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From Morphological Computation to Ecological Psychology: A Conceptual Reconsideration of Control in Soft Robotics

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Abstract. This article tackles a central problem in soft and tensegrity robotics: designing effective control strategies for adaptive behavior. According to the principle of morphological computation, this challenge can be addressed by "offloading" computation from the brain (controller) to the body, leveraging the agent's physical properties. I propose a conceptual reconsideration grounded in ecological psychology, whose focus on affordances highlights how soft devices can exploit body-environment interactions to enhance their adaptability to ever-changing conditions. Contributions: (i) a diagnosis of the limitations of morphological computation as a control paradigm for soft robotics; (ii) the articulation of the Design Principle of Agent-Environment Duality, which could reframe control as the regulation of affordance relations at the agent-environment scale.

1. Introduction: Soft Robotics and Morphological Computation

Soft robotics investigates how compliant materials – such as silicone, polymers, and hydrogels – can be used to build intelligent systems capable of large deformations and active interaction with the environment. To understand what is distinctive about these devices, it is helpful to contrast conventional robots with biological systems, which are the main source of inspiration for soft robotics.

First, conventional robots are typically rigid and low-dimensional to simplify control, whereas biological organisms exhibit highly nonlinear dynamics and many degrees of freedom, even for simple movements. In biological systems, nonlinear morphological[1] features contribute directly to control: for example, muscle and joint structures that stabilize movement on rough terrain.

Second, biological systems are tightly coupled to their environments. Their morphology is the result of evolution within specific ecological niches and embodies solutions to real-time dynamic problems (e.g., trout exploiting turbulent flow to swim upstream efficiently). This leads to robustness and energetic efficiency. By contrast, conventional robots are usually designed to minimize environmental influence, relying on tightly regulated settings and often failing in unstructured, open-world scenarios.

Third, the relation between body and control differs markedly. In traditional robotics, a digital controller is conceptually separated from the body, issuing commands to a passive plant. In living organisms, morphology predates brains and neural circuits, and bodies are already tuned to solve real-time control tasks. Neural systems then evolve to work *with* these morphologically "intelligent" structures, not to override them (Laschi et al., 2016; Mazzolai et al., 2022; Hauser et

[1] In the context of soft robotics and morphological computation, the term 'morphology' refers generally to the system's shape, sensors, actuators, and materials.

al., 2023). Thus, the distinction between controller and controlled becomes blurred. Soft robots, with their compliance and adaptability, make this continuity between controller, body, and environment particularly salient, thereby providing a fertile ground for philosophical reflection on the mind-body relation and the very nature of cognition.

Technically, these biological insights motivate efforts to engineer soft bodies with nonlinear dynamics, strong environmental coupling, and synergistic body-brain collaboration. Soft devices show promise in domains where interaction is contact-rich, conditions are variable, and fragility constraints are strict: for example, safe human-robot interaction, gentle manipulation of delicate items, efficient locomotion, and rich haptic sensing via deformable skins. In addition, soft robotics may reduce ecological footprint through recyclable or biohybrid materials and renewable power sources (Mazzolai et al., 2022; Hauser et al, 2023; Nanayakkara, 2024).

Nevertheless, nonlinear dynamics are difficult to model, and soft robots may exhibit potentially infinite number of degrees of freedom to manage. Classical control methods based on rigid-body assumptions often fail or are inapplicable[2]. Therefore, to fully exploit bioinspired systems, new control and design paradigms are required. One influential proposal is *morphological computation*, a principle that emphasizes how bodily features contribute to intelligent behavior by distributing tasks across controller, morphology, and environment. On this view, complex control tasks in noisy, unstructured environments can be managed by relatively simple controllers because some of the computation is "offloaded" to the physical dynamics of body-environment interaction.

Consider the passive dynamic walker, a classic example in the field: a minimal robot that can walk without motors or control electronics. Its gait depends entirely on the incline and the walker's mechanical parameters (leg segments length, mass distribution, foot shape), so walking emerges from mechanics alone (Pfeifer & Bongard, 2006; Hoffmann & Müller, 2017). Nonetheless, referring to this process as 'computation' beyond the purely metaphorical sense seems misleading: while morphology supports control, it does not perform any computation.

The remainder of the article is organized as follows. Section 2 assesses the principle of morphological computation and diagnoses why current uses fall short for control. Section 3 introduces the ecological framework as an alternative, articulating connections between ecological psychology and soft robotics, which are grounded in Bernstein's concept of dexterity. Section 4 states the Agent-Environment Duality design principle and outlines open questions for the ecological control of soft robots. Finally, section 5 is devoted to concluding remarks.

2. Beyond Morphological Computation

Fully leveraging the complex bodies of soft robots for control tasks requires rethinking the relationship between morphology and the digital controller, beyond what morphological computation typically implies. Two questions are central: how should morphology and controller relate, and how should control authority be distributed between them? The challenge is further complicated by the strong dependence of body-controller interactions on environmental conditions. The core problem, then, is to determine how the environment, the body, and the digital controller can act in concert to produce desired behaviors. Addressing these issues calls for a

[2] A general way to represent control is through state equations of the form:

$$\dot{x} = f(x, u) \tag{1}$$

where x denotes the system's state (e.g., position, velocity, or deformation), u the control input, and f the function that captures how body, controller, and environment interact over time. In rigid robots, f is usually simple enough to be explicitly modeled. By contrast, in soft robots the same relation becomes highly nonlinear and challenging to model, since morphology and material compliance actively shape the dynamics.

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critical reassessment of morphological computation, and a shift in how we understand what makes control successful in natural agents. While morphology can simplify control, its role is more accurately described as shaping the physical dynamics of the agent-environment system rather than literally performing computations.

Müller & Hoffmann (2017) survey examples in animals and robots to argue that the contribution of body morphology to cognition and control is seldom computational, in any meaningful sense of the word. They distinguish between *morphology that facilitates control*, *morphology that facilitates perception*, and the rare cases of *true morphological computation*, such as *reservoir computing*. Morphology facilitating control includes well-known examples such as the passive dynamic walker and the gecko with its special feet. The latter can be viewed as an "active extension" of the passive walker: the physical body is complemented by actuators and sensors linked in a simple control loop, yet physical interaction of the body with the environment remains central. In both cases, the body plays a decisive role in enabling physical behavior in the real world[3]. Such instances are often interpreted in the "offloading" sense, according to which the body is said to take over computations from the brain. For instance, the computation hypothetically required for walking is claimed to be fully offloaded from a controller to the morphology of the passive dynamic walker (Hoffmann & Müller, 2017).

Taken literally rather than metaphorically, however, the offloading view is problematic for two reasons. First, it is difficult to identify real-world cases where one could freely choose to solve a task 'through the brain' or 'through the body' and smoothly interchange their contributions. In practice, the extent to which tasks can be shifted from the controller to the body is limited. This has led to systems such as the passive dynamic walker that rely almost entirely on physical interactions as driving forces behind behaviors, yet possess little to no cognitive relevance. Second, even if leveraging morphology simplifies the controller – a benefit that indeed can be quantified – this does not mean that the body performs computations. To label these processes "computational" suggests a stronger claim: that what body-environment interaction achieves could also be achieved by a conventional computer. That interpretation is at odds with what most proponents of the morphological stance wish to emphasize: the indispensability of embodiment and its coupling with the environment (Pfeifer & Iida, 2006; Muller & Hoffmann, 2017).

Given these concerns, a better route is to consider morphology's role in control within a non-computational framework. Ecological psychology – a theory that emphasizes the emergent nature of behavior from continuous, reciprocal interactions between an agent and its environment, without relying on computational processing over internal representations – offers the tools to move beyond the limitations of morphological computation related to control. On this view, control is not a preprogrammed sequence of commands executed by the body, but rather an ongoing, dynamic negotiation with ever-changing external conditions. The next section examines how the foundational pillars of the ecological approach can be applied to soft robotics.

3. Ecological Psychology and Soft Robotics

[3] Since the present work addresses control in soft robotics, I restrict the scope to the first category – cases in which morphology directly supports control. That said, systems discussed under morphological computation concern not only control but also traditionally more "cognitive" capacities such as perception. A salient example is the fly's eye, where morphology critically shapes information flow: the types of sensory receptors – their mechanism of transduction – determine what signals the brain or controller receives from the environment.
In addition, there are cases where the whole system, the body, literally seems to compute. The example of this kind is reservoir computing, which refers to a machine learning framework that learns nonlinear and dynamical computational mappings in a supervised fashion.

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Ecological psychology, originally developed by James J. Gibson (1966, 1979), is a research program and theoretical approach to perception and action which can be summarized by four core principles (Turvey, 2018; Blau & Wagman, 2023; Favela, 2024):

1) Perception is direct. Organisms make unmediated contact with their environments by detecting ecological information. Perception is not a process of constructing mental representations of the environment. Rather, it picks up the energy layout of an agent's world (optic flow, haptic flow, acoustic flow, etc.), as constrained by its perceptual capacities.
2) Perception and action are continuous. Perceptual capabilities evolved to guide action, and action capabilities evolved to enable perception. Together they form a single closed loop. Action is not a distinct process from perception nor the outcome of neural computations, but emerges from activity across the agent-environment system.
3) Affordances. Coined by James J. Gibson (1979) from the verb "to afford", the term *affordance* refers to meaningful possibilities for action specified by ecological information. On this view, meaning does not derive from internal (i.e., cognitive, mental, etc.) rules, but from the direct perception of action possibilities offered by the environment; the agent and environment are complementary[4].
4) Organism-environment system. The appropriate unit of analysis is the spatiotemporal scale of organism and environment interactions. The aim is not to illuminate the brain-centered information-processing nature of cognition, but to explain perception-action as understood through the lens of affordances.

According to this perspective, perception is primarily of affordances, and its purpose is to guide *doing*: the execution of coordinated, goal-directed actions. A central source for this approach to coordination and control is the work of Nikolai Bernstein (1967; 1996), who asked how biological agents achieve dexterous control of their complex bodies. Bernstein identified the core problem of coordination as mastering the many degrees of freedom involved in a particular movement – a challenge that closely parallels two major problems in soft robotics: (i) designing complex systems capable of dexterous movements within their environments; and, as a corollary, (ii) managing the large number of degrees of freedom inherent in compliant, deformable structures.

3.1 Dexterity

The connection between ecological psychology and issues of control and design in soft robotics can be found in Bernstein's concept of dexterity, which is defined as the ability to find motor solutions across a wide range of external situations and conditions, and which becomes an increasingly dominant feature of action as the complexity of the agent increases (Bernstein, 1996; Newell, 1996). In this sense, a long-term goal of soft robotics is to build systems capable of dexterous interactions with their surroundings.

To explain dexterity, Bernstein proposed an anatomical and hierarchical model composed of four levels of movement construction:

A) Level of tone;
B) Level of muscular-articular links (i.e., synergies);
C) Level of space;
D) Level of action.

This hierarchy builds from the bottom up: starting with tone, then synergies, followed by the level of space, and culminating in the level of action, which integrates all the preceding levels. Only at the level of action is it possible to perform truly dexterous movements, and only the most complex and developed agents operate at this highest level. From an ecological perspective, higher dexterity is associated with greater exploitation of affordances, emphasizing the continuous and dynamic interaction between brain, body, and environment.

[4] The agent-environment complementarity will be clarified in section 5.2, where a formal definition of affordances will be provided.

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Motivated by the problem of explaining dexterous action in biological systems, Bernstein identified the core problem of coordination as mastering the many degrees of freedom involved in any movement. This is precisely the difficulty faced in controlling soft robots: managing a vast number of degrees of freedom inherent in compliant, deformable structures. In animals, the joints and permissible motions of the complex bio-kinematic chains that compose the musculoskeletal hardware comprise many degrees of freedom. For each coordinated act, theoretically, specific values for each degree of freedom would need to be prescribed. From a computational perspective, this would require a central controller to select, from an enormous set of possible muscle activation patterns, the one combination that accomplishes the task. However, while such problems may be solvable in theory using advanced algorithms, they are practically infeasible in real-time operation. An agent that must respond adaptively to the contingencies of its environment cannot afford the time or computational resources to search exhaustively through all possible combinations of bio-kinematic variables (Turvey, Shaw, Mace, 1978).

According to Bernstein, the solution to the degrees of freedom problem concerns the organization of the control of the motor apparatus. Degrees of freedom can be reduced through the formation of muscle linkages, or synergies. A group of muscles – each spanning multiple joints, and capable of independent contraction – can become functionally coupled to act as a single task-specific unit (Turvey, 1990).

Profeta and Turvey (2018) reinterpret Bernstein's view in an ecological-dynamical perspective, treating synergies as groupings of potentially independent anatomical components that work together as a functional unit to exploit information about affordances relevant to a given task. Within this framework, muscles are not merely motors, but also function as rulers, springs, struts, tuners, and brakes, adapting their role dynamically according to the behavioral demands. Synergies are task-specific organizations of these muscular components and are created by leveraging the resources provided by the level of tonus. The level of tonus – the body – is considered as a multi-fractal biotensegrity system, characterized by prestress (which refers to a structure's ability to maintain an equilibrium shape with all tensile members in tension and in the absence of external forces or torques; see Levin, 2002, 2006; Turvey & Fonseca, 2014; Profeta & Turvey, 2018). Information is included in the constraints that govern the emergence and enactment of synergies. Namely, the organizational structure of a goal-directed movement is shaped by environmental information, which can induce synergy re-organization. In this sense, the level of space constrains the formation of synergies. Conversely, synergies constrain information pickup. This bidirectional relationship encapsulates a fundamental tenet of ecological psychology: perception constrains action and action constrains perception (Gibson, 1979; Profeta & Turvey, 2018; Favela, 2024).

Overcoming the degrees of freedom problem involves understanding how information constrains action. In this regard, one must examine how structured information in the environment shapes the soft assembly of task-specific coordinative structures. This interaction provides a basis for developing an ecological design principle for tensegrity-based and other soft robotic systems, one that aligns morphological adaptation with environmentally structured information to achieve dexterous, context-sensitive behavior.

4. An Ecological Approach to Control in Soft Robotics

The ecological-dynamical reinterpretation of Bernstein's view identifies the level of tone with a biotensegrity system. Tensegrity structures, in general, consist of discontinuous stiff struts connected by a continuous net of tensional flexible strings. Over the past decade, engineers have increasingly explored tensegrity structures as a foundation for novel robotic systems, i.e., *tensegrity robots*.

Several devices have been developed based on tensegrity principles (for a detailed review of bioinspired tensegrity systems see Liu *et al.*, 2022). However, like other soft robots, they pose significant challenges in terms of design, construction, and control (Shah *et al.*, 2021). To date, no study has demonstrated a fully autonomous, untethered tensegrity robot capable of navigating unstructured terrain.

Conceptually, this challenge could be addressed by developing design principles grounded in the ecological reinterpretation of Bernstein's ideas. This section outlines the theoretical foundations that future work could implement in tensegrity – and more broadly, soft – robotic systems. In the ecological reinterpretation (Profeta & Turvey, 2018), Bernstein's level of action is closely associated with the notion of prospectivity. Within ecological psychology, perception is defined as the detection of specifying information, information that directly reveals affordances. Crucially, affordances are inherently dealing with the future. For instance, before catching a ball one must perceive that the ball is catch-able. Thus, attuning to conditions that allow actualization of affordances implies attuning to future states of affairs, i.e., prospective control (Turvey, 1992). This entails that affordances are not only spatially but also temporally nested. A particularly useful framework for conceptualizing this nestedness of affordances is a means-ends hierarchy (Wagman *et al.*, 2016). In such a hierarchy, upper levels functions as ends, while lower levels functions as means. The levels relate to one another in terms of three questions fundamental to performing an intended behavior: why, what, and how?

The highest level – the why level – represents an overarching goal (e.g., searching for a lost object). However, this level does not dictate the specific behaviors required to achieve that goal. That is, it does not specify which affordances need to be perceived and actualized to accomplish the goal. The middle level – the what level – comprises specific behaviors (e.g., kneeling on the floor) that would achieve the superordinate goal, but not the means by which to perform these behaviors. That is, it specifies a particular affordance to be perceived and actualized, but does not determine the precise motor strategies or physical means for doing so. The lowest level – the how level – comprises the means of performing the actions represented at the what level (e.g., bending at the waist). In other words, it specifies the means by which to actualize the affordance.

Within the context of the ecological-dynamical reinterpretation of Bernstein's work, these means are synergies. Conceptually, it is therefore possible to design a tensegrity robot whose control architecture is organized around a hierarchy of affordances. The why level represents what motivates the robot's behavior in the world, the main purpose behind the construction of this robot. The what level specifies the particular behaviors needed to achieve the superordinate goal. Finally, the how level – corresponding to the level of synergies – defines the means able to actualize those specific behaviors.

In this framework, synergies are understood as functional relationships among anatomically independent components. Their purpose is not to produce a particular movement, but rather to achieve a goal. A given function can be fulfilled by different anatomical components or different configurations of the same anatomical components. Thus, synergies are functional and flexible, not anatomical or stereotypic. Importantly, synergies are goal-preserving and self-organizing: their constituent components dynamically coordinate in response to task and environmental constraints, maintaining the integrity of the action even in the face of perturbations (Latash *et al.*, 2007; Bongers, 2023). This flexibility and robustness make synergies a powerful principle for the control of soft and tensegrity robots, which must operate under complex, nonlinear, and often unpredictable conditions.

Having outlined a conceptual control architecture organized as a hierarchy of affordances grounded in synergies, I now turn to the question of implementation. Specifically, the next section sketches how the notions of *direct perception* and *affordances* could be translated from ecological psychology into robotics. This, in turn, provides a hypothetical route to implementing the proposed architecture and highlights the benefits this conceptual apparatus offers for robotics.

4.1Toward Implementation? Affordances and Direct Perception in Robotics

Building on the foregoing, I now consider how notions such as affordances and direct perception can be rendered operational for robotic systems, and what this entails for sensing and control. In robotics, affordance research has been significantly influenced by developmental psychology, which demonstrates that the human capacity to perceive affordances emerges gradually through development, and it is the result of both exploratory and observational learning (Gibson & Pick, 2000; Adolph & Hoch, 2019). This line of research provides a crucial insight for roboticists: to effectively perceive affordances, a robot must first learn from its own sensorimotor interactions with the environment. In other words, affordances depend on the perceptual and motor capabilities of the agent (i.e., its *effectivities*), and the ability to perceive them is acquired by the agent through a sustained sensorimotor learning process. From this ecological perspective, the goal of perception is not to reconstruct the environment, but to enable effective action within it. Therefore, the robot does not need to generate exhaustive or high-fidelity representations of its surroundings. Instead, it must identify and extract the minimal task-relevant information necessary to perform actions and achieve goals (Jamone *et al*., 2018).

As a result, within an ecological approach to robotics, the notion of affordance supports a principle of "perceptual economy", by computing only the perceptual cues that are relevant to the agent's goals and action capabilities. This minimal and action-oriented mode of perception is known as "direct perception". The perception of affordances begins with the sensing of only those environmental stimuli that are relevant to the agent, given its specific sensorimotor capabilities. The key contribution of the affordance concept is that these stimuli are automatically translated into actions, or more precisely, action possibilities: the stimulus itself is not really perceived (e.g., represented, stored, memorized, reasoned upon), but instead it is directly converted (i.e., direct perception) into an action representation, bypassing the need for elaborate internal processing. In robotic systems, for example, visual stimuli may be captured by a camera and translated into electronic signals, typically numerical arrays or matrices. While this process does involve computations, the affordance-based approach emphasizes that such computational workload can remain minimal and efficient, provided that the system assumes the robot's own sensorimotor capabilities as a prior. This prior knowledge is typically acquired through learning: by exploring the environment using its own body, the robot gradually learns what minimal information must be extracted from the sensory stream in order to generate functional action representations (Andries *et al*., 2024).

These remarks are only preliminary indications of how key concepts from ecological psychology can be implemented in operating systems. The main message is that the conceptual work proposed in this article has engineering counterparts, and several research groups are already pursuing this line.

In what follows, I adopt Turvey's account of affordances to formulate an ecological design principle for soft and tensegrity robots. The next section introduces the principle of Agent-Environment Duality, which may provide fundamental guidelines for the construction of innovative devices.

4.2 Ecological Design Principle: Agent-Environment Duality

Before stating the ecological design principle, it is necessary to specify the relational primitive it presupposes. Affordances are central to the understanding of the mutual relationship between an agent and its environment. Thus, a precise definition of affordance paves the way for a system-level pairing of a robot and its surroundings. The notion of affordance at the basis of this study is defined as follows:

> A situation or event X affords action Y for animal Z on occasion O if certain relevant mutual compatibility relations between X and Z obtain […] The action Y (e.g., grasping)

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> materializes only if the situation X (current environmental conditions) and individual Z are compatible on dimensions relevant to Y. Formally, this can be defined as: the object X has a property p that affords Y. This possibility for action only exists because there is an individual Z that possesses a complementary property q (an effectivity, e.g., capability to grasp). When Xp and Zq are juxtaposed they form a system Wpq, which exhibits the behavior Y (Profeta & Turvey, 2018, p. 122).

With this concept of affordances in place, it becomes possible to formulate a first ecological design principle for robotics. To move beyond the limits of morphological computation – paraphrasing Shaw & Turvey (1981/2017) – the robot and its environment must not be regarded as rigidly separable entities, but rather as complementary constituents of a single system – an ecosystem. The environment of a robot as perceiver can be considered an affordance structure that is reciprocally isomorphic, or dual, to the effectivity structure of the robot as an actor upon that environment. The higher-order relational structure consisting of the dual affordance and effectivity structures, as defined for a specific type of robot, is the ecological system for the designated type of actor-perceiver. In this way, an environment (i.e., an affordance structure) is functionally defined for a robot as perceiver, and a robot as actor (i.e., an effectivity structure) is functionally defined for the stipulated environment as an econiche for that device. Accordingly, the experience of the robot is of the functionally specified environment itself, i.e., an affordance structure. Based on this theoretical grounding, a first ecological design principle for robotics can be formulated: the Principle of Agent-Environment Duality.

This principle has the potential to provide substantial advantages for the design and realization of artificial systems. First, adopting the Agent-Environment Duality principle allows for greater conceptual unity within soft robotics. Ecological psychology offers a single vocabulary – grounded in affordances and effectivities – that spans plants, animals, and humans. This meshes naturally with bio-inspired soft devices (which range from plantoids to humanoids). A theory that explains cognition and action across such a wide range supplies a common theoretical reference, countering the current fragmentation of morphological computation, whose usage often shifts with local contexts and metrics.

Second, the explicit agent-environment pairing encourages complementarity between robot and workplace: control is framed as keeping specific relations (affordances) within bounds given the robot's effectivities. In practice, this can allow designers to reduce computational burden (regulate task-level informational variables rather than reconstruct global state), align morphology and sensing with the structure of the physical world, and – potentially – lower energy demands. Furthermore, as systems come to behave in ways that are legible to human observers (smooth, compliant, contact-aware motions), this could also benefit human-robot interaction (HRI) by increasing predictability and comfort.

Third, because control is expressed in terms of affordances that already structure the environment, resulting behaviors are likely to be more congruent with ambient dynamics. This ecosystem-level legibility – compliant contact, low-impulse interactions, and reduced reliance on aggressive actuation – can decrease habitat disturbance (noise, vibration, scarring). As a result, such robots would be more readily perceived as *natural* not only by human partners but within the broader ecosystem, facilitating coexistence and reducing environmental impact over the device's life cycle.

Fourth, the approach is scientifically generative: by building artifacts that rely on affordances and effectivities, we can test hypotheses about biological agents in the spirit of the synthetic methodology – understanding by building. Soft robotics, with its compliant and flexible structures, serves as a fertile ground to test the core tenets of ecological psychology, enabling the design of more adaptive and resilient systems while contributing empirical support to the theoretical framework itself.

Notwithstanding these potential benefits, several open problems and points of tension with the current state of the art remain:

(1) The way affordances and direct perception have been used in robotics often departs from James Gibson's original formulation (e.g., see Şahin *et al.*, 2007). Bridging this gap demands careful operationalization, for instance, asking how to translate ecological information into robotic language. A challenge that requires research efforts.

(2) The field of soft robotics already has control strategies (e.g., open-loop control and closed loop control). Introducing a fundamentally different stance is non-trivial: teams face integration costs that must be offset by demonstrable gains in performance and robustness. Nonetheless, early deployments of ecological control on soft-robotic systems have been reported. For instance, Frazier *et al.* (2020) show how the ecological psychology's conception of "information" and "control" can simultaneously make sense of what it means for a plant to navigate its environment and provide a control scheme for the design of ecological plant-inspired robots[5].

(3) Practical engineering obstacles persist. For example, discovering reliable task-level variables in messy settings and aligning materials, sensing, and synergies so those variables stay available in the wild is by no means obvious.

Tackling these issues is crucial to moving from conceptual appeal to real-world performance. But the potential benefits – simpler controllers, lower energy demands, and behaviors more congruent with human and ecological contexts – indicate that the Agent-Environment Duality principle may allow artificial systems to operate seamlessly within the world rather than against it. This offers a promising path for advancing soft robotics toward the construction of more resilient and adaptive devices.

5. Conclusion

The complex, bioinspired, and compliant bodies of soft robots offer a broader range of action possibilities within their environments compared with traditional rigid robots. Yet, this morphological richness introduces significant difficulties in the control of such systems. The notion of morphological computation has been proposed as a potential way to address these challenges. However, it lacks a unifying framework that can produce fundamental design guidelines, and it still tends to preserve a conceptual separation between brain, body and environment, despite aiming to overcome it.

The ecological approach advanced in this article seeks to move beyond this limitation by shifting the reference frame from isolated components to the agent-environment ecosystem. Grounded in ecological psychology, this perspective leads to the formulation of an ecological design principle: the Principle of Agent-Environment Duality.

At this stage, the problem is primarily ontological. According to this principle we must assume a complementarity between robot and environment rather than treating them as two separate entities that merely interact. The device and its surroundings form a single functional unit, such that neither can be fully specified without reference to the other. On this view, the notion of

[5] Within the ecological perspective, control can be understood in terms of simple informational variables rather than complex state reconstructions. A paradigmatic example is the so-called τ variable (Lee, 1998; Lee, 2009):

$$\tau = \frac{x}{\dot{x}} \tag{2}$$

where x represents the distance to a target and $\dot{x}$ the rate of closure. τ specifies the time-to-contact directly available to a perceiver or agent, enabling guidance without the need for detailed internal models. Such variables exemplify how an ecological stance reframes control, shifting emphasis from internal computation to relations between agent and environment. Frazier *et al.* (2020) uses τ-guidance to provide a control scheme for plant-inspired robots.

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Embodied Intelligence in robotics, which has traditionally emphasized physical/sensorimotor embodiment and structural coupling through sensors and actuators (Pfeifer & Bongard, 2006; Ziemke, 2022), acquires a more ecological nuance: intelligence is understood as a property of the agent-environment system as a whole, rather than of the agent alone.

For this principle to offer a compelling framework for reconceptualizing the control problem in soft robotics, two further steps are required. First, we need an account of motor control in biological systems that is explicitly based on this view of affordances and effectivities. In this respect, recent work grounded in dynamical systems theory treats effectivities as dynamical properties of the organisms that are complementary to the affordance properties of the environment (see, for reference, Bennett *et al.*, 2024). Second, these insights must eventually be implemented in physical robots.

The road ahead is still long, but this trajectory may open promising avenues for designing soft robotic systems capable of dexterous, context-sensitive action in unstructured environments.

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