stimuli. Therefore, it is important to distinguish this from studies that use the term mechanical intelligence as a synonym for embodied intelligence or physical intelligence.[90–92] Mechanical intelligence aligns with an embedded computational system and the various strategies for implementing such a system (adaptive shape, adaptive functionality, and adaptive mechanics), with the addition that the artificial agent actively responds to changes in its environment in a preprogrammed way. Our perspective aligns with the perspective on mechanical intelligence given by Khaheshi and Rajabi,[93] in addition, offers a detailed definition and view of the implementation field, and focuses specifically on the preprogrammed responsiveness of an artificial agent.

As an example, a regular soft robotic gripper would exhibit mechanical intelligence if it could adapt its shape to different objects without compromising its functional performance. Zhou et al.[94] developed such a gripper with soft fingers filled with granular particles that jam at locations where the gripper contacts the target object. This adaptive mechanism allows the gripper to accommodate larger objects and maintain its gripping performance passively. Similarly, another example of mechanical intelligence is demonstrated in the reconfigurable miniature ferrofluidic robot developed by Fan et al.[95] This soft robot adapts its shape by stretching and splitting into multiple smaller robots, enabling it to navigate through variable spaces effectively, showcasing responsive behavior. Shah et al.[62] created a reconfigurable robot that adapts its locomotion mode based on the terrain, using either rolling or inchworm motion to achieve movement on flat and inclined surfaces, respectively. This responsive functionality exhibits mechanical intelligence, allowing the robot to adapt to changing environmental conditions. The robots developed by Hu et al.[96] are yet another example of mechanical intelligence that adapts its locomotion mode depending on the environment. Here, the magnetic field of the environment directly controls the locomotion mode of small-scale soft robots. This way, the robots are able to walk, swim, jump, roll, or crawl, depending on the demands of the environment. These examples illustrate how soft robots can embed mechanical intelligence through their responsive mechanics and functionalities, enabling them to adapt and interact effectively with their environments.

3.3. Enablers of Mechanical Intelligence

In order to facilitate an agent with mechanical intelligence, the agent should be able to respond to the environment by its predetermined responsive states. This means it is vital to anticipate the changing demands of the environment. During operation, the soft robot should ideally autonomously gather information from the environment through integrated sensors, subsequently translating this data into appropriate responses. To make optimal use of the agent's embedded intelligence, it should be encouraged to implement a control scheme that is associated with embedded computation in which both the control and sensing system are directly integrated within the agent's body. This type of control system has an advantage that no external power source is needed, thereby enabling the agent to operate fully autonomously.

The soft robots embedding fluidic circuits developed by Laake et al.[97] are an example of such an autonomous agent that integrates both its control system and sensing system. These robots' soft actuators are connected to specialized soft valves. These valves transform a continuous inflow of air into cyclic activation, and by connecting the actuators in parallel, the actuators can be stimulated in various sequences. The robot can switch between sequences based on physical cues from the environment, enabling it to autonomously respond to changing conditions. For instance, an impact force could prompt a shift in gait to navigate past obstacles or trigger drug release inside the body.

A strategy to embed mechanical intelligence would be to integrate materials that respond to external stimuli such as heat, light, pH value, or magnetism, also called smart materials, into the soft robot. Smart materials are already implemented in commercial mechatronic applications.[98] Recently published reviews show the upcoming interest and potential of smart materials integrated into soft robots,[99–103] microrobots,[104] or even smart textiles.[105,106] Programming soft robots with flexible metamaterials provides additional opportunities to embed soft robots with responsive states.[107,108] Energy-harvesting soft materials provide the potential for the development of autonomous soft robots without the need for external power sources.[109]

An example of a soft robot embedding mechanical intelligence by smart materials is the light-driven artificial flytrap developed by Wani et al.[110] This flytrap integrates a structure consisting of a light-responsive liquid-crystal elastomer. This material detects an object when it enters its field of view and, consecutively, initiates bending due to light-induced rearrangement of its molecular alignment, causing the flytrap to close. This way, this soft device autonomously recognizes objects and initiates closing without the need for an external power source. Other examples of soft robots embedding stimuli-responsive materials are the soft swimming robots developed by Karshalev et al.[111] These swimmers change their color to adapt their visibility in different environments, controlled by environmental stimuli. For instance, glow-in-the-dark swimmers start to emit green and purple light at night in response to solar light charging during the day.

Mechanical metamaterials show great potential for embedding mechanical intelligence into soft robots. Pressure actuation is widely used to actively change the properties of mechanical metamaterials, allowing for easy integration with conventional pneumatically actuated soft robots. When inflated of deflated, these metamaterials can change their shape, functionality, or mechanical properties due to the presence of internal channels or cavities inside a soft matrix.[112] For example, the actuator developed by Pan et al.[113] features local auxetic and nonauxetic structures that cause bending upon inflation. Similarly, the metamaterial developed by Chen et al.[114] changes stiffness when pneumatically changing the shape of integrated holes. Furthermore, by embedding smart materials in these mechanical metamaterials, these materials can become responsive to external stimuli. Mishra et al.[115] demonstrated this with a temperature-responsive soft fluidic finger that bends at low temperatures ($<30\,°C$) and expels fluid at high temperatures ($>30\,°C$), resulting in a gripper capable of mechanically and thermally manipulating heated objects based on the environmental conditions.

The design space for soft robots incorporating mechanical intelligence is characterized by the dynamic interplay between geometry and material properties. By adjusting the geometry of these robots, it becomes possible to provide them with new properties. For instance, designing a body as an airtight membrane with embedded particles allows the stiffness of the entire body to be modified through vacuum application. Model-based designing can provide fast iterations. New possibilities for complex geometries arise with the use of 3D and 4D printing.[116] Furthermore, the incorporation of specific materials can further enhance the capabilities of geometries. For instance, the integration of smart materials enables direct responsiveness to the environment or facilitates adjustable stiffness. Roh et al.[117] demonstrated a 4D-printed magnetically actuated soft gripper featuring a wavy structure that exhibits complex movements like contracting, grabbing, and releasing with a simple input force. These movements are feasible due to the combination of the gripper's wavy geometry and magnetically responsive materials. The potential of the design space for mechanical intelligence integration is immense, bridging various disciplines and offering a unique intersection of cutting-edge technologies. **Figure 6** shows a schematic visualization of the mentioned potential enablers of mechanically intelligent soft robots.

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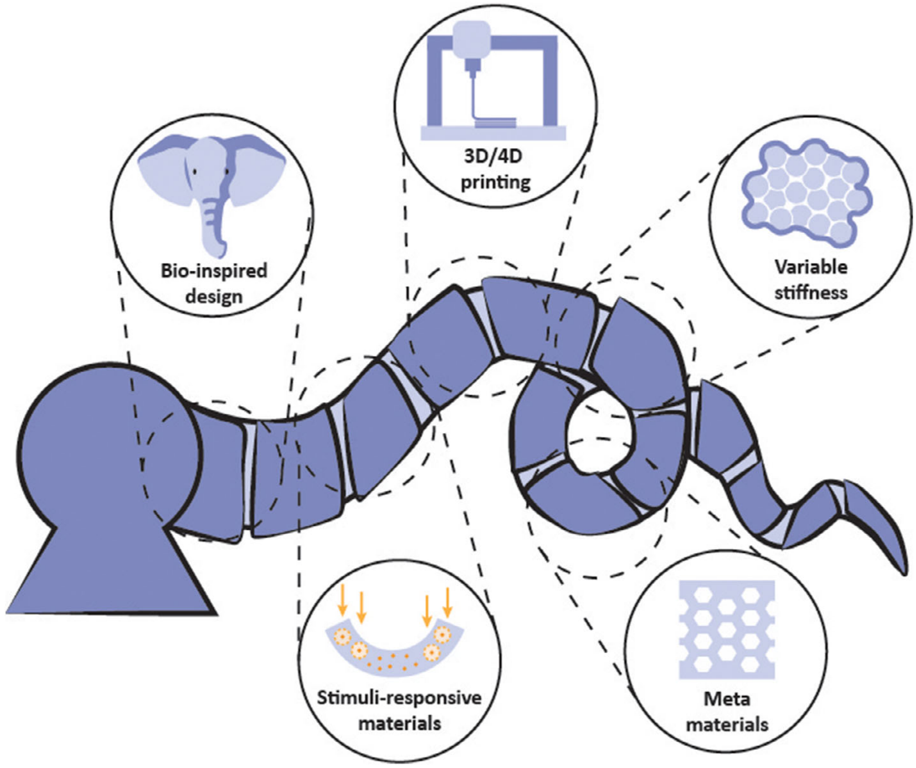

Figure 6. Schematic visualization of potential enablers of mechanical intelligent soft robots. Enablers of mechanical intelligent soft robots are diverse and include the use of bioinspired design methodologies, smart use of stimuli-responsive, and metamaterials that can be 3D/4D printed using state-of-the-art manufacturing facilities and can change their stiffness on demand.

4. Conclusion

The goal of this review article is to present an overview of the current strategies focused on integrating intelligence into soft robots. Different perspectives on intelligence were explored and we discussed different computational systems that support these different perspectives. Furthermore we classified strategies to provide soft robots with intelligence through their embodiments as follows: 1) intelligence by an agent's adaptive shape, 2) intelligence by an agent's adaptive functionality, and 3) intelligence by an agent's adaptive mechanics. Examples showed in what diverse ways these adaptive properties can be reached, where nature often functions as an excellent source of inspiration. The focus lies on the design of robots tailored for intricate environments through embodied intelligence.

It is important to acknowledge that the definitions of different perspectives on intelligence are subject to change over time, and the boundaries between different approaches tend to overlap. With the continuous growth of the soft robotic community, a diverse range of insights and technologies are being adopted. While this expansion broadens the horizons of this field, it also introduces challenges in maintaining clarity regarding the distinctions between various perspectives on embedded intelligence. On the other hand, deliberately bringing complementary fields toward each other could yield significant benefits. By drawing from the advancements in the current trend of AI, embodied intelligent soft robotics can enhance its adaptiveness to the environment. Integrating diverse perspectives on intelligence has the potential to facilitate soft robots that adapt to a wide range of environments while functioning optimally.

To bring the intelligence embedded within soft robots to the next level, we described a fresh perspective on embodied intelligence, emphasizing the robot's responsiveness to changing external conditions of a real-world environment. Integrating intelligence into the physical body contributes to reducing the energy consumption of robots through optimized sensor integration, adaptable locomotion, and collaborative behaviors, ultimately enhancing overall energy efficiency. Research should focus on the integration of fully embedded computational systems in the soft body of the robot, including the control system and sensing system. This opens opportunities toward fully autonomous systems that can operate in a wide range of remote or miniature applications, for example, applications in surgery, underwater applications, or applications in disaster areas. Inspiration could be taken from organisms in nature, such as pine cones, which show responsive behavior without an internal power source. As the design space for mechanical intelligence integration is immense, successfully incorporating mechanical intelligence into soft robots requires a strong multidisciplinary approach, building upon the existing diversity that characterizes the field of soft robotics. In this context, encouraging collaboration and communication between different disciplines, such as designers, engineers, material scientists, and biologists, becomes essential in unlocking the full potential of soft robots for various real-world applications.

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Conflict of Interest

The authors declare no conflict of interest.

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embodied intelligence, mechanical intelligence, morphological computation, physical intelligence, soft robotics

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