Foundations of Embodied Intelligence for Robotic Systems

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Fumiya Iida, Chapa Sirithunge, Perla Maiolino and Josie Hughes

ABSTRACT

Embodied Intelligence (EI) provides a foundational framework for understanding intelligent and adaptive behaviors in both biological and artificial systems. Emerging from early philosophical and scientific discussions on mind-body dualism, EI emphasises the intricate relationship between physical bodies and information processing, which enables meaningful sensory-motor interactions with the environment. Its theories and technologies span multiple disciplines, including mechanical, electrical and control engineering, as well as computer science and material sciences, making it a complex field for robotics researchers to navigate. However, a comprehensive understanding of EI is essential to addressing key challenges and avoiding the redundancy of past discoveries. This article introduces fundamental design principles of intelligent adaptive systems, followed by key paradigms in autonomous agent architectures, such as feedback control, behavior-based approaches, mechanical and material intelligence and embodied social interaction. It explores insights from biology, physics, cognitive science and philosophy, focusing on emerging applications in adaptive systems, human-robot collaboration and bio-hybrid technologies.

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Introduction

The concept of Embodied Intelligence originates from theological and philosophical debates on body-mind dualism and has evolved into a foundational framework for understanding how physical bodies contribute to adaptive intelligence in both biological and artificial systems. Initially explored in philosophy and cognitive science Descartes, 1999; Varela *et al.*, 2017, EI has gained increasing significance across disciplines such as biology, physics and robotics Pfeifer, 2006a.

At its core, EI suggests that intelligent behavior is fundamentally shaped by an agent's physical body, which serves as a mediator between the agent and the environment. While numerous mechanical and computational designs exhibit surprising emergent behaviors, the deeper implications of EI have been progressively uncovered through interdisciplinary studies, spanning not only in robotics and computer science Laschi *et al.*, 2012; Howard *et al.*, 2019; Takeda *et al.*, 2019; , but also in philosophy Varela *et al.*, 2017, psychology Glenberg, 2010, behavioral science, evolutionary biology, physics and mathematics Nandram *et al.*, 2017; Langton, 1997; Varela *et al.*, 2017.

Seminal contributions by early mathematicians and computer scientists laid the groundwork for self-organising systems, including reactiondiffusion models by Turing, 1990, self-replicating machines by Von Neumann, Burks, *et al.*, 1966 and cybernetics Wiener, 2019. These early conceptual frameworks provided a foundation for modern EI research, emphasising that intelligence is not merely a product of internal computation or centralized complex algorithms but rather an emergent property of the continuous interactions between an agent's body and its environment. Emergent properties in this context are system-level behaviors that arise from local interactions among simpler components, which cannot be predicted by analyzing the components in isolation Holland, 2000; Brooks, 1991. Unlike traditional computational models that rely purely on symbolic manipulation, embodied systems leverage physical system-environment interactions to offload complex control and computation onto the body's physical properties. For instance, in biological systems, muscle elasticity, passive dynamics and biomechanics significantly contribute to energy-efficient and adaptive movement. Similarly, self-organising principles, observed in swarm intelligence, cellular automata Wolfram, 1982 and artificial life Langton, 1997, demonstrate that complex, intelligent behaviors can emerge from simple local interactions, without the need for centralised control O'Keeffe *et al.*, 2017. This paradigm shift—from explicit programming to emergent intelligence—highlights the importance of studying physical embodiment. It is worth exploring self-organising systems which show how complex, adaptive behaviors can arise through local interactions between body and environment without centralized control.

More recently, the interplay between physical bodies and information processing in intelligent adaptive behavior has been examined across different timescales, particularly in ontogenetic development (how intelligence develops over an individual's lifetime) Krishna *et al.*, 2024 and phylogenetic evolution (how intelligence evolves across generations) Lungarella *et al.*, 2003; Nolfi and Floreano, 2000. Timescales matter in Embodied Intelligence as intelligent behavior emerges from interactions across multiple temporal layers at different speeds, such as faster events similar to reflexes, neural spikes (milliseconds to seconds) enable real-time responsiveness while slow events as learning, adaptation, morphological changes, hormonal regulation (minutes to days) shape behavior through experience. These timescales show how intelligence emerges from the interplay of evolution shaping body and brain design over millions of years across many generations, development tuning behavior and learning over one's life time and realtime interaction enabling adaptive, context-sensitive actions.

Biological learning processes are not only shaped by neural adaptation but also by bodily development, with cognitive functions co-evolving alongside changes in morphology. Similarly, the coevolution of brains and bodies has provided new insights into the role of embodiment in shaping information processing in real-world environments. These perspectives demonstrated the nontrivial yet essential role of the physical body in determining an agent's ability to learn, adapt and interact effectively with its surroundings.

The field of Embodied Intelligence integrates conceptual, theoretical and technological elements. Unlike many areas of robotics research, which often begin with formal first principles that can be extended systematically, **EI does not emerge from a single foundational theory. Instead, it begins with a broad conceptual landscape based on fundamental principles, which are then refined into concrete theoretical paradigms that serve as a basis for developing technologies and methodologies**. Following this approach, this article first introduces foundational concepts, then explores key paradigms and finally discusses their broader implications for robotics and intelligent systems. While numerous articles and textbooks have explored similar topics from different perspectives, including works by Pfeifer and Scheier Pfeifer, 2006a, Laschi et al. Laschi *et al.*, 2012 and Iida and Giardina Iida and Giardina, 2023, this review builds upon these foundational contributions, incorporating recent developments with a particular emphasis on robotics research. Compared to previous works, it aims to provide a broader and more integrative perspective, covering fundamental concepts, theories and paradigms that define the landscape of Embodied Intelligence .

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Foundations of Embodied Intelligence

The study of Embodied Intelligence has deep conceptual and philosophical foundations. For instance foundational works emphasize the interplay between brain, body and environment in shaping cognition Clark, 1998, while some explore the philosophical dimensions of embodiment within cognitive science Varela Francisco *et al.*, 1991. More recent perspectives highlight how embodied cognition differs fundamentally from traditional cognitive science Wilson and Golonka, 2013. Hence highlights that embodied cognition is not just about using the body in cognition but how it fundamentally changes the way we understand cognitive processes. In this context, cognition emerges through dynamic interactions between an organism and its environment, emphasizing real-time behavior rather than internal computation where it is grounded in sensorimotor experiences.

The real-world interactions are essential for developing intelligent behavior, moving away from purely representational models Brooks, 1991. Similarly, physical embodiment within real environments shapes adaptive responses and cognitive processes Pfeifer and Scheier, 2001. Additionally, cognition extends beyond the brain, relying on dynamic interactions between the body and the physical world Clark, 1998.

Motor actions enable the dynamic, real-time interactions that shape cognition, support embodiment and ground intelligence in physical experience—moving beyond internal representations to situated, action-driven understanding. While traditional neuroscience has primarily focused on understanding and optimizing simple, discrete motor actions—such as reaching, grasping, or eye movements—AI (Artificial Intelligence) research has progressed toward generating complex and diverse motor behaviors that span multiple tasks and contexts, often at the scale and flexibility of humanoid bodies Merel *et al.*, 2019; Team *et al.*, 2025. This laid the background to the emergence of hierarchical design principles in engineering flexible control systems. New advanced AI models focus on embodied reasoning, enhancing robots' spatial understanding and decision-making abilities. It integrates perception, state estimation, spatial reasoning, planning and code generation, enabling robots to perform tasks with improved safety and adaptability.

Rather than focusing on specific technologies or methods, study of Embodied Intelligence usually begins with broad perspectives and frameworks for understanding intelligent adaptive behaviors in animals and machines. Before diving into technical details in Section 3, this section introduces foundational concepts and principles to contextualize these discussions within the broader landscape of intelligence studies. A summary of these fundamental concepts is given in Table 2.1. These concepts are discussed in detail in later sections.

2.1 Bio-inspiration, Self-Organization and Physical System-Environment Interactions

2.1.1 Key Biological Inspirations

Embodied Intelligence primarily concerns systems that physically exist in the real world, rather than simulated environments that bypass physical constraints. This focus stems from the belief that the physical nature of systems is integral to adaptive intelligence, particularly in complex biological systems.

Typical examples for bio-inspired robots, such as RHex (Saranli *et al.*, 2001), RoboBee (Wood *et al.*, 2013) and Octobot (Laschi, 2017), mimic

Table 2.1: Fundamental principles of Embodied Intelligence

Principles	Descriptions
Situated, multi-purpose, autonomous agents	Autonomous agents require multi-purpose control architectures to achieve self-sufficiency. All physical and mechanical constraints need to be considered in the design architectures of intelligent adaptive behaviors.
Frame of reference problem	Intelligent adaptive behaviors cannot be understood by internal controllers in isolation. Embodied behaviors are always a result of system-environment interactions
Intelligence without representation	Symbolic representations and processing is not always required for intelligent adaptive behaviors.
Parallel and distributed processes	Embodied agents have always multiple facets inducing interactions in parallel. Computational processes should reflect these parallel interactions.
Exploiting physical constraints and interactions	Mechanical constraints and dynamics can be exploited for simplifying control and computation. Control and computation can be outsourced when physical interactions are exploited.
Timescale diversity and cross-timescale interactions	Embodied agents obtain dynamics in different timescales, from very fast events such as neuronal spikes, to very slow phenomena such as material deformation and degrading. Exploiting these cross-timescale dynamics provides diversity of intelligent adaptive behaviors.

the locomotion and sensing strategies of insects, birds and soft-bodied animals to achieve robust, adaptive behavior in complex environments. Ants and bees navigate using landmark-based strategies, path integration and pheromone trails rather than building complete maps Collett and Collett, 2002; Srinivasan, 2011. These insects rely on egocentric cues and local environmental features to find food and return to the nest efficiently. Inspired by this, robotic systems have adopted bio-inspired navigation methods such as visual homing, route learning and odor-based path planning Ardin *et al.*, 2016; Schmickl *et al.*, 2021, enabling robust movement in unknown or dynamic environments without requiring full SLAM maps.

Embodied intelligence framework is redrawn from Pfeifer *et al.*, 2007 in Figure 2.1. As shown here, a conceptual landscape of EI research can be structured into three interacting layers: information processing and control, physical body dynamics and morphology and external physical environment Pfeifer, 2006a. These three layers cannot be studied in isolation, as they continuously influence and shape each other. The physical body serves as the critical interface between information pro-

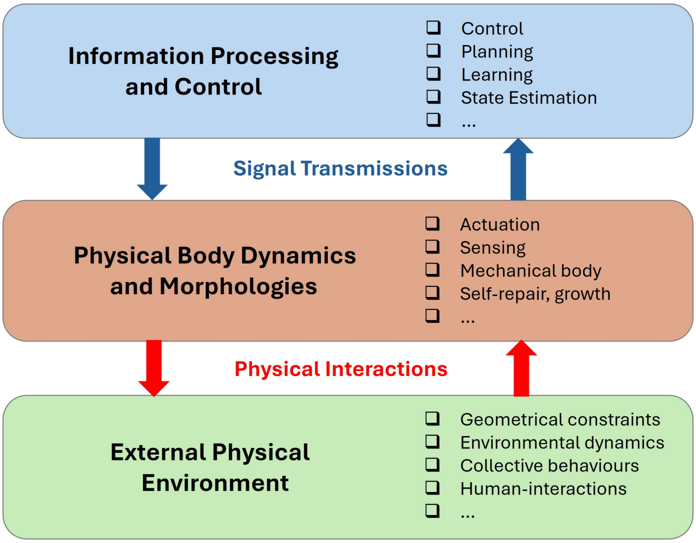

Figure 2.1: Overview of Embodied Intelligence theory, consisting of three-layer processes in information processing, physical body dynamics interacting with tasks and environment. Adapted from Pfeifer *et al.*, 2007.

cessing and physical interactions with the environment. Understanding EI requires examining how these layers interact rather than focusing on individual aspects in isolation. While each subfield presents its own significant challenges and technological complexities, a holistic perspective is necessary to grasp the fundamental principles underlying Embodied Intelligence in the physical real world.

Investigations centre on the interactions between physical systems and their environments across various scales and paradigms. These include molecular interactions Pattee, 2001, mechanical dynamics, energy exchanges Pfeifer, 2006b, brain processes Adami, 2002, DNA computing Adami, 2002 and protein folding Pattee, 2001. Understanding intelligent adaptive behaviors requires acknowledging the physical underpinnings of these processes, rather than reducing them to purely computational or mathematical frameworks Adami, 1998. This shift toward physically grounded models is equally critical in robotics, where embodied systems must integrate sensory input with dynamic interactions to produce adaptive, intelligent behavior.

Biomimetic robots, emulating biological systems—may need to account for contact dynamics to accurately interpret spatial information Evans *et al.*, 2010. Hence, dynamic interaction and probabilistic reasoning Xu *et al.*, 2013 in tactile perception systems lie at the core of adaptive and perceptive robotic platforms. In addition recognising features in human tactile perception related to concepts such as “softness” is key to making use of Embodied Intelligence in robots Abdulali *et al.*, 2024.

2.1.2 Lessons from Self-Orgnization

A self-organizing system operates as structres or patterns without central control, using local interactions to adapt and evolve. Simple individual actions combine into complex collective behavior, shaped by experience and environmental changes Di Marzo Serugendo *et al.*, 2003. More examples towards this can be found from the nature such as stripes on butterfly wings, animal growth, ant trails, antibodies detection and molecules formation. To exemplify, ants solve the complex optimization problem of finding the nearest food sources Deneubourg and Goss, 1989. Instead of performing extensive calculations or holding detailed environmental knowledge, they use a simple strategy: marking paths with pheromones. At crossings, ants follow the strongest scent, which naturally corresponds to the shortest routes—since ants return more quickly from closer sources, those paths accumulate stronger markings. Hence they make use of self-organization rather than cognitive power of each individual.

Herbert Simon in his analogy of “Simon’s Ant” illustrates how such complex behavior can arise from simple rules in interaction with the environment Simon, 1969. This concept highlights the fact that the intelligent and adaptive behaviors exhibited by physical systems cannot be fully explained by focusing solely on the internal mechanisms of autonomous agents. Instead, these behaviors are fundamentally the result of the dynamic interplay between the system and its environment. Ignoring the role of the environment risks oversimplifying and misinterpreting the true nature of intelligent adaptation Beer, 1995; Clark, 1998. Hence what appears as complex, goal-directed activity can often emerge from simple internal rules interacting with a structured environment. By shifting the analytical frame to include both the agent and its surroundings, researchers gain a clearer understanding of the mechanisms that produce adaptive, intelligent behavior.

Self-organization and emergent behaviors can be found across biological and robotic systems, demonstrating how complex structures and patterns arise from simple local interactions without centralized control. Bonabeau *et al.*, 1998 and Petersen *et al.*, 2019 show how insect colonies and robotic systems can self-assemble structures through decentralized mechanisms, while Farkas *et al.*, 2002, Kastberger *et al.*, 2010 and Pasquale *et al.*, 2008 highlight how collective waves, neuronal avalanches and swarm behaviors emerge dynamically in excitable systems. Another perspective is that swarm intelligence emerges from stigmergic interactions and environmental feedback. Drossel and Schwabl, 1992 provide a physical analogy, demonstrating self-organized criticality in fire dynamics, reinforcing the idea that many natural and artificial systems share universal principles of self-organization, adaptation and collective intelligence.

2.1.3 System-Environment Interaction

How external forces and interactions shape system behavior can be demonstrated by dynamical stability, nonlinear mechanics and synchronization phenomena. Kapitza, 1965 and Landau and Lifshitz, 1960 establish foundational principles in mechanics, showing how vibrational forces can stabilize otherwise unstable systems, such as the inverted pendulum. Strogatz, 2000 extend these ideas to real-world collective dynamics, illustrating how pedestrian-induced oscillations on the Millennium Bridge exemplify spontaneous synchronization, linking fundamental physics to emergent behaviors in human coordination.

Understanding synchronization, a principle for coordinated movement, in coupled oscillators is crucial for designing systems where coordinated behavior emerges from individual components Strogatz, 2000. In such systems, each agent follows local rules and responds to its immediate environment, yet a coherent group behavior arises from these distributed interactions. Synchronization and rhythmic motion—seen in both biological collectives and robot swarms—demonstrate how these emergent behaviors are inherently embodied, relying on the physical coupling between agents and their environment to maintain coordination. In such systems, each agent follows local rules and responds to its immediate environment, yet a coherent group behavior arises from these distributed interactions. Synchronization and rhythmic motion—seen in both biological collectives and robot swarms—demonstrate how these emergent behaviors are inherently embodied, relying on the physical coupling between agents and their environment to maintain coordination.

Above studies show that intelligence emerges through physical interactions with the environment, whether in bipedal locomotion, rhythmic motion, biological adaptation, or distributed swarm coordination. Instead of relying solely on computation, these systems highlight how mechanical structure, feedback control and environmental cues shape intelligent behavior in both biological and robotic systems.

2.2 Fundamental Principles of Embodied Intelligence

Initial stages of intelligence refer to foundational mechanisms such as simple computation, reflexive responses and basic learning, which enable systems to process information and act in dynamic environments. Turing *et al.*, 1936 laid the groundwork for computational theory by formalizing the concept of universal computation— a foundation that later influenced both artificial and biological models of cognition. Salomaa, 2014 extended this by developing automata theory, which describes how simple rule-based agents can generate complex behaviors, similar to how EI emerges from decentralized, embodied interactions. Ashar *et al.*, 1992 linked these theories to hardware design and sequential logic synthesis, which are essential for building robotic systems that integrate sensing, learning and real-time control. In Embodied Intelligence , however, these functions are not merely integrated—they emerge from the close coupling between the body, its physical interactions and the environment, highlighting a fundamental shift from centralized planning to distributed, adaptive behavior.

While most studies of embodiment focus on distinct facets of intelligence such as motor control and morphological computation, a shared research challenge across disciplines is to uncover the underlying patterns and structures that enable intelligent behaviors in both animals and machines. Biological systems, for example, exhibit remarkable motion patterns such as the undulatory swimming of eels, the rapid grasping reflexes in primates and the coordinated gait transitions in quadrupeds for efficient locomotion and manipulation Vogel, 2013, self-organize their sensory-motor pathways to develop new skills Bear *et al.*, 2020; Braitenberg, 1986 and adapt their body structures for resilience through developmental processes Mayer, 1943. Similarly, bio-inspired robots have been designed to study sensory-motor dynamics for efficient locomotion Ijspeert, 2014, self-structuring mechanisms for dexterous interactions with robotic hands Hughes *et al.*, 2018 and even the autonomous construction of their own bodies Mazzolai *et al.*, 2014. These examples highlight the rich diversity of behavioral patterns and structural adaptations that form the foundation of autonomy and adaptability in both natural and artificial systems.

2.2.1 Situated, Multi-Purpose and Autonomous Agents

Embodied intelligence is a field dedicated to the study of autonomous agents, which are systems designed to operate independently within the constraints of the real world. The concept of **autonomous agents** was originally proposed in Toda and Crombag, 1982. His framework outlined several fundamental characteristics that these agents should possess. According to Toda, autonomous agents must embody the essential traits of biological systems, including situatedness, redundancy, multi-purpose functionality, self-sufficiency and embodiment. He argued that these characteristics are crucial for understanding the nature of intelligence as it manifests in real-world contexts. In Toda's model, self-sufficiency means the agent can maintain its own functioning without external control or continuous input. For example, it must find food (fungus) to restore energy, manage internal states and respond to changes in the environment autonomously. This reflects how biological organisms survive and adapt through internal regulation and goal-directed behavior.

All biological systems have the ability of surviving in complex environments. This is a hard problem for artificial agents. There are "complete autonomous agents" that can resolve these problems. Toda's "Fungus Eaters" are such complete autonomous agents that are capable of behaving autonomously in an environment without human intervention. The "Solitary Fungus Eater" is a similar creature that has been sent to a distant planet to collect uranium ore. It gets a reward proportional to the amount of uranium it collects. It has a fungus store for energy, wheels or legs for locomotion, means of decision making such as a brain and collection such as arms. It further has sensors for vision and detecting uranium ore. Survival in this environment requires autonomy as it cannot be remote controlled and the fungus eater has to see the world in its own perspective. It further has to be self sufficient in energy and adaptive as the environment is unknown.

An agent is "situated" if an agent is capable of acquiring information through its sensors during the interaction with its environment. A situated agent can interact with its environment without the intervention of a human. While ants and Mars rovers can be considered situated agents, a remote-controlled car is not, as it does not perceive its environment through sensors but is instead directed entirely by a human. **Situatedness** refers to the fact that autonomous agents are physically embedded in the real world. Rather than being idealized or using abstract models, they must operate while accounting for all the complexities and constraints of their physical environments. This includes responding to unpredictable or dynamic situations, which cannot always be perfectly simulated Pfeifer and Scheier, 2001; Brooks, 1991.

Multi-purpose functionality enables robots to perform diverse tasks using the same body, sensors, and control systems by exploiting morphological adaptability, sensorimotor reuse, and body–environment interactions Pfeifer, 2006a; Hauser *et al.*, 2011. Such flexibility allows skills learned for one context to transfer to others, reducing the need for specialized hardware and supporting efficient, adaptive behavior across environments Laschi and Cianchetti, 2014.

The traits of redundancy, multi-purpose functionality and self-sufficiency emphasize the ability of autonomous agents to handle diverse tasks and processes necessary for their survival. These agents should be capable of functioning over extended periods without requiring external intervention, whether from humans or other systems. The

Fungus Eater model illustrates a minimal, hypothetical agent designed to mimic key features of lifelike intelligence. The agent must locate and consume fungus to sustain its energy, driving it to engage continuously with a dynamic environment. It performs multiple adaptive behaviors such as searching, approaching and consuming targets, while also dealing with uncertainty and disturbances. The model emphasizes redundancy—for instance, having overlapping sensory or motor capabilities—enhancing robustness. Crucially, intelligence in the Fungus Eater is not pre-programmed but arises through embodied interaction, where cognition, perception and action are tightly coupled with the agent's physical structure and environmental feedback Pfeifer *et al.*, 1996.

Beer, 1995 approaches autonomous agent behavior and adaptation through a dynamical systems framework, viewing the agent and its environment as a continuously coupled system rather than as separate entities. From this perspective, behavior emerges through ongoing interaction, without reliance on predefined symbolic representations or discrete computational steps. Adaptability, robustness, and the ability to manage diverse tasks are not explicitly programmed but arise naturally from the dynamics of the system itself. This highlights embodiment as more than the physical instantiation of a controller: it is the structural integration of body, environment, and control that enables traits such as redundancy, multifunctionality, and self-sufficiency to support survival in complex, real-world settings.

A similar lesson emerges when considering applied robotics. Analyses of the 2013 DARPA Robotics Challenge revealed persistent limitations in autonomy, particularly in perception, decision-making, and reliance on human intervention Murphy, 2015. Likewise, the Amazon Picking Challenge highlighted the difficulties of integrating perception, manipulation, and learning to cope with uncertainty in unstructured environments Eppner *et al.*, 2018. Both cases reinforce that Embodied Intelligence requires more than high-performing components: it depends on the seamless integration of sensing, action, and adaptation within the dynamics of real tasks. These examples underline the principle that robustness and autonomy emerge not from isolated subsystems, but from tightly coupled interactions across body, environment, and control. Taken together, these theoretical insights and real-world challenges point toward a broader principle: intelligence cannot be separated from the material and physical conditions under which it is realized. This provides a natural transition to considering how embodiment itself—through its constraints and affordances—fundamentally shapes the capacities of autonomous agents.

As a whole, the concept of embodiment plays an essential role in understanding autonomous agents. Embodiment imposes physical constraints such as space, volume, energy availability, weight and the limitations of actuation and sensing. These constraints are critical to developing a realistic understanding of intelligence. Ignoring or compromising on these physical realities risks distorting our comprehension of Embodied Intelligence , as they are integral to how agents perceive, interact with and adapt to the world around them.

By grounding autonomous agents in the principles of situatedness, redundancy, multi-purpose functionality, self-sufficiency and embodiment, we gain a clearer understanding of how intelligence functions in real-world settings. These principles form the foundation for advancing the study and design of truly autonomous, intelligent systems.

2.2.2 Frame of Reference Problem

A crucial principle in the study of autonomous agents is the Frame of Reference Problem, originally introduced by McCarthy and Hayes, 1981. Despite its many interpretations, the core of the Frame Problem is how to keep a model of a continuously changing environment aligned with the real world. Dennett, 1990 illustrates this problem using a robot employing propositional representation.

In essence, the Frame of Reference Problem emphasizes that intelligent adaptive behaviors must be analyzed within the context of system-environment interactions. Autonomous agents do not exist or operate in isolation; their ability to adapt and behave intelligently arises from their continuous interaction with the surrounding environment. For example, the movement of a robot or the navigation of a biological organism is not purely a product of its internal systems (e.g.: its control algorithms or mechanical design). Instead, it is shaped by external factors such as the terrain, obstacles and physical forces acting upon it

Simon, 1969; Beer, 1995; Clark, 1998.

In robotics research, this principle has significant implications. Many studies and theories focus extensively on the design of mechanical components or control systems without giving adequate consideration to the environment in which these systems operate. For instance, in the study of legged locomotion or robotic hand manipulation, designing intricate joint trajectories is insufficient if the robot's interaction with the environment is not properly accounted for. A robot's joint trajectories are not static; they are influenced and ultimately shaped by the external forces and conditions encountered during operation. Raibert's early work on dynamic balance in legged robots Raibert, 1986 illustrates how effective locomotion depends not only on preplanned trajectories but also on active responses to the terrain. Likewise, robust grasping and manipulation require considering the environment's constraints when designing robotic hands Bicchi, 2000.

By neglecting the environmental context, researchers risk designing systems that fail to perform effectively in real-world scenarios. For example, a robot designed to walk on a perfectly flat surface may perform poorly on uneven terrain if its design does not account for system-environment dynamics. Similarly, a robotic hand programmed for precise manipulation in controlled settings may struggle when interacting with objects of varying textures, weights or shapes.

To address the Frame of Reference Problem, it is essential to adopt a holistic approach in the design and analysis of autonomous agents. For instance, rather than isolating control algorithms or hardware components, researchers can integrate environmental feedback loops and emergent behaviors that arise from the agent's real-world context. This means not only optimizing internal mechanisms but also considering the dynamic, reciprocal interactions between the agent and its environment. Such an approach acknowledges that the complexity of real-world conditions often exceeds purely internal computations and that adaptive intelligence emerges from the continuous interplay between internal states and external constraints. By doing so, we can develop systems that demonstrate truly intelligent and adaptive behaviors in real-world conditions. These systems can better handle uncertainty, adapt to changing situations and maintain robust performance over extended periods, reflecting the essence of genuinely embodied and situated autonomy.

2.2.3 Symbol Grounding Problem

The symbol grounding problem addresses how can the semantic meaning of a formal symbol system become intrinsic to the system itself, rather than dependent on the interpretations in our minds Harnad, 1990. In other words, how abstract symbols (like words or internal representations in AI) acquire meaning that is connected to the real world, rather than just being manipulated formally. Harnad framed it as: how can a system's symbols be grounded in sensorimotor experience so they refer to actual objects, events, or states, instead of being mere tokens defined only by other symbols. To overcome this challenge robots require embodiment, allowing them to link symbols with real-world perception and action. Through continuous and rich sensorimotor interaction and social exchange, they will be able to refine these associations and develop intrinsic meanings.

In traditional AI, the meaning of symbols arises from how they are related to other symbols. However, doubts remain about whether such models can truly capture meaning while remaining disembodied from their environment. While traditional systems manipulate symbols without intrinsic semantics, LLMs capture usage regularities that approximate aspects of meaning. When integrated with sensorimotor data—such as vision, action, or embodied interaction—LLMs may serve as a bridge between symbolic representations and grounded experience. However, current models lack sufficient embodiment to fully address this problem.

2.2.4 Dynamical Systems Approach

In Embodied Intelligence research, dynamical systems theory provides a unifying mathematical framework to model and analyze how behavior emerges from the continuous coupling of body, control, and environment. Rather than treating perception, control, and environment as separate modules, this approach emphasizes that cognition arises directly from the evolving dynamics of the whole agent–environment system. Hence cognition is considered as continuous dynamical coupling with environment Varela *et al.*, 2017 and some argue that the cognition is better captured by dynamical systems than symbolic computation Van Gelder, 1998.

Robots and agents can be modeled as coupled dynamical systems with their environments. For instance, dynamical systems have been applied to robot learning, where robots acquire complex motor skills through imitation and adapt them to novel contexts and perturbations Hersch *et al.*, 2008. Similarly, central pattern generator models inspired by biological locomotion demonstrate how oscillatory neural dynamics can be exploited to produce adaptive, efficient movement in robots Ijspeert, 2008. Such studies show that adaptability and robustness are emergent properties of dynamic interaction, not add-ons to preprogrammed control. Hence Robots and agents are modeled as coupled dynamical systems with their environments.

This perspective extends to physical control, where the robot's body and environment are treated as a single nonlinear dynamical system. Milana *et al.*, 2025 identify four dynamical motifs—oscillation, sequence, reaction, and integration—that harness the body's own physics (mechanical rhythms, threshold-triggered state changes, and sensor-free feedback) to realize intelligent behavior with minimal electronics.

A related line of work is reservoir computing, which harnesses the rich internal dynamics of recurrent systems for information processing. While simulated reservoirs (e.g., echo state networks and liquid state machines) highlight how performance depends on internal stability, scaling, and node types Verstraeten *et al.*, 2007, physical reservoir computing extends these principles to the dynamics of actual physical substrates Nakajima, 2020. Here, intelligence emerges by exploiting the body's natural dynamics to transform and store information in time, with only minimal training at the output layer Jaeger, 2002; Jaeger and Haas, 2004.

Taken together, these strands of research demonstrate the fundamental principle of the dynamical systems approach to Embodied Intelligence : intelligent behavior is not imposed from above by symbolic control, but unfolds from the interaction of body, environment, and control as one coupled process. This view challenges the traditional separation between "controller" and "plant," reframing intelligence as a property of the system's dynamics rather than of its computation alone. By exploiting inherent physical properties—such as compliance, oscillation, and memory in materials—robots can offload complexity from centralized algorithms to the distributed body–environment system. As a result, traits such as robustness, adaptability, and context-sensitivity arise naturally from the ongoing dynamics, rather than being explicitly programmed. This makes the dynamical systems approach not just a mathematical formalism, but a design philosophy: to build intelligent robots, one must shape the dynamics of interaction, coupling neural, mechanical, and environmental processes into a coherent whole.

2.2.5 Intelligence Without Representation

This concept was first introduced in a seminal paper by Rodney Brooks in Brooks, 1991, which argued that intelligent and adaptive behaviors cannot be fully explained or achieved through reliance solely on an Internal World Model (IWM) or more generally Internal Representation. Brooks challenged the traditional approach of artificial intelligence that emphasized building detailed internal representations of the world, instead asserting that much of intelligent behavior arises from the interaction between a physical system and its environment Brooks, 1991.

This idea claims that intelligent behavior can emerge from direct sensorimotor coupling without the need for internal symbolic models; hence advocates behavior-based robotics. There are several findings that support this idea. One is that cognition should be understood as situated activity, not symbol manipulation, and demonstrates this with an agent interacting in real time Agre and Chapman, 1987. Secondly, human action is situated and cannot be fully explained by pre-defined plans or representations Suchman, 1987.

One key aspect of this argument is the Frame Problem, which highlights the inherent limitations of symbolically representing all possible physical interactions, from the molecular scale to the astronomical scale. Attempting to capture every detail of the external world in an internal model is not only infeasible but also unnecessary for achieving intelligent adaptive behavior McCarthy and Hayes, 1981; Dennett, 2017; Pylyshyn, 1987.

Another critical insight is that many intelligent behaviors do not require an elaborate IWM. Instead, they can emerge through system-environment interactions, leveraging the inherent dynamics of the physical world. Brooks emphasized that solving every problem by relying solely on brute computational power, such as exhaustive reasoning or simulation within an internal model, is neither elegant nor scalable. Intelligent systems can often achieve effective solutions by exploiting their interactions with the real-world environment in a direct and efficient manner Brooks, 1991; Brooks, 1990; Braitenberg, 1986; Beer, 1995. This aspect is further discussed in section 2.1.3: System Environment Interaction.

This approach allows incremental progression from simple systems to complex autonomous intelligence. At each stage, only a small component needs to be developed and integrated into an existing functional intelligent system. Directly comparing biological and artificial systems offers a promising approach, as each has distinct advantages—biological systems exhibit full functionality, while AI systems provide complete observability Diester *et al.*, 2024. Despite key differences, both share fundamental aspects in their IWMs. One crucial similarity is the role of time dimensions in IWMs, essential for predicting the outcomes of sensory inputs or actions by integrating and evaluating events over relevant time intervals. However, biological neural systems are constrained by sequential planning and limited working memory, whereas artificial systems can encode temporally ordered memory states continuously using long state vectors, allowing for parallel and efficient processing of past events.

Intelligence emerges from the interaction between cognition and the environment, supporting the embodied view that adaptive behavior is grounded in real-world engagement Simon, 1980. This perspective extends beyond the individual, as behavior and tool use actively shape an agent's adaptive potential Dawkins, 2016. Learning over time is crucial in this process—long short-term memory networks enable machines to capture temporally extended dependencies Hochreiter, 1997. To guide such learning, dynamic programming provides a structured way to make optimal decisions across sequential steps Bellman, 1957.

In the age of big data, this debate has gained renewed relevance. While it is true that large datasets combined with Internal World Models can produce non-trivial outcomes, it is important to remember that brute force approaches are not the only path forward. Systems designed to intelligently leverage real-world dynamics and interactions can often achieve more efficient and robust solutions without relying on vast computational resources or overly complex internal representations. This principle highlights the need to complement data-driven computation with insights into the physical embodiment of systems. Instead of relying solely on abstract models, we should exploit how physical form, material properties and environmental interaction contribute to problem-solving. Such systems can be more efficient, require less computational overhead and scale more naturally—aligning with the core ideas of Embodied Intelligence, where intelligence emerges from the interplay between body, environment and control.

2.2.6 Parallel and Distributed Processes

Many hierarchical control methods rely on rigidly arranged modules, leaving little room for emergence since everything is prespecified. To address this, control architectures were reimagined as collections of parallel, loosely coupled processes, each with its own implementation and coordination mechanisms.

Minsky's work from 1980s Minsky, 1986 claims that intelligence emerges from many simple agents working in parallel. Similarly cognition is considered as a distributed activity over simple units, taking place in multiple layers McClelland, 1988. Hence meaning and memory can emerge from networks of simple units. Clark, 1989 and Hutchins, 1995 extend this by highlighting that intelligence is not confined to internal representations but distributed across bodies, environments, and social systems—core principles of embodied intelligence.

An essential characteristic of intelligent adaptive behavior in biological systems is their parallel and distributed nature, evident across all levels of organization. Living organisms consist of numerous subsystems—such as organs, tissues and cells—each operating as a semiautonomous, self-regulating unit. Organs maintain homeostasis, while cells independently manage metabolic processes, replication and repair. These components often perceive and respond to environmental stimuli and, in some cases, exhibit rudimentary memory and decision-making capabilities Gentili and Stano, 2024; Baluška and Levin, 2016. This distributed organization enables robust and adaptive responses without centralized control.

Despite the decentralized nature of these subsystems, parallel distributed systems often exhibit behavior that appears centrally controlled. The system's global behavior emerges from local interactions. For instance, while the human body consists of billions of relatively independent cells, it can respond cohesively to significant external stimuli. This coordination is facilitated by mechanisms such as hormonal signaling, emotional regulation and the propagation of neural or chemical signals across the body. These processes allow distributed components to function as a unified organism, adapting effectively to complex environmental challenges. In the musculoskeletal system, interconnected tendons, muscles, and skin—combined with the inherent passivity of compliant tissues—further support this coordination by distributing loads, damping oscillations, and enabling smooth transitions between tasks without requiring explicit centralized computation.

The parallel and distributed architecture of biological systems also plays a critical role in ensuring redundancy, learning and growth. Redundancy allows biological systems to maintain functionality even when certain subsystems fail. For example, when specific functions or organs are impaired, backup mechanisms or alternative pathways can compensate, enabling an organism to continue operating. Research on plant-inspired robotics to show that intelligence is not exclusive to animals but can emerge from decentralized, material-driven adaptation in plants Lee and Calvo, 2022; Mazzolai *et al.*, 2014. Quantifies how biological cells process information and interact with their environment, reinforcing the role of embodied processes in cellular decision-making Milo and Phillips, 2015.

Distributed learning and information processing further enhance system resilience and efficiency. By processing information in parallel, biological systems can filter noise, adapt to their environments and optimize responses. For instance, distributed networks within the brain allow for imitation learning and accelerate cognitive processes. These networks enable adaptive learning and memory formation, even under noisy or incomplete data Rumelhart *et al.*, 1986; Hopfield, 1982; Kandel, 2001. Building upon these works, neural architectures that rely on interconnected units and parallel processing can adapt to changing inputs in real time, offering a robust mechanism for learning even with incomplete or noisy data. Echoing Bandura's insight into observational learning Bandura, 1977 and Rizzolatti & Craighero's study on mirror neurons Rizzolatti and Craighero, 2004, these distributed networks enable not only imitation but also deeper social understanding by aligning one's own neural patterns with those observed in others, thus fostering empathy and collaborative behavior.

Cellular Automata models, a distributed system that operate without centralized control, relying on local rules to produce global patterns Chopard and Droz, 1998; Wolfram, 2018. This shows how simple, discrete local interactions in cellular automata can lead to emergent complex behaviors.

Rhythmic coordination can be considered as an adaptive mechanism which produce self-sustaining rhythmic movement patterns without continuous top-down control. Strogatz, 2000 establishes the mathematical basis for synchronization using Kuramoto models, which is crucial in decentralized coordination, while Ijspeert, 2008 explores how central pattern generators (CPGs) govern locomotion in both animals and robots. Locomotion is not just movement; it is an intelligent response to environmental constraints Ijspeert *et al.*, 2007.

Central pattern generators (CPGs)—neural circuits that produce rhythmic outputs (e.g.: walking or breathing) without requiring rhythmic input- exemplify how complex motor patterns can be generated through simple, decentralized neural circuits Ijspeert, 2008. Robots which used decentralized control in its control architecture are shown in Figure 2.2. Salamandar robot shown here is decentralized in control, even though it uses central drive signals. The body CPG is implemented as a double chain of 16 locally coupled oscillators, and the limb CPG consists of 4 separate oscillators. These are coupled only locally, not coordinated through a single global controller. The left/right drive sig-

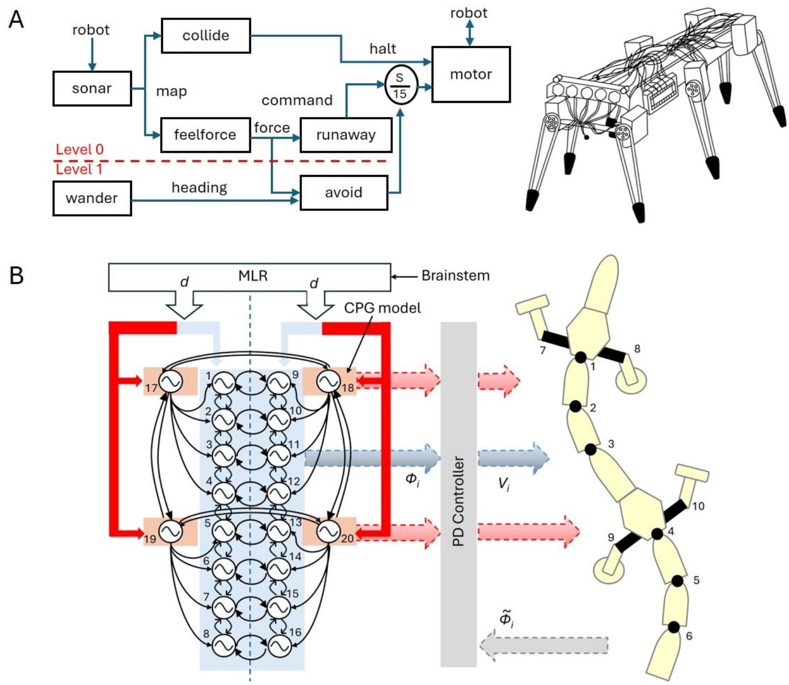

Figure 2.2: Examples of decentralized control for bio-inspired robots A) Genghis, a six legged insect-like robot created by roboticist Rodney Brooks at MIT around 1991 (right). Genghis is a well known platform to study different control strategies of the gait and different algorithms to solve the path-planning in uneven terrains (left). The robot had several sensors: two front whiskers, two inclinometers and six forward infrared sensors. (Adapted from Brooks, 1986. B) Salamander robot (right). The robot is powered by 10 DC motors—six actuating hinge joints along the spine (shown as black disks) and four actuating limb joints (black cylinders). The Central Pattern Generator (CPG) includes a body CPG, structured as a double chain of 16 coupled oscillators for spine control and a limb CPG, consisting of four oscillators for limb control (left). The control model receives left and right drive inputs, mimicking descending brainstem signals, which modulate the robot's speed, direction and gait pattern. Extracted from Ijspeert *et al.*, 2007.

nals (analogous to brainstem output) only set high-level parameters such as speed, direction, and gait pattern, but the actual movement coordination emerges from the local oscillator couplings. Because of the coupling structure, spine and limb motion synchronize without direct centralized computation of each joint's movement. Hence this can be considered as not purely centralized control, but rather a hierarchically modulated, locally coupled (decentralized) CPG system.

Growth is another hallmark of distributed biological systems. Almost all living organisms develop from a smaller, simpler structure into a larger, more complex one. This growth is driven by the replication and coordination of distributed subsystems, such as cells, which divide and specialize while maintaining overall system functionality. The ability to grow and self-organize reflects the adaptive and self-sufficient properties of distributed systems, underscoring their importance in both biological and bio-inspired systems.

The parallel and distributed nature of biological systems not only supports intelligent and adaptive behaviors but also ensures resilience, efficiency and scalability. By understanding how these systems operate cohesively despite their decentralized components, we can draw valuable insights for designing robust and adaptive artificial systems, particularly in robotics and distributed computing.

2.2.7 Exploiting Physical Constraints

When considering highly redundant systems, such as those containing many sensory and motor components, it is often very difficult or expensive to make decisions. For instance, when an arm or leg has many redundant degrees of freedom, a reaching task would have many solutions. In contrast, if the same system has only one degree of freedom, there is one solution, or no solutions at all, in such a case, the decision is much simpler and straight forward Bernstein, 1967; Liegeois *et al.*, 1977. This observation underpins a key principle in Embodied Intelligence: rather than viewing physical constraints as limitations, we can exploit them to reduce computational load and guide behavior. Hence exploiting physical constraints arises from system-environment interactions and this is discussed in detail under section 2.1.3.

Embodied systems have many such constraints because of the physical limitations. Such physical limitations include space, volume, material properties, processing speed, memory capacity and energy budgets. All of these physical constraints are, on the one hand, limitations for functions. On the other hand, the constraints that can be exploited for more elegant and intelligent means to solve problems.

Morphological computing, introduced as the mechanism by which the body, brain and environment are connected Pfeifer, 2006b, addresses redundancy by offloading computation to the body's physical structure. Instead of resolving all redundant options computationally, the body's shape, material properties and passive dynamics constrain and guide behavior. For example, compliant joints or body symmetry can naturally limit the movement space, reducing the number of viable solutions for a task. This simplifies control and decision-making by embedding solutions in the morphology itself—turning redundancy from a burden into an asset Pfeifer, 2006a; Hauser *et al.*, 2011. Thus transforming constraints into advantageous design features.

Carefully choosing materials can harness natural compliance or energy storage for efficient locomotion or manipulation, thereby reducing the need for extensive control algorithms. Standen et al. demonstrate how Polypterus fish, when raised on land, adapt their fin-based locomotion to function more similar to limb-based walking and illustrating how physical constraints—such as terrestrial substrate—drive developmental and behavioral adaptations and changes in musculoskeletal development Standen *et al.*, 2014. This supports Embodied Intelligence theory by highlighting how behavior emerges from dynamic interactions between morphology, control and environment. By viewing constraints as design opportunities, researchers can develop systems that are robust, adaptive and efficient under real-world conditions.

In robotics, soft bodies and compliant structures can similarly process information through their mechanical properties Nakajima *et al.*, 2015. Tensegrity-based locomotion demonstrates how mechanical dynamics serve as a computational resource, reducing reliance on centralized control Caluwaerts *et al.*, 2013. Similarly, spine dynamics in quadruped robots enable efficient control through physical interactions rather than explicit programming Zhao *et al.*, 2013.

While morphological computing and soft robotics offer a powerful strategy by embedding constraints into the body's physical design, there are several complementary approaches that enhance constraint-driven simplification. These help offload or manage redundancy in control and decision-making. One such method is the use of motor synergies, where groups of actuators or muscles are controlled together as a unit, effectively reducing the number of independent variables the system needs to handle d'Avella *et al.*, 2003. This simplification mirrors biological strategies and helps streamline complex motor tasks.

Environmental shaping is also a valuable approach in designing surroundings to naturally limit and guide interactions—further offloads decision-making. By structuring or designing the environment in a way that constrains the system's possible interactions, designers can offload part of the computational burden to the world itself. Passive dynamic walkers are a classic example, using gravity and structure to achieve locomotion without active control McGeer, 1990.

Finally, hierarchical control architectures offer another level of abstraction. These help manage redundancy by introducing layered control schemes. High-level controllers handle strategic decisions while delegating low-level execution to modules that abstract away the redundant details Todorov, 2009. Together, these strategies show that physical constraints—far from being obstacles—can be powerful tools for designing robust, adaptive and efficient embodied systems and these concepts will be discussed in detail in later sections of this chapter.

2.2.8 Timescale Diversity and Cross-timescale Interactions

One fundamental distinction between biological and artificial systems is the ability of biological systems to grow and evolve over time and across generations. Growth and self-replication are essential mechanisms that make biological organisms adaptive, robust and versatile. Without addressing these aspects centrally, it is questionable whether robots can truly be compared to animals in meaningful ways Pfeifer *et al.*, 2007.

Biological adaptation occurs across three timescales:

1. Phylogenetic Evolutionary Timescale: Changes across generations through genetic evolution.

2. Ontogenetic Developmental Timescale: Growth and structural changes during an individual's lifetime.

3. Here-and-Now Learning Timescale: Immediate behavioral adaptation to environmental stimuli.

Embodied systems inherently operate across a diversity of timescales, reflecting the dynamic nature of their physical and chemical properties. Materials and structures degrade or deform over time due to forces such as gravity or chemical reactions. Mechanical structures possess natural frequencies that determine their response to vibrations Haken, 2012; Pfeifer, 2006a. Organic composites, if present, interact with chemicals at varying rates depending on their composition and the nature of the reactions involved Kelso, 1995. Biological processes exemplify this diversity further: protein folding occurs at molecular timescales, neural spike trains propagate signals in milliseconds, hormonal signals operate over minutes or hours, while growth, social interactions and genetic evolution span far longer timescales Kandel, 2001; Varela Francisco *et al.*, 1991.

This intrinsic diversity of timescales is one of the critical reasons of studying embodiment: having an embodied physical structure inherently binds a system to the "laws of timescales" that govern the physical world Iida and Giardina, 2023. Every material and chemical component has its own dynamic nature, yet to achieve stability and consistency as an autonomous agent, these systems must navigate and reconcile the variations in timescale dynamics. Achieving such stability requires finding a compromise between competing timescales and understanding their interactions. This includes addressing cross-timescale dynamics such as coupling, separation and rejection.

Cross-timescale interactions play a pivotal role in the functionality of embodied systems. For instance, timescales can interact for the benefit of an organism, as seen in how evolutionary processes shape learning mechanisms. The gradual process of genetic evolution can lead to more efficient learning processes within individual organisms, enhancing adaptability across generations. Conversely, timescale separation can also be advantageous. For example, an individual must independently acquire knowledge through learning rather than inheriting pre-learned behaviors directly from its parents. This separation allows for flexibility and adaptability, ensuring that each organism can respond to its unique environmental context.

The interplay of timescales in embodied systems, whether through coupling or separation, is a fundamental aspect of their adaptability and resilience. Understanding and designing systems that account for these dynamics are key to creating stable, autonomous agents that operate effectively in the real world. Each subsystem—or even each component—evolves and stabilizes on its own timescale, yet these distinct processes must converge in a coherent whole for the system to function reliably. By properly accounting for the range of temporal dynamics, designers can ensure that fast processes (such as reflexive control) and slow processes (similar to growth or structural adaptation) harmonize, allowing the system to effectively adapt under real-world conditions. Ultimately, understanding and integrating these varying timescales is a key factor in creating stable, autonomous agents that maintain robust operation and learn from their environment over both short and long durations.

Time-scale issues are inherent to any complex hierarchical system, where processes occur at different temporal resolutions—ranging from rapid reflexes to slow planning. In embodied systems, however, the body itself introduces intrinsic timescales that emerge from physical dynamics, such as inertia, elasticity and damping Pfeifer, 2006a. These can be referred to as mechanical timescales.

Unlike purely computational systems, embodied agents can exploit these physical timescales for adaptive behavior. For example, passive dynamic walkers use the natural swing of limbs—driven by gravity and momentum—without active control at every time step Collins *et al.*, 2005. Similarly, compliant actuators and soft materials introduce delays and relaxation behaviors that effectively shape the temporal structure of movement, enabling smoother and more energy-efficient interaction with the environment Kim *et al.*, 2013; Rus and Tolley, 2015.

These embodied timescales reduce the need for fast feedback loops or high-frequency computation by allowing the body to act as a low-pass filter, smoothing inputs and generating rhythmic or oscillatory behaviors through physical means Hauser *et al.*, 2011. This principle is crucial in morphological computation, where physical properties substitute for explicit computation.

In conclusion, the context of Embodied Intelligence, the key distinction is that time-scale interactions are not just architectural but emergent from physical embodiment. In biological systems—and embodied robots—local physical interactions (e.g.: material deformation, passive dynamics) operate at fast timescales and directly influence higher-level behavior without requiring centralized mediation. This tight coupling across time and spatial scales is utilized as a computational and control resource, not just a structural consequence. Further exploration of these ideas, including more detailed discussions of cross-timescale interactions, can be found in Iida and Giardina, 2023.

3

Competing Paradigms and Architectures of Embodied Intelligence

The attempts to understand biological and artificial organisms as autonomous systems have led to the development of various paradigms and architectures, each offering unique perspectives. These paradigms have been explored for different purposes: some focus on mathematical or simulation models to understand animal behaviors, while others employ rigorous physics and engineering models to create functional autonomous artifacts. Regardless of their specific applications, these paradigms provide valuable insights into the nature of autonomous agents. In this section, we introduce several representative models that have been investigated over the years. While this selection is not exhaustive, these foundational approaches can help structure future research in the field.

This section surveys how Embodied Intelligence is realized in time: grouping control, physical, computational and collective strategies into six paradigms: Feedback Control, Sense-Think-Act Paradigm, Behavior-Based Approach, Mechanical Intelligence, Material Intelligence and Human Social Intelligence. How these paradigms are interconnected through different concepts is shown in Figure 3.1.

Robots were initially controlled using feedback control, inspired by

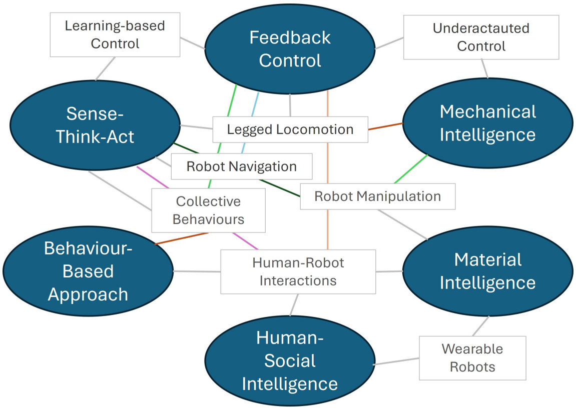

Figure 3.1: Based on the historical timeline and the emergence of key technologies, we identified six control paradigms that have shaped the development of Embodied Intelligence: feedback control, the sense-think-act cycle, behavior-based control, social intelligence, material intelligence and mechanical intelligence. These paradigms have been used to implement the concepts shown in grey, such as learning-based control, robot navigation, collective behaviors and legged locomotion—span multiple categories and these have sometimes been influenced by more than one paradigm as well.

biological reflexes and homeostasis. These systems rely on continuous sensory feedback to correct actions in real time. As tasks grew more complex, control shifted towards the sense-think-act cycle, which separates perception, planning and action into sequential stages—enabling deliberative reasoning and goal-directed behavior.

This was followed by behavior-based approaches, such as Brooks' subsumption architecture and Arkin's motor schemas, which emphasize reactive, real-time interactions with the environment. These approaches emerged to address the limitations of centralized planning in dynamic and unpredictable settings, prioritizing robustness and adaptability over perfect rationality.

To further reduce computational burden and enable more adaptive, embodied interactions, researchers turned to mechanical and material intelligence. These paradigms make use of the physical properties of morphology and soft materials to offload computation—allowing robots to exhibit intelligent behaviors through their structure and passive dynamics alone.

Yet, despite advances in physical intelligence, robots continue to struggle with fluid, context-sensitive interactions. As robots increasingly enter shared spaces with humans, the need for human-level social intelligence has emerged. This includes the ability to infer intentions, read emotions, coordinate nonverbally and adapt behavior based on social norms. Social intelligence in robots draws on principles from theory of mind, affective computing and human-human interaction to enable intuitive, safe and collaborative engagements.

3.1 Homeostasis and Feedback Control

One of the most fundamental paradigms for modeling autonomous agents is homeostasis and feedback control Wiener, 2019. This paradigm draws inspiration from the homeostatic behaviors widely observed in biological systems. These behaviors enable complex organisms to regulate their internal states, such as maintaining a stable body temperature in mammals or ensuring that the number of red and white blood cells stays within an optimal range. Homeostatic behavior can be modeled using a feedback control architecture. In this framework, the system maintains a "target reference state" and monitors deviations from this target. When a deviation occurs, the system reacts by initiating corrective actions to restore the target state. Even with this relatively simple approach, autonomous systems can demonstrate basic self-regulatory behaviors, enabling them to return to stable conditions after disruptions.

Figure 3.2 illustrates the control block diagram for feedback control and model predictive control including system-environment interaction. Similar to traditional feedback control, Model Predictive Control (MPC) continuously adjusts actions based on sensor data. However, unlike basic feedback controllers (e.g.: PID control), MPC predicts future system behavior using a model, optimizing control actions over a time horizon. Hence solves an optimization problem at each step to minimize a cost function while considering constraints. In addition to general components, Prediction Model in MPC predicts the future behavior of the system over a defined horizon based on current state estimates, control inputs and known disturbances. It uses system dynamics to simulate how the system will evolve. Optimizer solves a constrained optimization problem to find the optimal sequence of control inputs

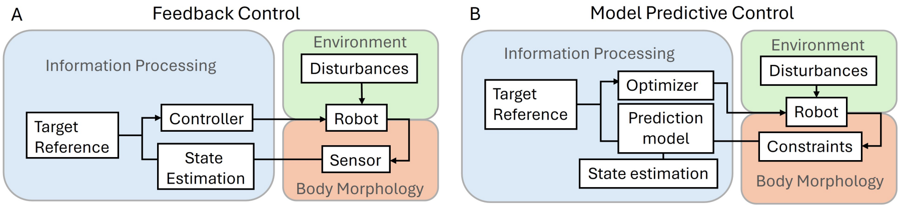

Figure 3.2: Control block diagram for A) feedback control and B) Model predictive control used as an example on control with
the system-environment interaction.

that minimize a cost function (e.g.: , tracking error, energy use) while satisfying system constraints. Only the first input is applied before re-solving at the next step. Together, they enable real-time planning and adaptation, ensuring the system behaves optimally and safely.

This feedback control paradigm can be extended to more sophisticated scenarios. For instance:

1. The system may need to manage multiple combinatory reference targets simultaneously (Multi-objective control).

2. Certain states within the system may be partially or entirely unobservable, requiring indirect methods of regulation such as state estimation using Kalman filter.

3. Goal-oriented behaviors and motion planning can also be incorporated. In these cases, target reference signals are not static but dynamically generated or planned, allowing the system to navigate complex trajectories and adapt to changing environments.

These advanced implementations illustrate how feedback control principles can go beyond simple regulation, enabling autonomous agents to engage in more complex and adaptive behaviors. This paradigm not only explains fundamental biological mechanisms but also serves as a cornerstone for designing artificial systems capable of robust and intelligent autonomy.

Case study: Locomotion

While monkeys display agility in brachiation and cheetahs move with speed, smoothness, and aesthetic grace, robots have achieved far less by comparison. Locomotion is one of the most representative research topics in Embodied Intelligence, which overarches many different paradigms, as shown throughout in this article. Feedback control is used in many locomotion robots including wheeled, legged, or any other modes such as swimming and crawling Geyer and Herr, 2010.

Biomechanics and physical constraints played a crucial role in the development of efficient locomotion strategies. This can go back to several million years where brachiation dynamics was shaped by morphology (e.g.: , arm length), influencing energy efficiency in swinging motion in primates Usherwood and Bertram, 2003. Modelling benthic bipedalism, revealed how simple reinforcement learning and morphology contribute to efficient aquatic walking gaits Giardina and Mahadevan, 2021. This can be seen under water, a different medium where scaling laws for aquatic locomotion Gazzola *et al.*, 2014 highlight how fluid interactions and body mechanics shape efficient swimming. Hence locomotion efficiency emerges from the interaction of body structure, environment a minimal control, a core principle of Embodied Intelligence in both biological and robotic systems. Embodied intelligence in locomotion leverages dynamic adaptations, mechanical compliance and energy efficiency. To improve these strategies, gait optimization strategies Kuo, 2007, exploitation of friction mechanics Radhakrishnan, 1998 and elastic actuators for energy-efficient motion Mettin *et al.*, 2010; Häufle *et al.*, 2012 have been used. Hopping robots with adaptive stiffness demonstrate how dynamically tuning leg compliance allows robots to conserve energy, improve stability, and adapt to varying terrains Guenther and Iida, 2016; Guenther *et al.*, 2019; Vu *et al.*, 2015.

Embodied intelligence makes use of adaptive compliance, passive dynamics and energy-efficient locomotion. Wolf *et al.*, 2015 and Collins *et al.*, 2015 optimize movement via variable stiffness actuators and unpowered exoskeletons. Heglund and Taylor, 1988; Alexander, 1984; Hreljac, 1993 highlight gait efficiency, while Iida *et al.*, 2008 use spring-such as biarticular muscles for dynamic walking and running. Intelligence is deeply embodied in physical constraints, adaptive mechanics and environmental interactions, shaping both biological and robotic movement strategies.

Legged locomotion can be considered as a use case of locomotion and this exemplifies feedback control in action, where sensory information is continuously used to adjust motor output for balance and stability. In both biological systems and legged robots, controllers use joint angle sensors, force sensors and inertial measurements to regulate limb trajectories and body posture. For instance, Boston Dynamics' quadrupeds employ real-time force feedback to stabilize their gait on rough terrain, adapting foot placement dynamically Raibert *et al.*, 2008. Similarly, human walking involves proprioceptive and vestibular feedback to correct for disturbances such as slips or uneven ground Peterka, 2002. Such systems highlight the hybrid nature of locomotion control—combining continuous limb dynamics with discrete foot to ground interactions—where state estimation and feedback laws are critical for maintaining stable gait cycles.

3.2 Sense-Think-Act Paradigm

The Sense-Think-Act paradigm extends the principles of feedback control by incorporating more advanced algorithms or learning mechanisms to "think through" the target values for feedback architectures and is illustrated in Figure 3.3. This paradigm is conceptually associated with the functions of an animal's brain, which involves processes such as memory, representation, decision-making, planning and adaptation to diverse situations. As tasks and environments grow more complex, so do the algorithms and learning methods required to manage them Russell and Norvig, 2016; Arkin, 1998.

A well-known historical example of the Sense-Think-Act (STA) architecture in robotics is Shakey the Robot, developed at SRI International in the late 1960s Nilsson *et al.*, 1984. Shakey was one of the first robots capable of reasoning about its actions and it exemplifies the classical STA model. Shakey's operation was structured in a sequential pipeline: it would first sense its environment using a combination of cameras, rangefinders and bump sensors. This sensory data was then used to up-

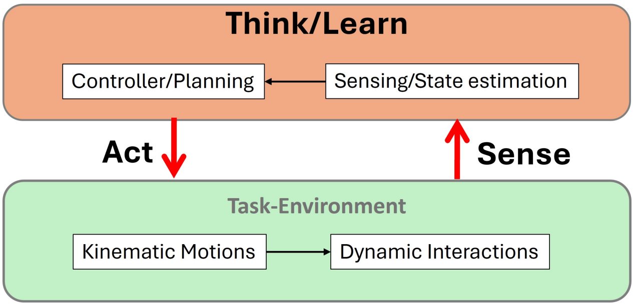

Figure 3.3: Sense-Think-Act paradigm

date a centralized internal representation—a world model—that allowed the robot to localize itself and understand its surroundings. The thinking stage involved complex planning and reasoning. Shakey used STRIPS (Stanford Research Institute Problem Solver), an early AI planning system, to generate sequences of actions needed to achieve high-level goals, such as navigating from one room to another. Finally, in the acting phase, Shakey would execute these planned commands by issuing low-level motor instructions to its drive and steering mechanisms. This architecture allowed Shakey to perform relatively sophisticated tasks for its time, such as navigating hallways, opening doors and pushing objects. However, the system was slow and computationally intensive due to its reliance on a central world model and symbolic reasoning.

At the core of centralized control in the classical Sense–Think–Act paradigm is the notion of an *internal world model* Nilsson *et al.*, 1984; Brooks, 1986. This model encodes the agent's representation of the external environment, including objects, states, and predicted consequences of actions. By consulting and updating a single, unified world model, the control system can plan motor commands, anticipate future states, and coordinate long-term goals. Such a structure enables symbolic reasoning and complex deliberation, making it a powerful tool in controlled, well-specified domains.

However, the reliance on an internal world model also exposes critical limitations. Because all decisions pass through the centralized representation, any error in perception, prediction, or learned dynamics can propagate system-wide, leading to brittle behavior. Furthermore, the computational burden of maintaining and updating a comprehensive world model grows rapidly with environmental complexity, creating inefficiencies and slower reaction times in dynamic, uncertain contexts Russell and Norvig, 2016. These issues are exemplified by the *frame problem* McCarthy and Hayes, 1981, which highlights the difficulty of deciding what knowledge to update in response to environmental change without exhaustive enumeration.

From the perspective of embodied intelligence, these challenges reveal a fundamental tension: centralized control assumes that cognition can be abstracted away into an internal model, while in practice, behavior emerges from the continuous coupling of body, environment, and control. This gap motivates alternative approaches—distributed, reactive, or dynamical systems—that reduce dependence on global internal models by exploiting direct interactions with the physical world.

Learning-based techniques also provide important perspectives in this context. Most mainstream approaches in machine learning and cognitive modeling—such as convolutional neural networks, deep neural networks, and reinforcement learning—treat computation as a simplified, discrete-time input–output process. While this framing has achieved remarkable success in perception, planning, and decision-making tasks, it abstracts away the distributed and continuous-time dynamics that are fundamental to embodied intelligence. These models often operate on static data or discrete sequences, rather than capturing the rich, ongoing interaction between body, control, and environment. This contrast highlights the need for alternative frameworks that integrate learning with physical and temporal dynamics, moving beyond purely symbolic or discrete representations Kober *et al.*, 2013; Nonaka *et al.*, 2023.

Hebbian learning explains how neural plasticity supports adaptive behavior through experience-driven changes in connectivity Gerstner and Kistler, 2002. In the context of Embodied Intelligence, it provides a neural mechanism for bottom-up cognition—where learning arises through continuous sensorimotor interaction with the environment Pfeifer *et al.*, 2014. This aligns with the principle that cognition and behavior are shaped dynamically through the body's engagement with the world. Complementing this, Hauser *et al.*, 2011 show how compliant morphologies can simplify control through morphological computation. Furthermore Loeb *et al.*, 1999 links reflexive and cognitive layers in a hierarchical sensorimotor model for adaptive movement. Together, these works illustrate how learning, embodiment and physical structure jointly give rise to intelligent behavior.

In human–robot physical interaction, tactile sensing is critical—it enables robots to perceive contact forces, adapt their responses in real time, and ensure safe, intuitive, and effective collaboration with humans. This capability bridges physical embodiment and social interaction, allowing robots to respond naturally to human touch, gestures, and shared tasks. Tactile sensing can be considered as a requirement in Embodied Intelligence. Although other sensing technologies are important, tactile sensing takes a special place in EI as it provides information regarding the direct contact between a body and its environment. Schmitz *et al.*, 2011 and Dahiya *et al.*, 2009 advance large-scale tactile sensors for robots, improving spatial awareness and dexterity. Park *et al.*, 2012 develop soft artificial skin with liquid conductors, enhancing sensitive touch perception. Sornkarn *et al.*, 2016 explores morphological computation in haptic sensing, demonstrating how material properties influence perception. These findings contribute to robotic adaptability and sensorimotor integration in Embodied Intelligence. Furthermore, action augmentation in soft-body palpation demonstrates how adaptive tactile feedback improves robotic sensing, a key principle in Embodied Intelligence Scimeca *et al.*, 2022.

ASIMO shown in Figure 3.4 has incorporated a sense-think-act approach through compliant motion control by integrating real-time force sensing, adaptive control a dynamic balancing mechanisms. It enables dynamic walking and human interaction. Equipped with cameras, gyroscopes, accelerometers, and joint sensors, ASIMO was able to gather detailed information about both its environment and its own body state. High-level algorithms were used to plan footsteps, generate walking trajectories, and decide when to switch behaviors such as climbing stairs, avoiding obstacles, or greeting a human. Planned motor commands were transmitted to ASIMO's actuators, coordinating the movement of its legs, arms, and torso. Actions were executed according to precomputed plans, with sensor feedback used for corrective adjustments. At the same time, its limitations—such as difficulty adapting to unpredictable

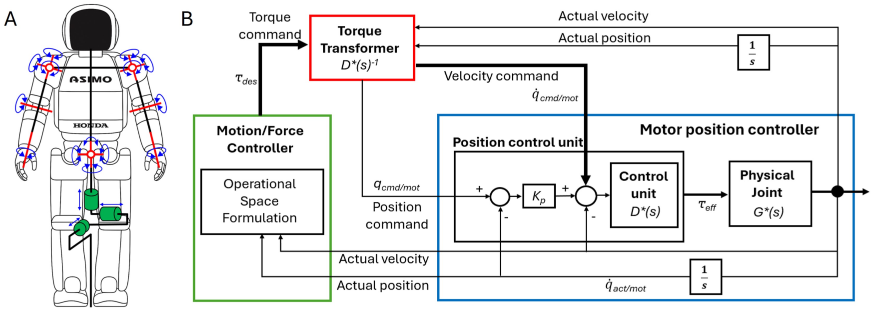

Figure 3.4: A) ASIMO's hierarchical control mirroring biological motor control, with reflex-like responses at the low level and adaptive motion planning at the high level. B) Its control architecture for compliant motion control. It incorporates feedback control to interact with the physical world dynamically, reinforcing the embodied approach to cognition. (Adapted from Yoshikawa and Khatib, 2009).

terrain or unstructured environments—highlighted the challenges of rigidly following a centralized Sense–Think–Act paradigm, in contrast to later approaches based on distributed, behavior-based, or dynamical systems frameworks.

3.3 Behavior-Based Approach

The Behavior-based approach emerged as a response to the limitations of the Sense-Think-Act paradigm Brooks, 1986; Brooks, 1990; Arkin, 1998; Braitenberg, 1986. Inspired by biological systems, which often react quickly and efficiently without complex central control, this approach relies on parallel, simpler reaction circuits rather than a single, centralized world model. It draws comparisons to reflexive behaviors in animals. For instance, human spinal reflexes—sensory-motor reactions governed by neural circuits in the spinal cord—can occur in milliseconds (on the order of 10 milliseconds) and are much faster than more complex behaviors involving cognitive processes, which can take hundreds of milliseconds Kandel *et al.*, 2000.

Brook's subsumption architecture was the first attempt towards behavior-based robotics Arkin, 1998. This is simply the division of a robot's control architecture into a collection of task-achieving behaviors. Here, higher level layers rely on lower level layers to function or in other terms, higher level layers subsume lower level ones. Instead of having a single sequence of information flow, subsumption architecture will include multiple- from sensing, perception to action. Behavior-based control architecture can be simplified and illustrated as in Figure 3.5.

Reflex-based control is another key strategy in Embodied Intelligence for decentralized control. Bekey and Tomovic, 1986 demonstrate that robotic reflex actions enhance adaptive responses to environmental changes, reducing reliance on centralized control. Park and Kwon, 2001 apply reflex-based control to bipedal robots, improving stability and locomotion on slippery surfaces. These works highlight fast, decentralized motor adaptations, crucial for real-world robotic interaction and autonomy.

Despite their simplicity, reflexive behaviors can achieve much more

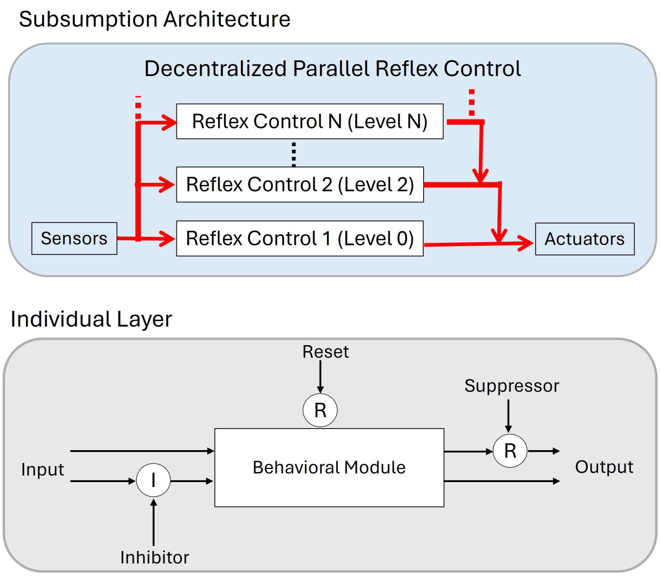

Figure 3.5: Subsumption architecture as a behavior-based approach for robot control. Subsumption architecture is organized in multiple independent layers, each representing a behavior. New layers can be added later without changing the existing ones. A layer can inhibit or be inhibited from receiving sensory input, and it can suppress or be suppressed from producing motor output. each layer is essentially a reflex-like control unit: it directly maps sensory input to motor output. Higher layers combine or override lower reflexes to build more complex behavior. This allows flexible coordination of behaviors while keeping the control structure simple and modular.

when combined, structured and coordinated. This is exemplified by subsumption architectures, which enable complex behaviors such as balance, walking and payload compensation Matarić, 1997; Brooks, 1986. These architectures bypass centralized world models, instead leverage distributed and reactive processes to adapt to complex situations Arkin, 1998. Furthermore, subsumption architectures was the first architecture to fully exploit the principle of parallel, loosely coupled systems. Similarly, spinal reflexes, muscle-based control, and distributed motor adaptation operate on the same principle, making them key strategies in Embodied Intelligence. Pearson, 2000 describe spinal reflex mechanisms essential for adaptive movement. Geyer and Herr, 2010 show that muscle-reflex models replicate human walking dynamics. Marques *et al.*, 2014 explore spontaneous motor activity as a basis for coordinated behavior. Espenschied *et al.*, 1996 demonstrate biologically inspired distributed control, improving hexapod locomotion on rough terrain through local reflexes and adaptive responses.

Sensory-motor coordination, active sensing a whisker-based perception as key strategies in achieving behavior-based perception and control. Pfeifer and Scheier, 1997 emphasize sensorimotor loops as fundamental to adaptive behavior. Diamond *et al.*, 2008 and Mitchinson *et al.*, 2007 show how biological whisker systems integrate “where” and “what” sensing for environmental interaction. Jung and Zelinsky, 1996, Russell and Wijaya, 2003 and Yu *et al.*, 2022 advance whisker-inspired robotic perception, enabling terrain identification, object recognition and roughness estimation for autonomous systems. These examples highlight that perception in embodied agents is not passive reception but an emergent property of active, goal-driven interaction—underscoring active perception as a key mechanism in Embodied Intelligence. Lungarella and Sporns, 2005 introduce the concept of “information self-structuring”, where embodied agents—whether biological or robotic—actively shape their sensory experiences through ongoing sensorimotor interactions. They argue that the continuous coupling between an agent’s body, brain and environment generates statistical regularities in sensory and motor data. These self-generated patterns become structured information streams essential for perceptual categorization, learning and development. They demonstrate how these emergent informational structures can be quantified using information-theoretic measures (e.g.: , mutual information, transfer entropy) in real-world robotic experiments. The key idea is that embodiment itself organizes data, creating rich, learnable input without relying on pre-defined models—thus enabling developmental learning grounded in the agent's physical interaction.

Braitenberg vehicles demonstrated how simple architectures can generate very complex behaviors in the real world Braitenberg, 1986 without cognition. This is shown in Fig. 3.6. By giving a basic "vehicle" just a pair of sensors and a pair of motors, Valentino Braitenberg demonstrated how slight adjustments (e.g.: crossing wires or altering sensitivity of the sensors used) can produce behaviors such as or "thinking", yet in real-world settings, they yield actions that observers may interpret as goal-directed or emotionally driven. This illustrates how even elementary reactive architectures—when properly linked to physical sensing and actuation—can exhibit complex, seemingly intelligent behaviors.

In the framework of Embodied Intelligence, distributed and decentralized control enables intelligent behavior without reliance on centralized

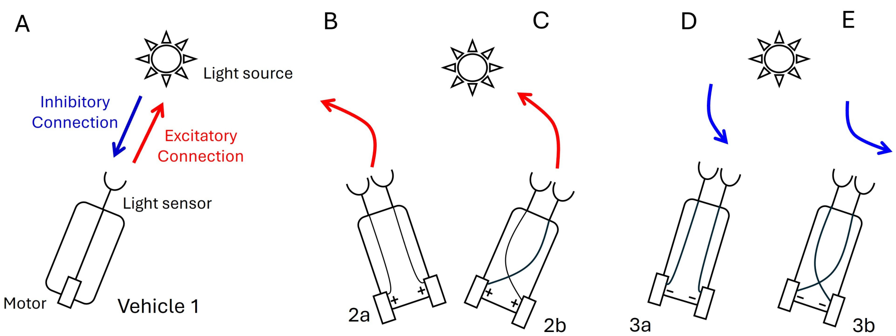

Figure 3.6: Braitenberg vehicles. A) A sensor is connected to the motor and this determines the speed and the forward motion of the motor. B-C) The vehicle has two motors and two sensors. Only the connections differ in vehicles 2a and 2b. Vehicle 2a and 2b in the vicinity of a light source. Vehicle 2b orients itself toward the source while vehicle a orients away from it. Right sensor of a is closer to the light source; hence gets more light. This stimulates the sensor more; hence the right motor turns faster. D-E) The sensors in the vehicles modulate the motors through inhibitory connections. Vehicle 3a turns towards the light source and stops as it gets very close to the light source. Similarly, vehicle 3b moves away from the source at a faster speed as it gets away from the light source.

planning or global representations. This approach is foundational to collective intelligence, where systems composed of many simple agents exhibit emergent capabilities far beyond those of individual units.

A prominent biological example is ant colony foraging, where ants use pheromone trails and local sensing to optimize food collection without a central commander—demonstrating stigmergy as a decentralized coordination mechanism Bonabeau *et al.*, 1999. Similarly, bird flocking and fish schooling exhibit globally coherent motion based solely on local interaction rules, as shown in Reynolds' "boids" simulation Reynolds, 1987, underscoring how spatial-temporal coordination can emerge from simple feedback loops.

Kilobot swarms Rubenstein *et al.*, 2014 and TERMES robots Werfel *et al.*, 2014 showcase how thousands of physically simple robots can achieve tasks such as shape formation and 3D structure building using only local sensing and communication. These systems highlight that intelligence can be encoded in the rules of interaction and the environment, not just internal computation.

This philosophy is also reflected in behavior-based robotics Brooks, 1991, where control is organized as a set of modular, reactive behaviors that map sensory inputs directly to motor outputs. Notably, Brooks' subsumption architecture enabled robots such as Genghis and Allen to exhibit agile locomotion and obstacle avoidance using no global map or planning Angle, 1989. In subsumption architecture, each new module in a robot, e.g: obstacle avoidance, is built on top of existing ones without altering what has already been implemented. Intelligence in such systems is emergent from embodiment and interaction, rather than symbolic reasoning.

The main message from these systems is that intelligence—especially in complex, dynamic environments—can arise from distributed coordination, local perception-action loops and physical coupling with the environment. This stands in contrast to centralized AI paradigms and is especially promising for embodied agents where real-time adaptability is critical.

The behavior-based approach offers feasible solutions for scenarios that require faster reaction times and reduced computational or energy demands, areas where the centralized Sense-Think-Act approach often struggles.

3.4 Mechanical Intelligence

The Mechanical Intelligence approach takes simplicity, efficiency and speed one step further. In this paradigm, physical mechanisms are used as inherent control systems, reducing or eliminating the need for active computational control. A classic example is the pendulum-such as dynamics of legs during walking or running. The natural oscillatory behavior of legs allows them to swing back and forth with minimal active motor control, automatically regulating gait patterns and maintaining stability, even in environments with disturbances McGeer, 1990; Collins *et al.*, 2005. Mechanical intelligence paradigm is shown in Figure 3.7.

Mechanical intelligence encompasses various types of mechanisms that enhance physical properties for adaptive functionality:

1. Passive dynamics and underactuated control: Mechanical structures can generate their own intrinsic mechanical dynamics, because of the momentum, elasticity, passive motions, that can

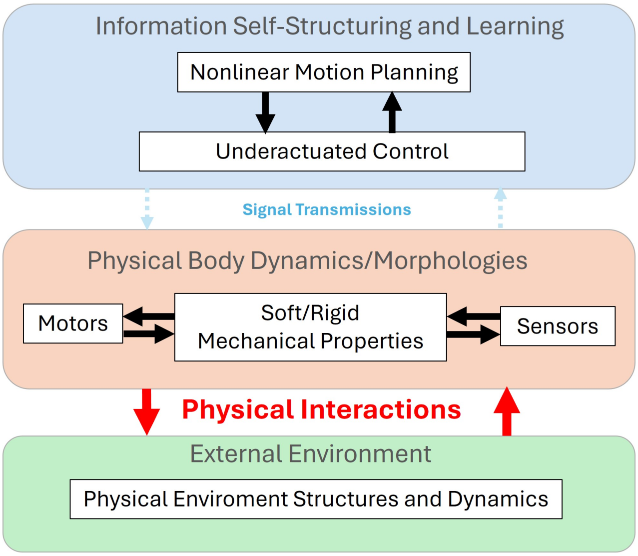

Figure 3.7: Mechanical Intelligence Paradigm

be exploited for various motor functions with significant control simplicity and energy efficiency Collins *et al.*, 2001.

2. Sensor Morphology: Mechanical structures filter, amplify or convert physical stimuli to suitable signal levels, enabling sensors to detect stimuli with appropriate sensitivity or within defined ranges Iida and Nurzaman, 2016. However, depending on the mechanism and morphology, these can be computationally slower compared traditional robots.

3. Musculoskeletal over-redundant systems: Mechanical intelligence refers to how physical structure and material properties contribute to behavior and control. Over-redundant musculoskeletal systems—such as the human arm, which has more muscles than strictly needed for joint DOFs—exemplify this. These systems enhance robustness, versatility and control flexibility by allowing multiple muscle activation patterns to achieve the same outcome. This redundancy enables local reflexive control and energy-efficient movement without centralized computation, aligning it with morphological computation. Over-redundancy contributes by enabling distributed compliance and task-dependent coordination, where control is shared between muscles, tendons a neural feedback loops, reducing the computational burden on the brain Valero-Cuevas, 2009. Thus, it represents a structural substrate for embodied mechanical intelligence.

Exploring how physical structures, biomechanics and control mechanisms shape adaptive motion and evolutionary dynamics in both biological and robotic systems can open up more paradigms of Embodied Intelligence. Evolution plays a fundamental role in shaping Embodied Intelligence by influencing how organisms—and, by extension, intelligent robotic systems—develop cognition, behavior and physical structures that are adapted to their environment. Quantitative frameworks have been introduced for measuring evolutionary rates, highlighting how biological intelligence evolves through incremental adaptations Haldane, 2022.

The acquisition of embodied skills can be acquired through human motor learning in dynamic conditions. The study on the mechanics of swinging, focusing on how individuals can increase their amplitude through coordinated body movements Jones, 1919 is a perfect example for this. By synchronizing movements with the swing's natural frequency, individuals effectively utilize their body's dynamics to achieve a desired outcome, exemplifying how physical interaction with the environment can lead to intelligent behavior. Compliant leg behavior explains fundamental walking and running dynamics, demonstrating how movement is shaped by body-environment interactions Geyer *et al.*, 2006. Investigations on human balance control using a time-delayed inverted pendulum model emphasize the role of feedback in stabilizing movement Milton *et al.*, 2009 where the nervous system employs an adaptive control mechanism, allowing small deviations to occur and making active corrections only when these deviations exceed a certain threshold. This approach highlights a form of passive control that arises from the interplay between delayed responses and environmental noise. Simple mechanical systems further contains intricate dynamics that can include periodic, quasi-periodic and chaotic behaviors Holmes, 1982.

In the context of Embodied Intelligence, appropriate mechanical design can lead to stable and adaptive behaviors. This simplifies the requirement of external computation for solutions. Blind Jugglers are robotic systems that perform juggling without visual or sensory feedback. Their design relies on carefully tuned open-loop dynamics to achieve passive stability. Remarkably, they can juggle balls at heights up to 2 meters purely through mechanical timing and coordination, demonstrating that adaptive control can emerge from exploiting system dynamics rather than relying on active sensing Fontana *et al.*, 2013. Stability is achieved through mechanical properties and open-loop control strategies through careful design of a system's physical characteristics Reist and D'Andrea, 2012. The rhythmic feedback control system for a robotic juggler shows that rhythmic entrainment and mechanical predictability can lead to Embodied Intelligence Ronsse *et al.*, 2007.

Soft robots, passive dynamic walkers and sensor morphology represent key pillars of mechanical intelligence: leveraging advanced materials for adaptability, optimized structures for energy-efficient motion and embedded sensors for precise feedback and interaction. These aspects highlight how physical properties and integration can reduce reliance on complex control systems while enabling robust, autonomous behavior. Examples in this context are shown in Figure 3.8A and B.

Case study: Underactuated Systems and Passive Motion

Embodied intelligence benefits from underactuated mechanical systems, where intelligence emerges from physical constraints rather than direct control Spong, 2005. Studies have considered human walking as an energy-efficient inverted pendulum system Kuo *et al.*, 2005 where human

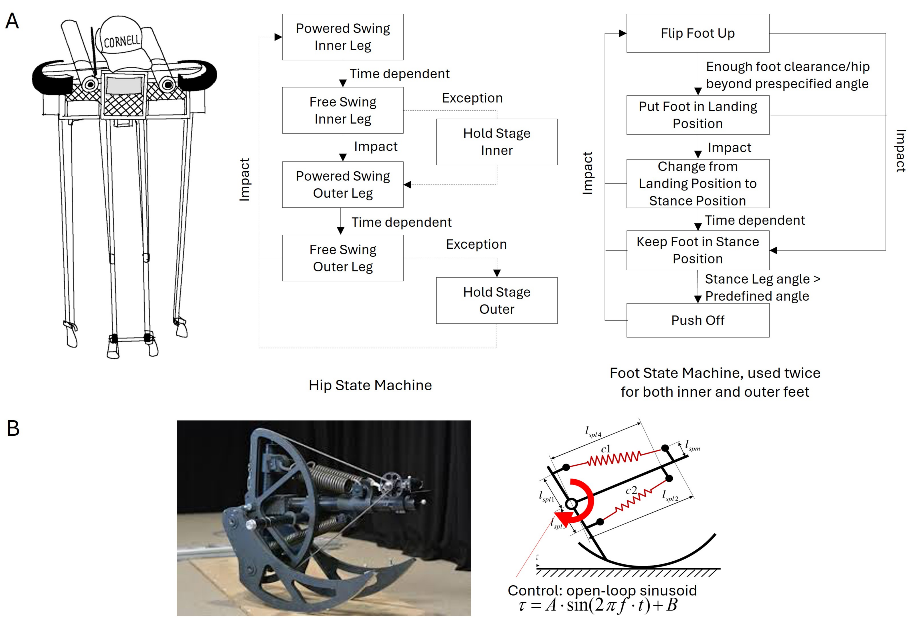

Figure 3.8: Examples of passivity-based control for locomotion robots A) Ranger, four-legged biped robot developed by Cornell University is a passivity-based bipedal robot capable of energy-efficient walking (left). Three separate state machines: hip state machine and 2*foot state machine were used in the robot at the walk controller level (right). Having multiple state machines in this robot reduced the total amount of states. Adapted from Cortell *et al.*, 2008 B) CARGO, heavy payload carrying hopping robot (left). This 30 kg robot can carry payloads up to 150 kg with minimal adjustments to its open-loop control (right), primarily due to the parallel elastic actuation system, which uses four robust springs to suspend the load. Adapted from Guenther and Iida, 2016.

gait naturally follows passive mechanical principles, an essential concept for energy-efficient robotic locomotion.

Passivity-mimicking control laws enable bipedal robots to achieve natural, efficient locomotion Goswami *et al.*, 1997, passive dynamic walkers McGeer, 1990; Collins *et al.*, 2005, low-power reflex-based walking Bhounsule *et al.*, 2014 and simplified dynamic walking model exist where intelligent movement can emerge from body dynamics alone Garcia *et al.*, 1998; Collins *et al.*, 2001. Such systems inform the design of robots that move in a biomechanically optimal way rather than relying on computationally expensive controls. These studies collectively show that intelligence in motion arises from physical properties, passive dynamics and adaptive control, rather than relying solely on computation.

3.5 Material Intelligence

In the framework of Embodied Intelligence , the role of a robot's physical body is not merely passive but actively contributes to its behavior and control. Materials intelligence refers to the capability of materials and physical structures to participate in sensing, actuation and computation—effectively distributing intelligence across the body, rather than centralizing it in a controller.

This concept is exemplified by three emerging classes of robots:

1. Soft robots: make use of compliant, elastomeric materials to achieve continuous deformation, allowing them to navigate unstructured environments and interact safely with humans Kim *et al.*, 2013. These robots embody intelligence through material elasticity and distributed actuation, reducing control complexity and enabling proprioceptive feedback via body deformation.

2. Chemical robots: these robots including edible and metabolically powered robots, utilize biodegradable, biocompatible materials or embedded chemical systems for locomotion, sensing, or energy generation Sharova *et al.*, 2021; Miriyev *et al.*, 2017. These systems encode function into their material substrate, allowing energy autonomy or task-specific biodegradability—critical for medical, environmental and swarm applications.

3. Bio-hybrid robots: integrate living cells or tissues (e.g.: , cardiomyocytes or skeletal muscle) with synthetic scaffolds to create robots capable of growth, healing and adaptation Cvetkovic *et al.*, 2014. These systems blur the boundary between artificial and biological intelligence, leveraging cellular activity for actuation, control and learning in ways conventional machines cannot achieve.

Together, these robot classes represent a shift from rigid, centralized systems to distributed, material-embedded intelligence—redefining what it means for a machine to be "smart" by design.

Material intelligence paradigm is most clearly exemplified in soft robotics, where compliant, deformable bodies made from elastomers, gels, or other flexible polymers enable robots to adapt to unstructured environments and interact safely with humans Kim *et al.*, 2013. These robots exploit their mechanical properties to achieve functions such as gripping, locomotion and shape transformation without complex control algorithms. For instance, a soft gripper can conform to diverse object geometries by passive deformation, reducing the need for high-precision sensing and planning Rus and Tolley, 2015.

Intelligence in soft robotics manifests through adaptive shape, functionality and mechanics, emphasizing responsiveness to environmental changes via tailored design and computational strategies Kortman *et al.*, 2024. By harnessing the physical dynamics and properties of materials and structures, the mechanical intelligence approach enables systems to adapt their behavior directly through morphology—without requiring complex control. This form of embodied adaptation allows for faster, cheaper and sometimes simpler solutions than behavior-based methods, demonstrating how physical design itself can support intelligent, real-time adaptation in changing environments.

Series elastic actuators (SEAs) improve force regulation and adaptability in robotic systems Pratt and Williamson, 1995. By integrating high-compliance SEAs, robotic legs achieve more efficient and robust locomotion Hutter *et al.*, 2012. In human-robot collaboration, safe physical interaction relies on compliance and reflex-based control to prevent injury Haddadin and Croft, 2016. These findings highlight how soft actuation and controlled elasticity enable adaptive, safe and intelligent robot behavior.

Smart materials further extend this idea by integrating actuation and sensing capabilities into the material itself. Examples include shape memory alloys, dielectric elastomers, liquid crystal elastomers and piezoelectric polymers, which respond to stimuli such as heat, light, or voltage. These materials allow robots to morph, self-heal, or adapt autonomously—pushing the boundary between structure and function Miriyev *et al.*, 2017.

Beyond materials, mechanical intelligence—the use of carefully designed passive structures to simplify control—also plays a role. Examples include spring-loaded joints, bistable elements, or geometrically tuned limbs that exploit morphological computation to stabilize walking or enable energy-efficient movement Pfeifer *et al.*, 2007. These mechanisms reduce computational overhead by embedding intelligence in physical form.

Together, materials and mechanical intelligence highlight a shift in robotics from top-down control to distributed, body-centric intelligence. This not only leads to more robust and adaptive systems but also aligns with biological principles, where form and function co-evolve.

3.6 Human Social Intelligence

Human social intelligence arises from the interplay between the physical body, cognitive processes, and societal embeddedness. In the context of embodied social human–robot interaction (HRI), these same three dimensions provide a framework for analyzing and replicating humanlike features in robots.

1. **Embodied physical interaction:** the physical body plays a fundamental role in social interaction. For humans, the body provides the means to perceive, act and communicate through gestures, facial expressions and spatial positioning. Physical presence in robots increases user trust, engagement and the perceived social presence of the robot Wainer *et al.*, 2007. The robot's morphology—shape, size and movement—contributes to its social legibility, making its actions interpretable to human partners Dragan *et al.*, 2013.

Embodied interaction supports grounded, real-time exchanges, where meaning is co-constructed through shared perceptual and physical contexts Pfeifer, 2006a; Dautenhahn, 2007.

Human social intelligence is deeply rooted in embodied interactions and cultural learning. A fundamental mechanism supporting this development is imitation learning—the process by which individuals acquire new behaviors by observing and replicating the actions of others. Early imitative behaviors are central to the acquisition of social and linguistic skills, suggesting that human communication is inherently grounded in embodied social learning within cultural contexts Tomasello, 2009.

Communication in biological organisms is fundamentally embodied. From facial expressions and gaze to haptics and body posture, humans use a rich variety of physical cues to convey meaning, emotions and intent Pearson *et al.*, 2019; Levinson and Holler, 2014. These nonverbal cues are not mere supplements to language but serve as primary communication channels in many social situations Fitch, 2000. Similarly, animals such as dolphins, birds and primates use coordinated motion, gesture and touch to maintain social bonds and coordinate group behavior Moreno and Macgregor, 2019; King and Janik, 2013.

A striking difference in robot-human communication lies in their respective sensorimotor capacities. Robots can acquire multiple gigabits of raw sensory data per second via high-resolution cameras, LiDAR and tactile sensors, yet often lack the computational bandwidth to process this input efficiently and meaningfully in real time. Conversely, humans process sensory data at a modest rate (around 1 MB/s), but this input is refined through layers of adaptive perception, attention and cognition developed through evolution. Similarly, robot actuators can operate rapidly, generating outputs at rates near 500 b/s, while human motor output is comparatively slower. However, the richness of embodied human actuation—supported by evolved musculoskeletal dynamics and predictive control—enables expressive, context-aware behavior that robots struggle to replicate Fitch, 2000; Pfeifer *et al.*, 2007.

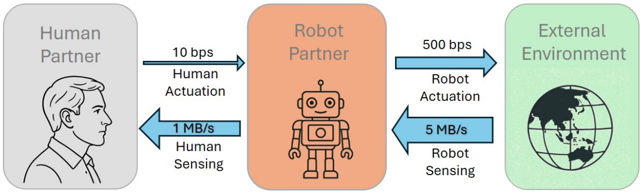

Figure 3.9: Human-Robot Interaction Paradigm

This idea is illustrated in Figure 3.9.

2. **Embodied cognition:** Cognitive processes refer to the robot's internal mechanisms for perceiving, reasoning and responding in social contexts. This includes social attention, learning, memory and theory of mind capabilities. For effective HRI, robots must recognize human intentions and adapt their behavior accordingly Scassellati, 2002. Mutual predictability in joint actions arises when robots model human beliefs and expectations, thus enabling smoother and more natural interactions Dragan *et al.*, 2013. Grounding robot cognition in sensorimotor interaction cycles enhances its capacity for social adaptation and coordination Barsalou, 2008; Vernon *et al.*, 2007.

   Neurologically, imitation learning described above, is supported by mirror neuron systems, which activate both when performing an action and when observing the same action performed by others Rizzolatti and Craighero, 2004. This shared activation underpins our ability to infer others' intentions and emotions—an essential component of theory of mind. The associative sequence learning model Heyes, 2010 further explains how Hebbian learning reinforces these mappings over time, making social perception more intuitive and automatic.

   In robotic systems, communication has historically relied on speech or text, but recent developments have emphasized the potential of multi-modal, embodied communication.

3. **Societal embeddedness:** societal embeddedness concerns the cultural, ethical and relational dimensions that shape social behavior. Humans act within social roles and shared norms; robots

operating in such environments must navigate expectations around politeness, authority, group membership and emotional appropriateness Tennent *et al.*, 2019. Social robots gain acceptance by embodying context-appropriate behaviors and maintaining social bonds over time Leite *et al.*, 2013. This includes participating in rituals, respecting boundaries and adapting to shifting group dynamics Fong *et al.*, 2003; De Graaf *et al.*, 2015.

Together, these three dimensions—body, cognition and society—form a framework for understanding and designing robots as socially embodied agents. Hence their intelligence emerges not from isolated functions but from their integration into embodied, cognitive and cultural systems of interaction.

Over the past two decades, the development of robots has revealed key insights into what enables meaningful human-robot interaction. Among them embodiment Wainer *et al.*, 2006; Sirithunge *et al.*, 2023, context-awareness Breazeal *et al.*, 2016, nonverbal cues Lakatos *et al.*, 2014, requirement of clear clarity of robots' role Forlizzi and DiSalvo, 2006, consideration of individual and cultural differences Sirithunge *et al.*, 2024a; Bartneck *et al.*, 2005 play an important role in developing capable robots that are accepted for long-term interaction.

Case study: Applications of Embodied Social Interactions

Embodied social cognition in robotics therefore not only enhances communication efficiency but also opens new avenues for adaptive, trust-building and resilient interactions in complex environments. By physically grounding social cues, robots can engage more naturally with human partners, moving from command-based interaction to fluid, shared experiences Darling, 2016; Dautenhahn, 1997. Bridging the human-robot gap begins with abstracting key design principles that prioritize functional distinction over humanlikeness, fostering ethical and behaviorally acceptable diversity in social environments Sirithunge *et al.*, 2024b; Sirithunge and Dahn, 2023.

A recent example for this type of human-robot interaction is "robopatient", which is shown in Figure 3.10. It allows clinicians or robots to

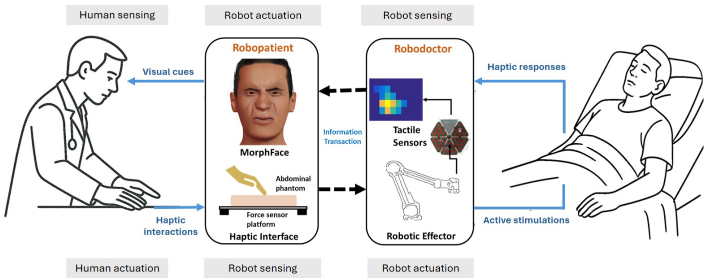

Figure 3.10: Example of Human-robot interaction in a robotic patient: RoboPatient. Adapted from Lalitharatne *et al.*, 2022.

practice diagnosis via palpation. Robopatient is a face-mediated human–robot interaction system designed to enable remote palpation through a multimodal, closed-loop interface. The system architecture integrates four principal entities: a physician, a robopatient, a robodoctor and a human patient.

The patient's reactive responses, emerging from complex sensory, musculoskeletal and cognitive systems, are recorded through high-resolution tactile sensors embedded in the robodoctor. These high-dimensional sensory data are relayed to the robopatient, a robotic facial interface responsible for translating the raw haptic information into socially and emotionally meaningful expressions. To achieve this, a face morphable robotic face was used, synthesizing visual feedback through facial Action Units (AU) based on Ekman's facial action coding system (FACS). These facial expressions serve as an embodied communication channel that bridges the physical experience of the patient and the physician's perceptual-motor loop. The physician interprets the expressions of the robopatient in real time, modulating palpation strategies through an internal model that accounts for context, hypothesis-driven diagnosis and embodied understanding of human responses. This loop enables intuitive, fine-tuned adaptation to patient cues despite physical separation. In addition to serving as universal patients, such robots enable grounding of physical-cognitive hybrid concepts such as "pain" and support the study of human embodiment.

Beyond functional interaction, robots are increasingly capable of expressing immersive art and human emotions Nadipineni *et al.*, 2025.

Human-robot orchestration in musical performances Schofield *et al.*, 2024 exemplifies new, affective pathways for connecting with people—expanding how robots engage audiences beyond traditional task-oriented roles.

4

Discussions and Perspectives

This review focuses on the fundamental principles of Embodied Intelligence from the perspective of robotics research. However, it is important to acknowledge that numerous principles, paradigms and concepts have not been included in this discussion but have contributed to shape the study of Embodied Intelligence.

4.1 Biological Principles and Bio-Inspired Robotics: Missing Paradigms and Cross-Paradigm Architectures

Biology and robotics share a uniquely symbiotic relationship in the Embodied Intelligence research. Robotics often draws inspiration from nature to improve technological systems, while engineering methods in robotics provide novel tools and perspectives for studying biological systems. This interdisciplinary approach, often referred to as biologically inspired robotics, underpins the field of bio-robotics, where the feedback loop between biology and robotics research drives innovation and understanding. Recent work continues to harness robotics as a means to investigate biological systems using insect navigation and sensorimotor systems Lu *et al.*, 2025, primate anatomy Gilday *et al.*, 2025 and paleontology Ishida *et al.*, 2024.

While this article introduces a broad overview of Embodied Intelligence for robotics research, it is inevitably incomplete. The principles and paradigms presented here form a preliminary and evolving landscape, not an exhaustive framework.

With the expansion of human-robot interaction, inclusion of "human factors" plays an important role in the study of Embodied Intelligence. Humans are different from other animals because of their complex behaviors, social structures, memory capacity and advanced information processing. Hence embodiment has a multifaceted role in enhancing the proactive capabilities of robots Sirithunge *et al.*, 2024b. This area, termed "Embodied Social Intelligence", explores imitation learning, human-in-the-loop control, human-robot interactions and cooperation. These areas are fundamental to expanding the scope of Embodied Intelligence research.

Another emerging area of interest is *Bio-hybrid Robotics*, including innovations such as Xenobots Pai *et al.*, 2024 in synthetic biology. These technologies merge biological and artificial systems, offering new perspectives on adaptive intelligence. This work extends to concepts such as "Extended Phenotype", where intelligence is augmented through tools and external structures, to entirely new species of bio-hybrid systems. Such developments could redefine our understanding of intelligent adaptive systems. Furthermore, "growing systems"— robots that physically grow, extend, or reshape their bodies— offer a novel approach to addressing key challenges in adaptability, autonomy and environmental interaction. Unlike fixed-morphology robots, growing systems dynamically change their embodiment, allowing the body itself to participate in problem-solving.

Unconventional computation models, often referred to as nature-inspired or natural computing, provide alternative perspectives on how information can be processed in embodied systems. *Cellular automata* are one such example: they treat space and time as discrete, updating the states of cells synchronously according to simple transition rules. Despite their simplicity, cellular automata can generate highly complex patterns of behavior. Conway's Game of Life Gardner, 1970 illustrates this, demonstrating computational universality while modeling phenomena such as communication, growth, reproduction, and evolution. These models resonate with embodied intelligence by showing how simple, locally applied rules can produce emergent, system-level intelligence without centralized control.

Another form of *natural computation* is neural computation in humans and animals. The nervous system integrates perception, action, and adaptation through continuous sensorimotor loops, rather than abstract input–output mappings. Although neural computation has inspired artificial neural networks, in the context of embodied intelligence the focus shifts to how neural processes are coupled to bodily morphology and environmental dynamics Clark, 1998; Beer, 1995. Furthermore, the study of *evolutionary systems* highlights natural computation across much larger timescales. Evolution can be seen as a computational process that "searches" through the design space of morphologies and behaviors, optimizing agents for survival in dynamic environments Fogel, 2006; Pfeifer *et al.*, 2007. In embodied robotics, evolutionary algorithms and artificial life approaches exploit this principle to automatically generate adaptive, resilient behaviors. However, these remain underexplored in the field of embodied intelligence.

4.2 Robotics Complexity Challenges

The history of robotics has been marked by progressively increasing complexity. Early robots, such as mechanical automata Neumann, 1966 and Karakuri Masao, 2001, evolved into systems incorporating electric motors and sensors, followed by digital control and computation. Despite this impressive progress, robots today remain far less complex than biological systems.

Measuring or comparing complexity across systems is a non-trivial challenge. However, consider that an adult human body contains approximately 10^{13} cells, several million times more components than the most sophisticated man-made systems, such as the Airbus A380 Iida and Giardina, 2023. This comparison highlights the limitations of current robotics technology.

The theory of Embodied Intelligence posits that intelligence arises from the interaction between brain, body and environment, emphasizing physical grounding and sensorimotor coupling as central to cognition

Pfeifer *et al.*, 2007. This contrasts with traditional AI paradigms that often rely on abstract symbol manipulation or disembodied data processing.

Modern AI—particularly with the rise of large language models and deep learning—has achieved remarkable success in tasks such as language, image generation and planning. However, these systems often lack grounding in physical experience, resulting in limitations in adaptability, generalization and robustness in the real world Lake *et al.*, 2017; Brooks, 1991. EI offers a pathway to mitigate these issues by embedding AI systems in bodies that can interact with and learn from the environment through real-time feedback loops Mengaldo *et al.*, 2022.

Combining EI with modern AI leads to embodied AI, where learned representations are informed by action and perception. For instance, recent work integrates reinforcement learning with physical simulation or robotic platforms to train agents that learn behaviors grounded in physical tasks Andrychowicz *et al.*, 2020. Soft robotics and morphological computation further enhance this synergy, using the body's physical dynamics to offload computation and simplify control Hauser *et al.*, 2023.

This hybrid approach allows AI to benefit from the evolutionary efficiency of biological systems while maintaining the flexibility and scalability of data-driven models. It supports richer models of social interaction, autonomy and sensorimotor learning in complex, uncertain environments. Furthermore, advancing Embodied Intelligence will require a significant leap in both technological capabilities and theoretical understanding to bridge the complexity gap between artificial and biological systems.

4.3 Implications and Applications

While this article primarily discusses the foundational principles of Embodied Intelligence , the field has significant implications for real-world applications. Autonomy and adaptability remain challenging for conventional engineering approaches. Although recent advances have been made in areas such as factory automation, autonomous aerial and underwater vehicles and autonomous driving, many challenges remain, especially in tasks that require higher levels of autonomy and adaptability.

Examples of such challenges include:

1. Specialized vs General-Purpose Systems: A core challenge in Embodied Intelligence is balancing task-specific embodiment with the flexibility of general-purpose robots. Specialized robots often achieve remarkable efficiency by tailoring their morphology and control to a particular task—e.g.: , a soft crawling robot mimicking a worm's locomotion. However, such embodiment limits adaptability across diverse tasks. General-purpose robots, by contrast, require abstract control strategies and adaptable morphologies that can embody multiple functions without sacrificing efficiency. Designing reconfigurable or material-adaptive bodies remains a major hurdle for embodied generality.

2. Human-in-the-Loop vs Fully Autonomous Systems: Embodied intelligence emphasizes distributed, sensorimotor-driven behavior, yet achieving robust autonomy without human oversight remains difficult. While humans can provide adaptive, high-level correctionns, especially in physical HRI, the long-term goal of fully autonomous embodied systems remains a challenge. Such systems must sense, interpret and act on environmental cues using their bodies, often in unpredictable or noisy contexts. Building robots that can autonomously reorganize their behavior using embodied feedback—such as humans adjusting gait on ice—is still largely unresolved.

3. Cyborgs, Synthetic Biology and Inorganic Robots: Each of these domains proposes different material instantiations of Embodied Intelligence , yet all face open questions. Cyborg systems grapple with long-term integration and mutual adaptation between biological and robotic components. Synthetic biology robots promise metabolic intelligence, but lack scalability and controllability. Inorganic soft robots excel at passive adaptation but struggle with autonomy and complex decision-making. Creating physically intel-

ligent systems that combine the adaptability of biological tissue with the predictability and scalability of synthetic systems is a central challenge moving forward.

Beyond the above, several long-term challenges remain in the following research areas.

- Tedious, repetitive tasks in cleaning, washing, or harvesting, which are still performed by human laborers despite being unfavorable. These tasks often require context-specific adaptations, fine motor skills and the ability to function in dynamic, unpredictable environments—areas where Embodied Intelligence can offer more flexible and responsive solutions than rigid, pre-programmed systems.
- Unstructured environments, such as forests, construction environments, search-and-rescue missions or operations in disaster zones, where robots must deal with unknown terrain, debris, or hazardous conditions. Conventional control systems struggle in these settings, whereas Embodied Intelligence supports robots that can adapt their movement and behavior in real time, leveraging their physical form and sensory feedback to navigate and act effectively.
- Medical and healthcare applications, where safe and trustworthy human-robot interactions are critical. These include assistive technologies, rehabilitation robotics, or surgical support systems. Embodied intelligence enables robots to interpret nuanced human cues, respond gently and appropriately to physical contact and operate safely in close proximity to humans—key factors for acceptance and effectiveness in sensitive care settings.

The principles of Embodied Intelligence offer potential solutions to these challenges, providing new frameworks for addressing problems that conventional robotics paradigms have struggled to solve. By advancing this field, researchers can contribute to developing systems capable of operating autonomously and adaptively in complex and dynamic environments.

4.4 Conclusions

Embodied intelligence offers a transformative lens through which to understand and design intelligent systems by grounding cognition in physical interaction, material constraints and sensorimotor dynamics. In contrast to traditional disembodied AI, the embodied approach reveals how intelligence emerges not merely from computation but through dynamic engagement with the environment across multiple scales and timescales. By integrating mechanical structure, chemical bonding, biological insight and real-world context, Embodied Intelligence opens new possibilities for robotics that are adaptive, resilient and energy-efficient.

Throughout this chapter, we explored foundational principles and competing paradigms, from feedback control to mechanical intelligence. We discussed how biological systems make use of redundancy, self-organization and morphological constraints to simplify control and enhance adaptability. We also introduced critical concepts such as the frame of reference problem, intelligence without representation and the use of distributed architectures and underactuated systems. These illustrate that complex, intelligent behavior can emerge without centralized planning, from simple physical interactions alone.

The implications of these principles extend far beyond theory. In real-world applications—such as autonomous navigation in unstructured terrain, safe human-robot collaboration in medical settings, or tactile perception for object manipulation—embodied strategies offer more scalable and robust solutions than traditional AI pipelines. Moreover, integrating embodied principles with advances in soft robotics, material intelligence and deep learning may define the next frontier of autonomous systems.

Despite these advances, significant challenges remain. Artificial systems inspired by biological systems demands novel methodologies to handle complexity, evolution and growth. Moreover, ethical and societal implications of embodied robots—especially in healthcare, caregiving, or social environments—require careful, interdisciplinary reflection.

This chapter has outlined the conceptual terrain of Embodied Intelligence from the perspective of robotics research, with an emphasis on physicality, autonomy and adaptation. By situating intelligence within the body and environment, Embodied Intelligence offers a framework not only for understanding cognition, but also for engineering machines that think, move and interact as part of the physical world. As robotics continues to advance, these principles will be critical for designing systems that are not just capable but context-aware, safe and socially meaningful within real-world environments.

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References

Abdulali, A., A. C. Cornellà, C. Sirithunge, and F. Iida. (2024). "Effect of Material Viscosity on Tactile Compliance Discrimination": 1177–1182.

Adami, C. (1998). *Artificial Life VI: Proceedings of the Sixth International Conference on Artificial Life*. Vol. 6. MIT Press.

Adami, C. (2002). "What is complexity?" *BioEssays*. 24(12): 1085–1094.

Agre, P. E. and D. Chapman. (1987). "Pengi: An implementation of a theory of activity". In: *Proceedings of the sixth National conference on Artificial intelligence-Volume 1*. 268–272.

Alexander, R. M. (1984). "The gaits of bipedal and quadrupedal animals". *The International Journal of Robotics Research*. 3(2): 49–59.

Andrychowicz, M. *et al.* (2020). "Learning dexterous in-hand manipulation". *The International Journal of Robotics Research*. 39(1): 3–20.

Angle, C. (1989). "Genghis, a six legged autonomous walking robot". *PhD thesis*. Massachusetts Institute of Technology.

Ardin, P., F. Peng, M. Mangan, K. Lagogiannis, and B. Webb. (2016). "Using an insect mushroom body circuit to encode route memory in complex natural environments". *PLoS computational biology*. 12(2): e1004683.

Arkin, R. (1998). “Behavior Based Robotics”. *MIT Press google schola.* 2: 14–23.

Ashar, P., S. Devadas, and A. R. Newton. (1992). *Sequential logic synthesis.* Springer Science & Business Media.

Baluška, F. and M. Levin. (2016). “On having no head: cognition throughout biological systems”. *Frontiers in psychology.* 7: 902.

Bandura, A. (1977). “Social learning theory”. *Englewood Cliffs.*

Barsalou, L. W. (2008). “Grounded cognition”. *Annu. Rev. Psychol.* 59(1): 617–645.

Bartneck, C., T. Nomura, T. Kanda, T. Suzuki, and K. Kato. (2005). “Cultural differences in attitudes towards robots”. In: AISB.

Bear, M., B. Connors, and M. A. Paradiso. (2020). *Neuroscience: exploring the brain, enhanced edition: exploring the brain.* Jones & Bartlett Learning.

Beer, R. D. (1995). “A dynamical systems perspective on agent-environment interaction”. *Artificial intelligence.* 72(1-2): 173–215.

Bekey, G. and R. Tomovic. (1986). “Robot control by reflex actions”. 3: 240–247.

Bellman, R. (1957). “Dynamic programming princeton university press”. *Princeton, NJ*: 4–9.

Bernstein, N. A. (1967). “The co-ordination and regulation of movements”.

Bhounsule, P. A., J. Cortell, A. Grewal, B. Hendriksen, J. D. Karssen, C. Paul, and A. Ruina. (2014). “Low-bandwidth reflex-based control for lower power walking: 65 km on a single battery charge”. *The International Journal of Robotics Research.* 33(10): 1305–1321.

Bicchi, A. (2000). “Hands for dexterous manipulation and robust grasping: A difficult road toward simplicity”. *IEEE Transactions on robotics and automation.* 16(6): 652–662.

Bonabeau, E., M. Dorigo, and G. Theraulaz. (1999). *Swarm intelligence: from natural to artificial systems.* No. 1. Oxford university press.

Bonabeau, E., G. Theraulaz, J.-L. Deneubourg, N. R. Franks, O. Rafelsberger, J.-L. Joly, and S. Blanco. (1998). “A model for the emergence of pillars, walls and royal chambers in termite nests”. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences.* 353(1375): 1561–1576.

Braitenberg, V. (1986). *Vehicles: Experiments in synthetic psychology.* MIT press.

Breazeal, C., K. Dautenhahn, and T. Kanda. (2016). "Social robotics". *Springer handbook of robotics*: 1935–1972.

Brooks, R. (1986). "A robust layered control system for a mobile robot". *IEEE Journal on Robotics and Automation*. 2(1): 14–23.

Brooks, R. A. (1990). "Elephants don't play chess". *Robotics and autonomous systems*. 6(1-2): 3–15.

Brooks, R. A. (1991). "Intelligence without representation". *Artificial intelligence*. 47(1-3): 139–159.

Caluwaerts, K., M. D'Haene, D. Verstraeten, and B. Schrauwen. (2013). "Locomotion without a brain: physical reservoir computing in tensegrity structures". *Artificial life*. 19(1): 35–66.

Chopard, B. and M. Droz. (1998). "Cellular Automata Modeling of Physical Systems (Cambridge: CUP)". *P., Cambridge, England, UK*: 122–137.

Clark, A. (1989). *Microcognition: Philosophy, cognitive science, and parallel distributed processing*. Vol. 6. MIT Press.

Clark, A. (1998). *Being there: Putting brain, body, and world together again*. MIT press.

Collett, T. S. and M. Collett. (2002). "Memory use in insect visual navigation". *Nature Reviews Neuroscience*. 3(7): 542–552.

Collins, S., A. Ruina, R. Tedrake, and M. Wisse. (2005). "Efficient bipedal robots based on passive-dynamic walkers". *Science*. 307(5712): 1082–1085.

Collins, S. H., M. B. Wiggin, and G. S. Sawicki. (2015). "Reducing the energy cost of human walking using an unpowered exoskeleton". *Nature*. 522(7555): 212–215.

Collins, S. H., M. Wisse, and A. Ruina. (2001). "A three-dimensional passive-dynamic walking robot with two legs and knees". *The International Journal of Robotics Research*. 20(7): 607–615.

Cortell, J., B. Hendriksen, J. Karssen, and A. Ruina. (2008). "Ranger Robot". *Tech. rep.* Cornell University.

Cvetkovic, C., R. Raman, V. Chan, B. J. Williams, M. Tolish, P. Bajaj, M. S. Sakar, H. H. Asada, M. T. A. Saif, and R. Bashir. (2014). "Three-dimensionally printed biological machines powered by skeletal muscle". *Proceedings of the National Academy of Sciences*. 111(28): 10125–10130.

d'Avella, A., P. Saltiel, and E. Bizzi. (2003). "Combinations of muscle synergies in the construction of a natural motor behavior". *Nature neuroscience*. 6(3): 300–308.

Dahiya, R. S., G. Metta, M. Valle, and G. Sandini. (2009). "Tactile sensing—from humans to humanoids". *IEEE transactions on robotics*. 26(1): 1–20.

Darling, K. (2016). "Extending legal protection to social robots: The effects of anthropomorphism, empathy, and violent behavior towards robotic objects": 213–232.

Dautenhahn, K. (1997). "I could be you: The phenomenological dimension of social understanding". *Cybernetics & Systems*. 28(5): 417–453.

Dautenhahn, K. (2007). "Socially intelligent robots: dimensions of human–robot interaction". *Philosophical transactions of the royal society B: Biological sciences*. 362(1480): 679–704.

Dawkins, R. (2016). *The extended phenotype: The long reach of the gene*. Oxford University Press.

De Graaf, M. M., S. B. Allouch, and T. Klamer. (2015). "Sharing a life with Harvey: Exploring the acceptance of and relationship-building with a social robot". *Computers in human behavior*. 43: 1–14.

Deneubourg, J.-L. and S. Goss. (1989). "Collective patterns and decision-making". *Ethology Ecology & Evolution*. 1(4): 295–311.

Dennett, D. C. (1990). "Cognitive wheels: The frame problem of AI." *The philosophy of artificial intelligence*. 147: 170.

Dennett, D. C. (2017). *Brainstorms: Philosophical essays on mind and psychology*. MIT press.

Descartes, R. (1999). *Meditations and other metaphysical writings*. Penguin.

Di Marzo Serugendo, G., N. Foukia, S. Hassas, A. Karageorgos, S. K. Mostéfaoui, O. F. Rana, M. Ulieru, P. Valckenaers, and C. Van Aart. (2003). "Self-organisation: Paradigms and applications": 1–19.

Diamond, M. E., M. Von Heimendahl, P. M. Knutsen, D. Kleinfeld, and E. Ahissar. (2008). "'Where'and'what'in the whisker sensorimotor system". *Nature Reviews Neuroscience*. 9(8): 601–612.

Diester, I., M. Bartos, J. Bödecker, A. Kortylewski, C. Leibold, J. Letzkus, M. M. Nour, M. Schönauer, A. Straw, A. Valada, *et al.* (2024). "Internal world models in humans, animals, and AI". *Neuron*. 112(14): 2265–2268.

Dragan, A. D., K. C. Lee, and S. S. Srinivasa. (2013). "Legibility and predictability of robot motion". In: *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE. 301–308.

Drossel, B. and F. Schwabl. (1992). "Self-organized critical forest-fire model". *Physical review letters*. 69(11): 1629.

Eppner, C., S. Höfer, R. Jonschkowski, R. Martín-Martín, A. Sieverling, V. Wall, and O. Brock. (2018). "Four aspects of building robotic systems: lessons from the amazon picking challenge 2015". *Autonomous Robots*. 42(7): 1459–1475.

Espenschied, K. S., R. D. Quinn, R. D. Beer, and H. J. Chiel. (1996). "Biologically based distributed control and local reflexes improve rough terrain locomotion in a hexapod robot". *Robotics and autonomous systems*. 18(1-2): 59–64.

Evans, M., C. W. Fox, M. J. Pearson, N. F. Lepora, and T. J. Prescott. (2010). "Whisker-object contact speed affects radial distance estimation". In: *2010 IEEE International Conference on Robotics and Biomimetics*. IEEE. 720–725.

Farkas, I., D. Helbing, and T. Vicsek. (2002). "Mexican waves in an excitable medium". *Nature*. 419(6903): 131–132.

Fitch, W. T. (2000). "The evolution of speech: a comparative review". *Trends in Cognitive Sciences*. 4(7): 258–267.

Fogel, D. B. (2006). *Evolutionary computation: toward a new philosophy of machine intelligence*. John Wiley & Sons.

Fong, T., I. Nourbakhsh, and K. Dautenhahn. (2003). "A survey of socially interactive robots". *Robotics and autonomous systems*. 42(3-4): 143–166.

Fontana, F., P. Reist, and R. D'Andrea. (2013). "Control of a swinging juggling robot". In: *2013 European Control Conference (ECC)*. IEEE. 2317–2322.

Forlizzi, J. and C. DiSalvo. (2006). "Service robots in the domestic environment: a study of the roomba vacuum in the home". In: *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*. 258–265.

Garcia, M., A. Chatterjee, A. Ruina, and M. Coleman. (1998). "The simplest walking model: stability, complexity, and scaling".

Gardner, M. (1970). "Mathematical games". *Scientific american*. 222(6): 132–140.

Gazzola, M., M. Argentina, and L. Mahadevan. (2014). "Scaling macroscopic aquatic locomotion". *Nature Physics*. 10(10): 758–761.

Gentili, P. L. and P. Stano. (2024). "Living cells and biological mechanisms as prototypes for developing chemical artificial intelligence". *Biochemical and Biophysical Research Communications*. 720: 150060.

Gerstner, W. and W. M. Kistler. (2002). "Mathematical formulations of Hebbian learning". *Biological cybernetics*. 87(5): 404–415.

Geyer, H. and H. Herr. (2010). "A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities". *IEEE Transactions on neural systems and rehabilitation engineering*. 18(3): 263–273.

Geyer, H., A. Seyfarth, and R. Blickhan. (2006). "Compliant leg behaviour explains basic dynamics of walking and running". *Proceedings of the Royal Society B: Biological Sciences*. 273(1603): 2861–2867.

Giardina, F. and L. Mahadevan. (2021). "Models of benthic bipedalism". *Journal of the Royal Society Interface*. 18(174): 20200701.

Gilday, K., C. Sirithunge, F. Iida, and J. Hughes. (2025). "Embodied manipulation with past and future morphologies through an open parametric hand design". *Science Robotics*. 10(102): eads6437.

Glenberg, A. M. (2010). "Embodiment as a unifying perspective for psychology". *Wiley interdisciplinary reviews: Cognitive science*. 1(4): 586–596.

Goswami, A., B. Espiau, and A. Keramane. (1997). “Limit cycles in a passive compass gait biped and passivity-mimicking control laws”. *Autonomous Robots*. 4: 273–286.

Guenther, F. and F. Iida. (2016). “Energy-efficient monopod running with a large payload based on open-loop parallel elastic actuation”. *IEEE Transactions on Robotics*. 33(1): 102–113.

Guenther, F., H. Q. Vu, and F. Iida. (2019). “Improving legged robot hopping by using coupling-based series elastic actuation”. *IEEE ASME Transactions on Mechatronics*. 24(2): 413–423.

Haddadin, S. and E. Croft. (2016). “Physical human–robot interaction”. *Springer handbook of robotics*: 1835–1874.

Haken, H. (2012). *Advanced synergetics: Instability hierarchies of self-organizing systems and devices*. Vol. 20. Springer Science & Business Media.

Haldane, J. B. S. (2022). *Suggestions as to quantitative measurement of rates of evolution*. Routledge. 127–132.

Harnad, S. (1990). “The symbol grounding problem”. *Physica D: Nonlinear Phenomena*. 42(1-3): 335–346.

Häufle, D. F., M. Taylor, S. Schmitt, and H. Geyer. (2012). “A clutched parallel elastic actuator concept: Towards energy efficient powered legs in prosthetics and robotics”. In: *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*. IEEE. 1614–1619.

Hauser, H., A. J. Ijspeert, R. M. Füchslin, R. Pfeifer, and W. Maass. (2011). “Towards a theoretical foundation for morphological computation with compliant bodies”. *Biological cybernetics*. 105: 355–370.

Hauser, H., T. Nanayakkara, and F. Forni. (2023). “Leveraging morphological computation for controlling soft robots: Learning from nature to control soft robots”. *IEEE Control Systems Magazine*. 43(2): 114–129.

Heglund, N. C. and C. R. Taylor. (1988). “Speed, stride frequency and energy cost per stride: how do they change with body size and gait?” *Journal of Experimental Biology*. 138(1): 301–318.

Hersch, M., F. Guenter, S. Calinon, and A. Billard. (2008). "Dynamical system modulation for robot learning via kinesthetic demonstrations". *IEEE Transactions on Robotics*. 24(6): 1463–1467.

Heyes, C. (2010). "Where do mirror neurons come from?" *Neuroscience & Biobehavioral Reviews*. 34(4): 575–583.

Hochreiter, S. (1997). "Long Short-term Memory". *Neural Computation MIT-Press*.

Holland, J. H. (2000). *Emergence: From chaos to order*. OUP Oxford.

Holmes, P. J. (1982). "The dynamics of repeated impacts with a sinusoidally vibrating table". *Journal of Sound and Vibration*. 84(2): 173–189.

Hopfield, J. J. (1982). "Neural networks and physical systems with emergent collective computational abilities." *Proceedings of the national academy of sciences*. 79(8): 2554–2558.

Howard, D., A. E. Eiben, D. F. Kennedy, J.-B. Mouret, P. Valencia, and D. Winkler. (2019). "Evolving embodied intelligence from materials to machines". *Nature Machine Intelligence*. 1(1): 12–19.

Hreljac, A. (1993). "Preferred and energetically optimal gait transition speeds in human locomotion." *Medicine and science in sports and exercise*. 25(10): 1158–1162.

Hughes, J., P. Maiolino, and F. Iida. (2018). "An anthropomorphic soft skeleton hand exploiting conditional models for piano playing". *Science Robotics*. 3(25): eaau3098.

Hutchins, E. (1995). *Cognition in the Wild*. MIT press.

Hutter, M., C. D. Remy, M. A. Hoepflinger, and R. Siegwart. (2012). *High compliant series elastic actuation for the robotic leg Scarl ETH*.

Iida, F. and F. Giardina. (2023). "On the timescales of embodied intelligence for autonomous adaptive systems". *Annual Review of Control, Robotics, and Autonomous Systems*. 6(1): 95–122.

Iida, F. and S. G. Nurzaman. (2016). "Adaptation of sensor morphology: an integrative view of perception from biologically inspired robotics perspective". *Interface focus*. 6(4): 20160016.

Iida, F., J. Rummel, and A. Seyfarth. (2008). "Bipedal walking and running with spring-like biarticular muscles". *Journal of biomechanics*. 41(3): 656–667.

Ijspeert, A. J. (2014). "Biorobotics: Using robots to emulate and investigate agile locomotion". *science*. 346(6206): 196–203.

Ijspeert, A. J. (2008). "Central pattern generators for locomotion control in animals and robots: a review". *Neural networks*. 21(4): 642–653.

Ijspeert, A. J., A. Crespi, D. Ryczko, and J.-M. Cabelguen. (2007). "From swimming to walking with a salamander robot driven by a spinal cord model". *science*. 315(5817): 1416–1420.

Ishida, M., F. Berio, V. Di Santo, N. H. Shubin, and F. Iida. (2024). "Paleoinspired robotics as an experimental approach to the history of life". *Science Robotics*. 9(95): eadn1125.

Jaeger, H. (2002). *Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the echo state network approach*. Vol. 5. No. 1. Citeseer.

Jaeger, H. and H. Haas. (2004). "Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication". *science*. 304(5667): 78–80.

Jones, A. T. (1919). "" Working Up" in a Swing". *Science*. 50(1279): 20–21.

Jung, D. and A. Zelinsky. (1996). "Whisker based mobile robot navigation". 2: 497–504.

Kandel, E. R. (2001). "The molecular biology of memory storage: a dialogue between genes and synapses". *Science*. 294(5544): 1030–1038.

Kandel, E. R., J. H. Schwartz, T. M. Jessell, S. Siegelbaum, A. J. Hudspeth, S. Mack, *et al.* (2000). *Principles of neural science*. Vol. 4. McGraw-hill New York.

Kapitza, P. L. (1965). "Dynamical stability of a pendulum when its point of suspension vibrates, and pendulum with a vibrating suspension". *Collected papers of PL Kapitza*. 2: 714–737.

Kastberger, G., F. Weihmann, and T. Hoetzl. (2010). "Complex social waves of giant honeybees provoked by a dummy wasp support the special-agent hypothesis". *Communicative & Integrative Biology*. 3(2): 179–180.

Kelso, J. (1995). *Dynamic patterns: The self-organization of brain and behavior*. MIT Press.

Kim, S., C. Laschi, and B. Trimmer. (2013). “Soft robotics: a bioinspired evolution in robotics”. *Trends in biotechnology*. 31(5): 287–294.

King, S. L. and V. M. Janik. (2013). “Bottlenose dolphins can use learned vocal labels to address each other”. *Proceedings of the National Academy of Sciences*. 110(32): 13216–13221.

Kober, J., J. A. Bagnell, and J. Peters. (2013). “Reinforcement learning in robotics: A survey”. *The International Journal of Robotics Research*. 32(11): 1238–1274.

Kortman, V. G., B. Mazzolai, A. Sakes, and J. Jovanova. (2024). “Perspectives on intelligence in soft robotics”. *Advanced Intelligent Systems*: 2400294.

Krishna, A., B. E. Kaplan, J. Pope, S. Todorovic, K. E. Adolph, and O. Ossmy. (2024). “A computer-vision approach for testing developmental changes in object manipulation”: 1–6.

Kuo, A. D. (2007). “Choosing your steps carefully”. *IEEE Robotics & Automation Magazine*. 14(2): 18–29.

Kuo, A. D., J. M. Donelan, and A. Ruina. (2005). “Energetic consequences of walking like an inverted pendulum: step-to-step transitions”. *Exercise and sport sciences reviews*. 33(2): 88–97.

Lakatos, G., M. Gácsi, V. Konok, I. Brúder, B. Bereczky, P. Korondi, and Á. Miklósi. (2014). “Emotion attribution to a non-humanoid robot in different social situations”. *PloS one*. 9(12): e114207.

Lake, B. M., T. D. Ullman, J. B. Tenenbaum, and S. J. Gershman. (2017). “Building machines that learn and think like people”. *Behavioral and brain sciences*. 40: e253.

Lalitharatne, T. D., L. Costi, R. Hashem, I. Nisky, R. E. Jack, T. Nanayakkara, and F. Iida. (2022). “Face mediated human–robot interaction for remote medical examination”. *Scientific reports*. 12(1): 12592.

Landau, L. D. and E. M. Lifshitz. (1960). *Mechanics*. Vol. 1. CUP Archive.

Langton, C. G. (1997). “Artificial life: An overview”.

Laschi, C. (2017). “Octobot-a robot octopus points the way to soft robotics”. *IEEE Spectrum*. 54(3): 38–43.

Laschi, C. and M. Cianchetti. (2014). “Soft robotics: new perspectives for robot bodyware and control”. *Frontiers in bioengineering and biotechnology*. 2: 3.

Laschi, C., M. Cianchetti, B. Mazzolai, L. Margheri, M. Follador, and P. Dario. (2012). “Soft robot arm inspired by the octopus”. *Advanced robotics*. 26(7): 709–727.

Lee, J. and P. Calvo. (2022). “Enacting plant-inspired robotics”. *Frontiers in Neurorobotics*. 15: 772012.

Leite, I., C. Martinho, and A. Paiva. (2013). “Social robots for long-term interaction: a survey”. *International Journal of Social Robotics*. 5(2): 291–308.

Levinson, S. C. and J. Holler. (2014). “The origin of human multi-modal communication”. *Philosophical Transactions of the Royal Society B: Biological Sciences*. 369(1651): 20130302.

Liegeois, A. *et al.* (1977). “Automatic supervisory control of the configuration and behavior of multibody mechanisms”. *IEEE transactions on systems, man, and cybernetics*. 7(12): 868–871.

Loeb, G. E., I. E. Brown, and E. J. Cheng. (1999). “A hierarchical foundation for models of sensorimotor control”. *Experimental brain research*. 126: 1–18.

Lu, Y., J. Cen, R. Alkhoury Maroun, and B. Webb. (2025). “Insect-inspired Embodied Visual Route Following”. *Journal of Bionic Engineering*: 1–27.

Lungarella, M., G. Metta, R. Pfeifer, and G. Sandini. (2003). “Developmental robotics: a survey”. *Connection science*. 15(4): 151–190.

Lungarella, M. and O. Sporns. (2005). “Information self-structuring: Key principle for learning and development”. In: *Proceedings. The 4th International Conference on Development and Learning, 2005.* IEEE. 25–30.

Marques, H. G., A. Bharadwaj, and F. Iida. (2014). “From spontaneous motor activity to coordinated behaviour: a developmental model”. *PLoS computational biology*. 10(7): e1003653.

Masao, Y. (2001). “4 Karakuri”. *Japan at Play*: 72.

Matarić, M. J. (1997). “Learning social behavior”. *Robotics and Autonomous Systems*. 20(2-4): 191–204.

Mayer, E. (1943). "On growth and form. By D'Arcy Wentworth Thompson. A new edition. Cambridge and New York, University Press and Macmillan, 1942, 1116 pp., 554 illustrations, 211/2 cm. Price, 12.50".

Mazzolai, B., L. Beccai, and V. Mattoli. (2014). "Plants as model in biomimetics and biorobotics: new perspectives". *Frontiers in bioengineering and biotechnology*. 2: 2.

McCarthy, J. and P. J. Hayes. (1981). "Some philosophical problems from the standpoint of artificial intelligence". In: *Readings in artificial intelligence*. Elsevier. 431–450.

McClelland, J. L. (1988). "Parallel distributed processing: Implications for cognition and development". *Tech. rep.*

McGeer, T. (1990). "Passive dynamic walking". *The international journal of robotics research*. 9(2): 62–82.

Mengaldo, G. *et al.* (2022). "A concise guide to modelling the physics of embodied intelligence in soft robotics". *Nature Reviews Physics*. 4(10): 595–610.

Merel, J., M. Botvinick, and G. Wayne. (2019). "Hierarchical motor control in mammals and machines". *Nature communications*. 10(1): 1–12.

Mettin, U., P. X. La Hera, L. B. Freidovich, and A. S. Shiriaev. (2010). "Parallel elastic actuators as a control tool for preplanned trajectories of underactuated mechanical systems". *The international journal of robotics research*. 29(9): 1186–1198.

Milana, E., C. D. Santina, B. Gorissen, and P. Rothemund. (2025). "Physical control: A new avenue to achieve intelligence in soft robotics". *Science Robotics*. 10(102): eadw7660.

Milo, R. and R. Phillips. (2015). *Cell biology by the numbers*. Garland Science.

Milton, J., J. L. Cabrera, T. Ohira, S. Tajima, Y. Tonosaki, C. W. Eurich, and S. A. Campbell. (2009). "The time-delayed inverted pendulum: implications for human balance control". *Chaos: An Interdisciplinary Journal of Nonlinear Science*. 19(2).

Minsky, M. (1986). *Society of mind*. Simon and Schuster.

Miriyev, A., K. Stack, and H. Lipson. (2017). "Soft material for soft actuators". *Nature communications*. 8(1): 596.

Mitchinson, B., C. J. Martin, R. A. Grant, and T. J. Prescott. (2007). "Feedback control in active sensing: rat exploratory whisking is modulated by environmental contact". *Proceedings of the Royal Society B: Biological Sciences*. 274(1613): 1035–1041.

Moreno, K. R. and R. P. Macgregor. (2019). "Bubble trails, bursts, rings, and more: A review of multiple bubble types produced by cetaceans". *Animal Behavior and Cognition*. 6(2): 105–126.

Murphy, R. R. (2015). "Meta-analysis of autonomy at the DARPA robotics challenge trials". *Journal of Field Robotics*. 32(2): 189–191.

Nadipineni, S., C. Hong, T. Ramlall, C. Sirithunge, K. Althoefer, F. Iida, and T. D. Lalitharatne. (2025). "Human Emotion-Mediated Soft Robotic Arts: Exploring the Intersection of Human Emotions, Soft Robotics and Arts". In: *2025 IEEE 8th International Conference on Soft Robotics (RoboSoft)*. IEEE. 1–6.

Nakajima, K. (2020). "Physical reservoir computing—an introductory perspective". *Japanese Journal of Applied Physics*. 59(6): 060501.

Nakajima, K., H. Hauser, T. Li, and R. Pfeifer. (2015). "Information processing via physical soft body". *Scientific reports*. 5(1): 10487.

Nandram, S., P. Bindlish, and N. Keizer. (2017). "Understanding Integrative Intelligence. Embodied in S Model".

Neumann, J. v. (1966). "Theory of self-reproducing automata". *Edited by Arthur W. Burks*.

Nilsson, N. J. *et al.* (1984). *Shakey the robot*. Vol. 323. Sri International Menlo Park, California.

Nolfi, S. and D. Floreano. (2000). *Evolutionary robotics: the biology, intelligence and technology of self-orgnizing machines*. MIT press.

Nonaka, T., A. Abdulali, C. Sirithunge, K. Gilday, and F. Iida. (2023). "Soft robotic tactile perception of softer objects based on learning of spatiotemporal pressure patterns". In: *2023 IEEE International Conference on Soft Robotics (RoboSoft)*. IEEE. 1–7.

O'Keeffe, K. P., H. Hong, and S. H. Strogatz. (2017). "Oscillators that sync and swarm". *Nature communications*. 8(1): 1504.

Pai, V., L. Pio-Lopez, M. Sperry, P. Erickson, P. Tayyebi, M. Levin, and M. Levin. (2024). "Basal Xenobot Transcriptomics: Gene Expression Changes in wildtype cells comprising one form of biobot".

Park, J. H. and O. Kwon. (2001). “Reflex control of biped robot locomotion on a slippery surface”. 4: 4134–4139.

Park, Y.-L., B.-R. Chen, and R. J. Wood. (2012). “Design and fabrication of soft artificial skin using embedded microchannels and liquid conductors”. *IEEE Sensors journal*. 12(8): 2711–2718.

Pasquale, V., P. Massobrio, L. Bologna, M. Chiappalone, and S. Martinoia. (2008). “Self-organization and neuronal avalanches in networks of dissociated cortical neurons”. *Neuroscience*. 153(4): 1354–1369.

Pattee, H. H. (2001). “The physics of symbols: bridging the epistemic cut”. *Biosystems*. 60(1-3): 5–21.

Pearson, J. C., P. E. Nelson, S. Titsworth, and L. H. Hosek. (2019). *Human communication*. McGraw-Hill Education.

Pearson, K. (2000). “Spinal reflexes”. *Principles of neural science*.

Peterka, R. J. (2002). “Sensorimotor integration in human postural control”. *Journal of neurophysiology*. 88(3): 1097–1118.

Petersen, K. H., N. Napp, R. Stuart-Smith, D. Rus, and M. Kovac. (2019). “A review of collective robotic construction”. *Science Robotics*. 4(28): eaau8479.

Pfeifer, R. (2006a). *How the body shapes the way we think: A New View of intelligence*. MIT Press.

Pfeifer, R. *et al.* (1996). “Building fungus eaters: Design principles of autonomous agents”.

Pfeifer, R. (2006b). “Morphological computation: Connecting brain, body, and environment”. In: *Biologically Inspired Approaches to Advanced Information Technology: Second International Workshop, BioADIT 2006, Osaka, Japan, January 26-27, 2006 2*. Springer. 2–3.

Pfeifer, R., F. Iida, and M. Lungarella. (2014). “Cognition from the bottom up: on biological inspiration, body morphology, and soft materials”. *Trends in cognitive sciences*. 18(8): 404–413.

Pfeifer, R., M. Lungarella, and F. Iida. (2007). “Self-organization, embodiment, and biologically inspired robotics”. *science*. 318(5853): 1088–1093.

Pfeifer, R. and C. Scheier. (1997). “Sensory—motor coordination: The metaphor and beyond”. *Robotics and autonomous systems*. 20(2-4): 157–178.

Pfeifer, R. and C. Scheier. (2001). *Understanding intelligence*. MIT press.

Pratt, G. A. and M. M. Williamson. (1995). “Series elastic actuators”. 1: 399–406.

Pylyshyn, Z. W. (1987). “The robot’s dilemma: The frame problem in artificial intelligence”.

Radhakrishnan, V. (1998). “Locomotion: dealing with friction”. *Proceedings of the National Academy of Sciences*. 95(10): 5448–5455.

Raibert, M., K. Blankespoor, G. Nelson, and R. Playter. (2008). “Bigdog, the rough-terrain quadruped robot”. *IFAC Proceedings Volumes*. 41(2): 10822–10825.

Raibert, M. H. (1986). *Legged robots that balance*. MIT press.

Reist, P. and R. D’Andrea. (2012). “Design and analysis of a blind juggling robot”. *IEEE Transactions on Robotics*. 28(6): 1228–1243.

Reynolds, C. W. (1987). “Flocks, herds and schools: A distributed behavioral model”. In: *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*. 25–34.

Rizzolatti, G. and L. Craighero. (2004). “The mirror-neuron system”. *Annu. Rev. Neurosci.* 27(1): 169–192.

Ronsse, R., P. Lefevre, and R. Sepulchre. (2007). “Rhythmic feedback control of a blind planar juggler”. *IEEE Transactions on Robotics*. 23(4): 790–802.

Rubenstein, M., A. Cornejo, and R. Nagpal. (2014). “Programmable self-assembly in a thousand-robot swarm”. *Science*. 345(6198): 795–799.

Rumelhart, D. E., J. L. McClelland, P. R. Group, *et al.* (1986). *Parallel distributed processing, volume 1: Explorations in the microstructure of cognition: Foundations*. The MIT press.

Rus, D. and M. T. Tolley. (2015). “Design, fabrication and control of soft robots”. *Nature*. 521(7553): 467–475.

Russell, R. A. and J. A. Wijaya. (2003). “Object location and recognition using whisker sensors”: 761–768.

Russell, S. J. and P. Norvig. (2016). *Artificial intelligence: a modern approach*. Pearson.

Salomaa, A. (2014). “Theory of Automata Oxford”. *UK: Pergamon*.

Saranli, U., M. Buehler, and D. E. Koditschek. (2001). "RHex: A simple and highly mobile hexapod robot". *The International Journal of Robotics Research*. 20(7): 616–631.

Scassellati, B. (2002). "Theory of mind for a humanoid robot". *Autonomous Robots*. 12(1): 13–24.

Schmickl, T., M. Szopek, F. Mondada, R. Mills, M. Stefanec, D. N. Hofstadler, D. Lazic, R. Barmak, F. Bonnet, and P. Zahadat. (2021). "Social integrating robots suggest mitigation strategies for ecosystem decay". *Frontiers in Bioengineering and Biotechnology*. 9: 612605.

Schmitz, A., P. Maiolino, M. Maggiali, L. Natale, G. Cannata, and G. Metta. (2011). "Methods and technologies for the implementation of large-scale robot tactile sensors". *IEEE Transactions on Robotics*. 27(3): 389–400.

Schofield, L., C. Sirithunge, A. Abdulali, and F. Iida. (2024). "Multiple Musical Skills Framework for Robotic Musicianship". In: *IOP Conference Series: Materials Science and Engineering*. Vol. 1321. No. 1. IOP Publishing. 012015.

Scimeca, L., J. Hughes, P. Maiolino, L. He, T. Nanayakkara, and F. Iida. (2022). "Action augmentation of tactile perception for soft-body palpation". *Soft robotics*. 9(2): 280–292.

Sharova, A. S., F. Melloni, G. Lanzani, C. J. Bettinger, and M. Caironi. (2021). "Edible electronics: The vision and the challenge". *Advanced Materials Technologies*. 6(2): 2000757.

Simon, H. A. (1969). "The sciences of the artificial MIT Press". *Cambridge, Ma.*

Simon, H. A. (1980). "Cognitive science: The newest science of the artificial". *Cognitive science*. 4(1): 33–46.

Sirithunge, C., K. S. Boralessa, W. Eranga, B. P. Jayasekara, D. Chandima, and M. U. Hemapala. (2023). "Exploring Embodied Resources in Gaze in Human-Robot Collaborative Environments". In: *IOP Conference Series: Materials Science and Engineering*. Vol. 1292. No. 1. IOP Publishing. 012013.

Sirithunge, C. and N. Dahn. (2023). "How Do We Trust Our Robots?" In: *IOP Conference Series: Materials Science and Engineering*. Vol. 1292. No. 1. IOP Publishing. 012014.

Sirithunge, C., A. B. P. Jayasekara, and D. Chandima. (2024a). "Experience-based Learning and Adaptive Behavior for Improved Situation-Awareness of a Social Robot". In: *IOP Conference Series: Materials Science and Engineering*. Vol. 1321. No. 1. IOP Publishing. 012016.

Sirithunge, C., T. D. Lalitharatne, and F. Iida. (2024b). "Embodiment, Socially Intelligent Behaviour and Proactive Robots". In: *IOP Conference Series: Materials Science and Engineering*. Vol. 1321. No. 1. IOP Publishing. 012004.

Sornkarn, N., P. Dasgupta, and T. Nanayakkara. (2016). "Morphological computation of haptic perception of a controllable stiffness probe". *PloS one*. 11(6): e0156982.

Spong, M. W. (2005). "Underactuated mechanical systems". In: *Control problems in robotics and automation*. Springer. 135–150.

Srinivasan, M. V. (2011). "Honeybees as a model for the study of visually guided flight, navigation, and biologically inspired robotics". *Physiological reviews*. 91(2): 413–460.

Standen, E. M., T. Y. Du, and H. C. Larsson. (2014). "Developmental plasticity and the origin of tetrapods". *Nature*. 513(7516): 54–58.

Strogatz, S. H. (2000). "From Kuramoto to Crawford: exploring the onset of synchronization in populations of coupled oscillators". *Physica D: Nonlinear Phenomena*. 143(1-4): 1–20.

Suchman, L. A. (1987). *Plans and situated actions: The problem of human-machine communication*. Cambridge university press.

Takeda, M., Y. Hirata, Y.-H. Weng, T. Katayama, Y. Mizuta, and A. Koujina. (2019). "Accountable system design architecture for embodied AI: a focus on physical human support robots". *Advanced Robotics*. 33(23): 1248–1263.

Team, G. R., S. Abeyruwan, J. Ainslie, J.-B. Alayrac, M. G. Arenas, T. Armstrong, A. Balakrishna, R. Baruch, M. Bauza, M. Blokzijl, *et al.* (2025). "Gemini robotics: Bringing ai into the physical world". *arXiv preprint arXiv:2503.20020*.

Tennent, H., S. Shen, and M. Jung. (2019). "Micbot: A peripheral robotic object to shape conversational dynamics and team performance". In: *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE. 133–142.

Toda, M. and H. F. M. Crombag. (1982). *Man, robot, and society: Models and speculations.* Springer.

Todorov, E. (2009). "Efficient computation of optimal actions". *Proceedings of the national academy of sciences.* 106(28): 11478–11483.

Tomasello, M. (2009). *The cultural origins of human cognition.* Harvard university press.

Turing, A. M. *et al.* (1936). "On computable numbers, with an application to the Entscheidungsproblem". *J. of Math.* 58(345-363): 5.

Turing, A. M. (1990). "The chemical basis of morphogenesis". *Bulletin of mathematical biology.* 52: 153–197.

Usherwood, J. R. and J. E. Bertram. (2003). "Understanding brachiation: insight from a collisional perspective". *Journal of Experimental Biology.* 206(10): 1631–1642.

Valero-Cuevas, F. J. (2009). "A mathematical approach to the mechanical capabilities of limbs and fingers". In: *Progress in Motor Control: a Multidisciplinary Perspective.* Springer. 619–633.

Van Gelder, T. (1998). "The dynamical hypothesis in cognitive science". *Behavioral and brain sciences.* 21(5): 615–628.

Varela, F. J., E. Thompson, and E. Rosch. (2017). *The embodied mind, revised edition: Cognitive science and human experience.* MIT press.

Varela Francisco, J., T. Evan, and R. Eleanor. (1991). *The embodied mind: Cognitive science and human experience.* Cambridge, Mass.: MIT Press.

Vernon, D., G. Metta, and G. Sandini. (2007). "The icub cognitive architecture: Interactive development in a humanoid robot". In: *2007 IEEE 6th international conference on development and learning.* Ieee. 122–127.

Verstraeten, D., B. Schrauwen, M. d'Haene, and D. Stroobandt. (2007). "An experimental unification of reservoir computing methods". *Neural networks.* 20(3): 391–403.

Vogel, S. (2013). *Comparative biomechanics: life's physical world.* Princeton University Press.

Von Neumann, J., A. W. Burks, *et al.* (1966). "Theory of self-reproducing automata".

Vu, H. Q., X. Yu, F. Iida, and R. Pfeifer. (2015). "Improving energy efficiency of hopping locomotion by using a variable stiffness actuator". *IEEE/ASME transactions on mechatronics*. 21(1): 472–486.

Wainer, J., D. J. Feil-Seifer, D. A. Shell, and M. J. Mataric. (2006). "The role of physical embodiment in human-robot interaction". In: *ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication*. IEEE. 117–122.

Wainer, J., D. J. Feil-Seifer, D. A. Shell, and M. J. Mataric. (2007). "Embodiment and human-robot interaction: A task-based perspective". In: *RO-MAN 2007-The 16th IEEE international symposium on robot and human interactive communication*. IEEE. 872–877.

Werfel, J., K. Petersen, and R. Nagpal. (2014). "Designing Collective Behavior in a Termite-Inspired Robot Construction Team". *Science*. 343(6172): 754–758. DOI: 10.1126/science.1245842.

Wiener, N. (2019). *Cybernetics or Control and Communication in the Animal and the Machine*. MIT press.

Wilson, A. D. and S. Golonka. (2013). "Embodied cognition is not what you think it is". *Frontiers in psychology*. 4: 58.

Wolf, S., G. Grioli, O. Eiberger, W. Friedl, M. Grebenstein, H. Höppner, E. Burdet, D. G. Caldwell, R. Carloni, M. G. Catalano, *et al.* (2015). "Variable stiffness actuators: Review on design and components". *IEEE/ASME transactions on mechatronics*. 21(5): 2418–2430.

Wolfram, S. (1982). "Cellular automata as simple self-organizing systems". *Tech. rep.*

Wolfram, S. (2018). *Cellular automata and complexity: collected papers*. crc Press.

Wood, R., R. Nagpal, and G.-Y. Wei. (2013). "Flight of the robobees". *Scientific American*. 308(3): 60–65.

Xu, D., G. E. Loeb, and J. A. Fishel. (2013). "Tactile identification of objects using Bayesian exploration": 3056–3061.

Yoshikawa, T. and O. Khatib. (2009). "Compliant humanoid robot control by the torque transformer". In: *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. 3011–3018.

Yu, Z., S. H. Sadati, H. Hauser, P. R. Childs, and T. Nanayakkara. (2022). "A semi-supervised reservoir computing system based on tapered whisker for mobile robot terrain identification and roughness estimation". *IEEE Robotics and Automation Letters*. 7(2): 5655–5662.

Zhao, Q., K. Nakajima, H. Sumioka, H. Hauser, and R. Pfeifer. (2013). "Spine dynamics as a computational resource in spine-driven quadruped locomotion". In: *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. 1445–1451.