

# On the Timescales of Embodied Intelligence for Autonomous Adaptive Systems

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## Keywords

embodiment, autonomous adaptive systems, cross-timescale interactions, bioinspired robotics

## Abstract

Embodiment is a crucial concept for the autonomy and adaptivity of systems working in the physical world with high degrees of uncertainty and complexity. The physical bodies of autonomous adaptive systems heavily influence the information flow from the environment to the central processing (and vice versa), requiring us to consider the full triad of brain, body, and environment to investigate intelligent behavior. This article provides a structured review of embodied intelligence with a special emphasis on the concept of timescales and their role in self-organization and the emergence of complex behavior. We classify embodied interactions into three types—cross-timescale matching, separation, and nontemporal sequences—and discuss how these interactions were studied in the past as well as how they can contribute to the systematic investigation of complex autonomous and adaptive systems in both biological and artificial entities.

## 1. INTRODUCTION

All biological and artificial systems in the real physical world have embodiment, i.e., physical bodies that interact with their environment. The importance (and unimportance) of embodiment has been debated over centuries. In philosophy, the concept of body–mind dualism was used to explain two types of physical and mental processes coexisting in human beings, and the existence of mind was regarded as a mystery of living beings (1–3). The importance of embodiment was investigated further as we learned more about the biological nature of ourselves. As described later in this article, our biological bodies are merely mechanistic realizations that follow the commands of the mind, but there are numerous layers of physiological, biomechanical, biochemical, and biomaterial dynamics that influence not only simple mechanical motions and reflexive behaviors but also more complex functions, such as memories, value systems, goal-oriented behaviors, and more generally conscious and ethical behaviors. In this context, studies of embodiment have been conducted in a wide spectrum of disciplines—not only in robotics (4–7) and computer science (8, 9) but also in philosophy (3), psychology (10, 11), linguistics (12), physiology (13), biomechanics (14), evolutionary biology (15), physics (16), mathematics (17), and material sciences (18).

A considerable body of modern embodiment research has been grounded in the field of biologically inspired robotics (16, 19). Inspired by the discrepancies between animals and machines, a synthetic methodology—i.e., an understanding-by-building approach (20)—is employed to investigate the fundamental principles of autonomy and adaptability, including self-regulation, self-stability, self-organization, developmental and evolutionary processes, and complex systems in general. This approach was influenced by mid-twentieth-century works on homeostasis (21), morphogenesis models (22), and self-replicating machines (23); subsequent works on artificial life (24), evolutionary and developmental robotics (25, 26), and behavior-based robotics (27); and, more recently, works on passive dynamics and mechanical and embodied intelligence (20) and soft robotics (28). The history of the last century can be outlined by the discoveries of diverse mechanisms and paradigms that characterize the intelligent adaptive behaviors of animals and their translations into intelligent machines.

Even though most studies of embodiment investigate distinct aspects of intelligence, a common research challenge across the disciplines is to gain further insights into patterns and structures leading to intelligent adaptive behaviors in animals and machines. For example, biological systems exhibit numerous sophisticated motion patterns for locomotion and other movements (29), self-structure their information-processing channels to acquire new sensory-motor skills (30), and adapt their body structures for robustness and resilience through developmental processes (31). Also, many bioinspired robots have been developed to analyze sensory-motor dynamics for locomotion (32), self-structuring of body shapes for robotic hand interactions (33), and construction of their own bodies (34). These examples illustrate the diversity of patterns and structures in animals' and machines' behaviors, which are the foundation of their autonomy and adaptability. Nevertheless, despite their similarities in patterns and structures, these processes are based on completely different types of underlying physical processes, such as biochemical muscles or electromagnetic motors interacting with terrains, nervous or computer systems processing sensory-motor information, and cell differentiation or 3D printing of materials for structural growth. This diversity is, on the one hand, a crucial foundation of embodied intelligence, but, on the other, makes it difficult to systematically develop a common ground toward a more comprehensive understanding of higher degrees of complexity, autonomy, and adaptability.

The goal of this article is to provide a structured review by using the timescales of physical processes as a basis to investigate and analyze the patterns and structures that give rise to embodied autonomous and adaptive systems. We argue that the key characteristic of embodied

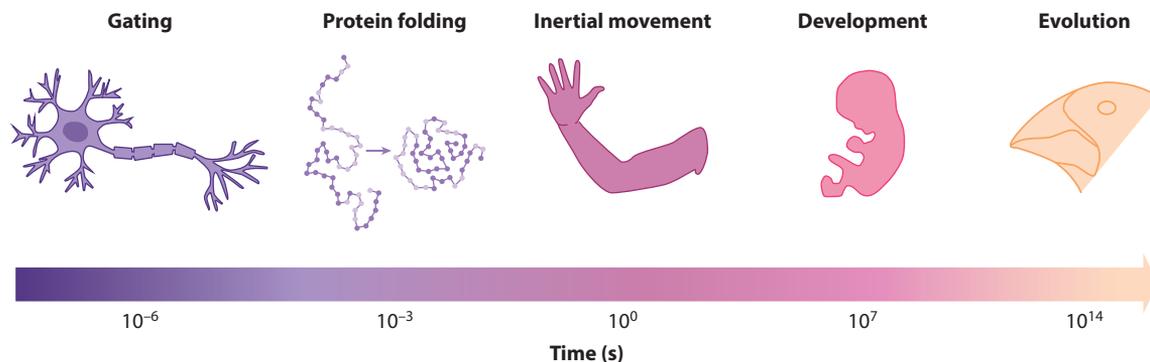
systems is their grounding in the physical world, where dynamic and temporal interactions with the environment are critical; hence, timescales should provide fundamental insights into embodied processes. This article specifically shows that diverse patterns and structures for autonomous adaptive systems can be characterized by three types of cross-timescale interactions, describes how they have been studied in previous embodied intelligence research, and discusses the functions of such dynamics in the context of autonomy and adaptability. This high-level discussion is essential, especially when we analyze the complex dynamics in, e.g., biological systems, which exhibit a wide spectrum of timescales (from milliseconds to years), cross domains (physical and informational), and have high degrees of uncertainty and unstructured surroundings.

The structure of this article is as follows: We first review various timescales in biological systems and discuss how we can analyze them in theoretical terms. Second, based on the basic understanding of timescales, we introduce different aspects of timescales from a functional standpoint. Finally, we conclude the discussions with further challenges and perspectives.

## 2. TIMESCALES OF BIOLOGICAL AND ARTIFICIAL SYSTEMS

Biological systems have an impressive diversity of physical dynamics, from very short timescales to very long ones. As shown in **Figure 1**, our autonomy and adaptability rely on mechanisms over many variations of timescales. For example, biological species evolved through natural selection processes at very long timescales of millions of years, the ontogenetic developmental process manifests itself over months to years, our bodily motions can be observed on the order of seconds, and our molecular and nervous dynamics act on timescales of milliseconds and microseconds.

All of these different autonomous and adaptation processes are driven by different underlying biochemical processes, and therefore these timescales are not arbitrarily set. The synaptic transmission of signals in the nervous systems, for example, makes use of propagation of electric action potentials; protein folding of molecular structures uses chemical and physical interactions; bodily motions use inertial, gravitational, and actuation mechanisms; and evolutionary and developmental processes rely on genetic and reproductive processes. These examples illustrate the fact that there are underlying embodied (biochemical or mechanical) processes determining the overall timescales of dynamics, and that no dynamics with a single timescale can explain overall autonomy and adaptability. Even though the timescales of embodied systems' dynamics are not an easy concept to grasp because of the overlapping and parallel nature of these processes, interactions



**Figure 1**

The diversity of biological timescales. The examples shown are ion channel gating ( $\sim 10^{-6}$  s; microseconds) (35), protein folding (as short as  $\sim 10^{-3}$  s; milliseconds) (35), movement of mammalian limbs ( $\sim 10^0$  s; seconds), development of mammalian organisms ( $\sim 10^7$  s; months to years), and evolution ( $\sim 10^{14}$  s; millions of years, the duration of a Darwin unit) (36).

and coordination among dynamics over different timescales are essential. For a systematic exploration of such a complex concept, in this section, we discuss some theoretical foundations of such dynamics observed in living organisms and other bioinspired machines, with which we aim to analyze large-scale interactions across timescales.

## 2.1. Formulation of Embodied Timescales

The definition of timescales can be made precise by deriving a mathematical formulation for the system's dynamics. For instance, the motion of a spring–mass system when moved away from the resting point can be described by the equations of an unforced harmonic oscillator as

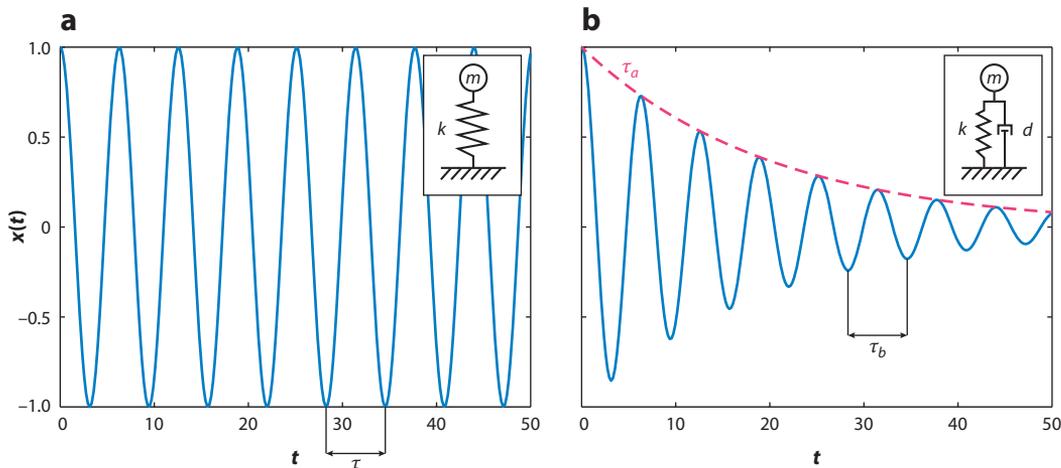
$$m\ddot{x} + kx = 0, \quad 1.$$

where  $m$  is the mass of the object that is attached to the spring with stiffness  $k$ . There is exactly one timescale that can be computed with these two parameters:  $\tau = \sqrt{m/k}$ . The significance of the timescales derived from the dynamical equations is reflected in its solution  $x(t) = a_0 \sin(\frac{1}{\tau} t)$ : Every  $2\pi\tau$  seconds, the mass circles back to its initial position, as shown in **Figure 2a**. Hence, timescales govern the solution of a dynamical system and can inform us about its behavior without the need to explicitly solve the underlying differential equations.

The introduction of additional physical processes can give rise to further timescales. Real springs are not perfect and dissipate energy to heat as they compress and extend. This effect can be accounted for by adding a damping term  $d$  in Equation 1, and gives rise to the damped harmonic oscillator equation

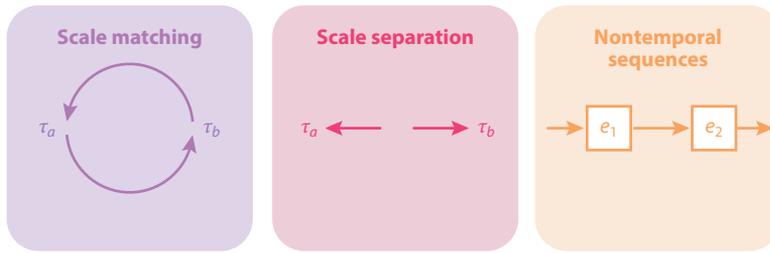
$$m\ddot{x} + d\dot{x} + kx = 0. \quad 2.$$

One can construct two timescales with the three parameters. The first timescale,  $\tau_a = 1/\omega\zeta$ , where  $\zeta = d/2\sqrt{km}$  and  $\omega = \sqrt{k/m}$ , determines the decay rate of the oscillation's envelope, as shown in **Figure 2b**. Every  $\tau_a$  seconds, the oscillation amplitude decays by a factor of  $1 - e^{-1} \approx 0.63$ . The second timescale,  $\tau_b = \omega\sqrt{1 - \zeta^2}$ , determines the duration of oscillation, analogous to



**Figure 2**

Dynamics associated with an (a) undamped ( $m = 1, k = 1$ ) and (b) damped ( $m = 1, k = 1, d = 0.1$ ) harmonic oscillator. The undamped system has one timescale  $\tau$  describing the period of oscillation. The damped system has two timescales associated with the decay of the oscillation envelope,  $\tau_a$ , and the period of oscillation,  $\tau_b$ .



**Figure 3**

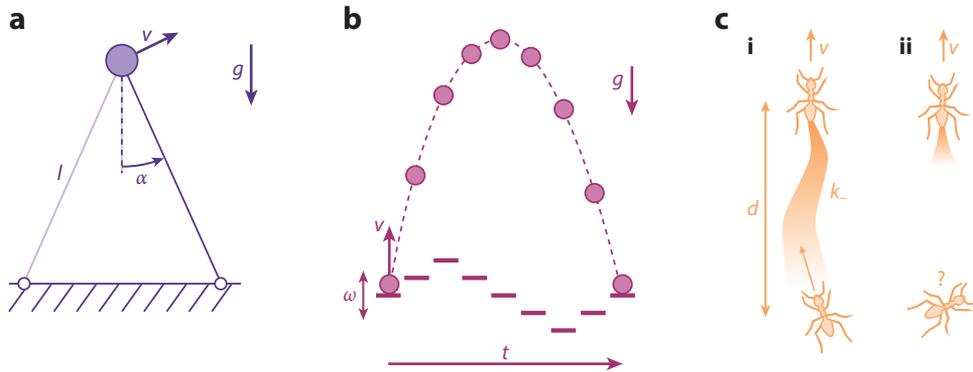
The relations among different timescales in an embodied system give rise to three distinct cases. In scale matching, timescales ( $\tau_a$ ,  $\tau_b$ ) are equal or of similar order; in scale separation, they are distinct; and in nontemporal sequences, only the sequence of events matters ( $e_1$ ,  $e_2$ ), not their duration.

$\tau$  in Equation 1. Again, the knowledge of the timescales determines the behavior of the solution in a concise and intuitive way. Note that the harmonic oscillations described by Equations 1 and 2 are more general than a description of a point-mass system and can describe a wealth of physical systems, including clocks and radios. In fact, it is common for a physical process to reduce to a known mathematical model, and it becomes straightforward to compute the relevant timescales by replacing the model parameters in the known timescale expressions. The analysis of timescales can thus help connect seemingly disparate aspects of embodied systems by placing them on a common conceptual ground.

In physical tasks of embodied systems, the timescales are influenced predominantly by the extrinsic environmental parameters (e.g., gravitational acceleration  $g$ , viscosity  $\mu$ , and inertia of external mass  $m_e$ ) and intrinsic parameters (e.g., body size  $l$ , velocity  $v$ , body inertia  $m_b$ , and stiffness  $k$ ). Extrinsic and intrinsic parameters define a system's timescales, and their interrelation provides an effective description of its embodiment. Desirable dynamical properties such as emergent behavior, self-organization, and self-stability arise in the context of relations among timescales. The remainder of this section investigates three cases of timescale relations, namely scale matching, scale separation, and nontemporal sequences, all of which have a unique and pivotal influence on the embodiment of a system. An overview of the three cases is shown in **Figure 3**. Scale matching occurs in systems where the relevant timescales are of similar order such that the underlying processes cannot be analyzed and understood independently. The opposite is true for scale separation, where timescales are different enough for processes to be understood independently. Finally, nontemporal sequences occur in physical processes where only the sequence of processes matters, not their duration.

## 2.2. Scale Matching

Most complex, interesting, and efficient behavior occurs when intrinsic and extrinsic timescales of an embodied system are equal or of similar order. Take a very intuitive example: the playground swing. The dynamics of a swing can be accurately approximated by that of a pendulum, and as such, its mathematical solution will reveal a periodic timescale associated with the back-and-forth motion of the swing of  $\tau = \sqrt{l/g}$ , where  $l$  is the length of the swing ropes and  $g$  is the gravitational acceleration. As most of us have experienced, it is very easy to increase the amplitude when sitting on the swing—one simply extends one's legs after the back swing and retracts them after the forward swing. The slight increase in potential energy induced by the resulting torque allows us to pump energy into the swing, thus increasing the amplitude (37). The timescales of the swing and the leg motion are matched. Any unmatched leg control strategy will not perform as well for swing-up. In the same vein, such scale matching is ubiquitous in dynamical processes such as



**Figure 4**

Models of embodied systems. (a) A pendulum-like walking model with leg length  $l$ , center-of-mass velocity  $v$ , and stance leg angle  $\alpha$  under the effect of gravity. (b) A simple model of a paddle oscillating at frequency  $\omega$  juggling a ball under the effect of gravity. (c) An agent moving at speed  $v$  and laying a pheromone trail with evaporation rate  $k_-$ , followed by a second agent at distance  $d$ . The timescale due to the evaporation parameter determines whether other agents can pick up the trail (i) or not (ii).

locomotion (38), balance (39), and juggling (40) and generally in underactuated systems (41). The effect of scale matching on the embodied behavior is apparent in both individual and collective systems, as discussed next.

**2.2.1. Individual systems.** An important dynamical process for physical agents is that of locomotion. A bipedal gait such as walking can be approximately modeled using an inverted pendulum (42–44). The scales to be matched in walking are the time it takes for the stance leg to cover the angle  $2\alpha$  (see **Figure 4a**), given by  $\tau_a = 2l\alpha/v$ , with  $l$  the leg length and  $v$  the center-of-mass velocity, and the time it takes for the other leg to swing past the stance leg. If the leg swing timescale is passive, then it is determined by gravity and is approximately  $\tau_b = \sqrt{l/g}$ . When these two timescales are matched by carefully designing the mechanical properties of a walker and its environment, something interesting happens. Systems with this matching, called passive dynamic walkers (45–47), are capable of walking down shallow slopes without the need for muscles or motors (one example is shown in **Figure 5a**). Such systems have inspired energy-efficient robot designs that can walk efficiently on flat ground (51). Similar arguments of scale matching in locomotion can be made for brachiation (52), benthic locomotion (53), and swimming (54).

When it comes to manipulation, timescales are often strongly influenced by gravity and ballistics. In juggling, for instance, the object to be juggled cycles back to where it came from with the timescale  $\tau_a = v/g$ . In order to juggle, we must make sure that the timescale between throwing and catching,  $1/\omega$ , matches the flight duration of the ball, as shown in **Figure 4b** (a physical robotic implementation is shown in **Figure 5b**). Knowledge of this process enables the design of so-called blind jugglers (48, 55), where a ball is juggled by a robotic system without the need for any sensory feedback.

There are many more examples in individual systems where timescales are matched: Earth rotates at the same timescale as our sleep–wake cycle, deciduous trees lose their foliage at the same timescale as Earth revolves around the sun, our arms swing at the same rate as our legs when we run, and so on. The matching of timescales in natural and artificial individual systems may appear obvious in some of the examples presented here, but it is important to note that this concept pervades embodied systems. In particular, when interactions become more complex and less intuitive, the concept of scale matching can become a crucial guide for designing embodied systems with emergent and self-organizing properties.



**Figure 5**

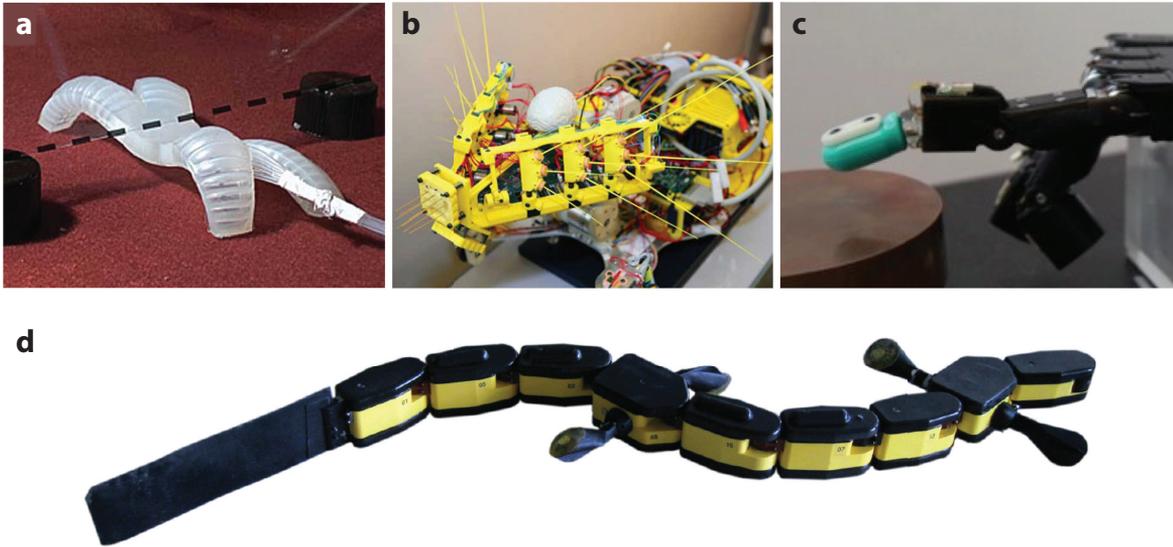
Examples of passivity-based robotic systems. (a) A passive dynamic walker is made of a purely mechanical structure without motors or sensors and can walk down a shallow slope by converting potential energy into kinetic energy (46). (b) A blind juggling robot achieves stable juggling of a black ball without using any sensors (48). Panel a reproduced with permission from Reference 49; panel b reproduced with permission from Reference 50.

**2.2.2. Collective systems.** Consider a colony of insects that use pheromones as a means for communication and navigation (56). An agent moving at speed  $v$  is producing a volatile pheromone that decays at a rate  $k_-$ . The distance over which ants travel is on the order of tens of meters—call it  $d$ . For ants to perform chemotaxis, we require that  $\tau_a = 1/k_- \sim d/v = \tau_b$ . If  $\tau_a \gg \tau_b$ , then the pheromone decays too slowly, and before long, the neighborhood will be saturated with pheromone. On the other hand, if  $\tau_a \ll \tau_b$ , then the pheromone decays too quickly, and by the time an ant has traveled the distance  $d$ , it cannot detect any signal (**Figure 4c**, subpanel *ii*). Only when the two timescales are matched can we expect to see pheromone-driven cooperation and coordination of a swarm (**Figure 4c**, subpanel *i*) and the emergence of stigmergy (57). Note that a collective system with matched timescales is likely to exhibit emergent behavior; however, this does not guarantee task-oriented behavior. This is exemplified in so-called death spirals of army ants (58), where a group of ants lose the pheromone trail from the main foraging party and follow each others' pheromones to exhaustion. The use of matched timescales of pheromone-like fields has been exploited in various robotic implementations for cooperative problem-solving (59–61).

Next, consider a system of weakly coupled oscillators, as captured with the Kuramoto model

$$\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i), \quad 3.$$

where the natural frequency  $\omega_i$  of each of the  $N$  oscillators  $i$  is drawn from a probability density  $g(\omega)$ .  $K$  is called the coupling constant and determines the strength of interaction between oscillators. Kuramoto showed that, for symmetric and unimodal distributions of  $g(\omega)$ , the oscillators that are sufficiently close in their intrinsic timescale (i.e.,  $|\omega_i| \leq Kr$ , where  $r$  is the radius



**Figure 6**

Examples of bioinspired robotic systems. (a) A soft crawling robot inflates and deflates five elastic air chambers independently to change its locomotion gaits. (b) A whisker robot is equipped with sensorized sticks that are actively oscillated back and forth to physically interact with the environment for tactile perception. (c) A tactile robot hand uses a soft tactile sensor installed in a fingertip that can actively interact with the environment. (d) A salamander robot is composed of eight actuated modules that can be controlled by the bioinspired central pattern generator for locomotion on land and underwater. Panels *a–d* reproduced with permission from References 65, 66, 67, and 64, respectively.

of phase coherence) eventually synchronize (62). This concept has been leveraged in robotic systems by employing coupled central pattern generators that generate gait patterns in walking and swimming agents (63, 64) (**Figure 6d**). These systems are furthermore coupled to the natural timescales of the environment (68, 69).

### 2.3. Scale Separation

In contrast to matched timescales and their innate dynamical coupling, the separation of timescales opens up the possibility to solve problems independently. In collective systems in particular, small-timescale processes can lead to an emergence of a larger timescale. Take, for instance, the pheromone-driven cooperation discussed previously. While the timescales associated with the motion of individual agents are small, the construction of nests in animals and robots is observed on a larger timescale (70, 71). There is often a hierarchy of small–large-timescale separations in biological systems, such as molecules forming proteins, proteins forming cells, and cells forming multicellular organisms. Each timescale arguably dictates the behavior of a separate problem, yet the timescales are interdependent. A similar observation can be made for the Mexican wave observed at large sports events (72). The wave travels around a stadium on a timescale on the order of minutes, while the action that gives rise to it—standing up and sitting down by the individual spectators—takes place on the order of seconds. The long timescale is an emergent property of the reaction of spectators to their neighbors. Similar emergent temporal patterns are also observed in other excitable media, such as neuronal avalanches (73), giant honeybees (74), and wildfires (75).

In engineering, examples of embodied timescale separation abound: the fast vibrations of Kapitza’s pendulum that stabilize the slow dynamics of the pendulum around the unstable fixed point (76, 77), the fast oscillations of an amplitude-modulated radio signal that carry a slower

acoustic signal, the fast stepping frequency of people over a bridge versus the duration of catastrophic failure due to resonance (78), the fast vibrations required for an insect robot to hover and the slow timescale for attitude control (79), or the fast mechanical oscillations in a pocket watch that make the hour hand spin every 12 hours. In robotics, the realization that processes with different timescales can operate in parallel and independently from one another yet work toward a common goal has led to an innovative approach in the field of artificial intelligence. The subsumption architecture (80) for behavioral programming of robots decomposes the behavior of a system into subbehaviors that operate independently and on independent timescales, yet are hierarchical such that some processes subsume others. Along the same lines, systems like W. Grey Walter's mechanical tortoise (81) and Braitenberg's "vehicles" (82) are other examples of systems that can run processes of diverging timescales in parallel. The realization that engineered systems benefit from hierarchical and parallel control structures has also been emphasized in the field of reinforcement learning (83).

## 2.4. Nontemporal Sequences

Keeping track of all dynamical states in a system over time is challenging, and it can be helpful to capture only discrete events, such as a step in a walking gait, a throw in juggling, or the deposition of a material unit in nest construction. These events are agnostic to their temporal history. For example, the time difference between two steps can happen over seconds, minutes, or years, yet the outcome of the two events is the same: One step is taken. In such a framework, time's only purpose is to define the order of sequences, not their duration. We have arrived in a realm of automata (84), Turing machines (85), and sequential logic (86). These nontemporal sequences allow problems to be solved literally one step at a time rather than in a continuous dynamical system. The concept of nontemporal sequences has profoundly influenced the way engineers design artificially intelligent systems. In nature, the mastery of nontemporal computations appears to be beneficial as it relates to problems of contact that are consequential for survival. For instance, the collision of two bodies occurs in many existential events, and there is a discrete state change from before to after the event. Examples include a predator catching prey, impact upon a fall, space occupation, and reproduction. It is unclear to what degree animals use the power of nontemporal computations, but it appears reasonable to assume that the discrete nature of spikes observed in neuronal signal transduction allows for the manipulation of such sequences for planning and computation. There are other physical processes in nature where the duration of a process is irrelevant for the outcome. This is the case for systems operating in viscous fluids, as pointed out by Purcell (87; see also 88). Living systems with low Reynolds numbers do not depend on the speed of their executed action, but only on the sequence of actions. Similar observations in crawling and slithering locomotion have inspired a geometric theory of locomotion (89).

Nontemporal sequences are the cornerstone of modern computers, which essentially carry out sequences of discrete operations. We generally consider only the property of causality of temporal processes, and not their duration. This way of thinking has led to enormous insight into artificial life (90, 91), collective behavior (92), and neural networks (93, 94), to name a few. It is worth pointing out that we do not know whether the best representation for natural intelligence is as a nontemporal sequence process or if certain aspects of intelligent systems are better explained using temporal processes.

## 3. FUNCTIONAL ASPECTS OF CROSS-TIMESCALE INTERACTIONS

As shown in the previous section, cross-timescale dynamics can be observed in many embodied systems, and their interactions have been studied in various biological, physical, and engineering

contexts. Although these phenomena are interesting in their own right, embodied intelligence studies have also shown that they are useful and important from the functionality viewpoint. A functional understanding of cross-timescale interactions is a critical step forward. The underlying embodied dynamics determine the intrinsic timescales of the processes, but it is not clear how these dynamics interact with each other to provide benefits of autonomy and adaptability, eventually contributing to survival in nature or practical engineering applications.

In what follows, we discuss the three interaction types of cross-timescale dynamics from a functionality viewpoint. This overview will provide the general principles of cross-timescale dynamics, in which timescales are not set arbitrarily but are fully grounded in the physical properties of embodied systems, while they are used for various practical functions necessary to make systems autonomous and adaptive.

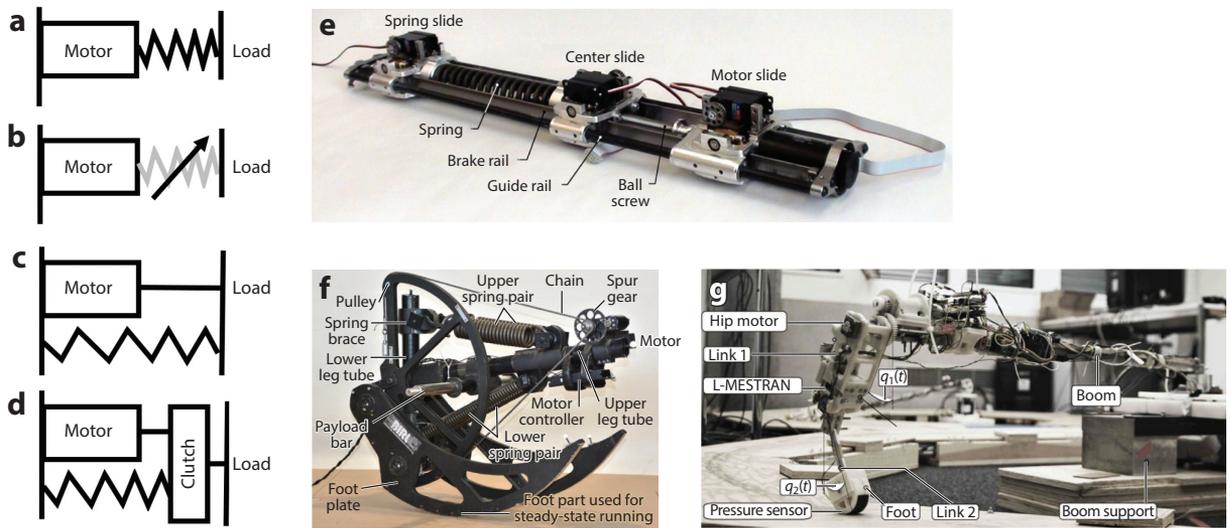
### 3.1. Energy Efficiency and Behavioral Diversity

One of the most direct benefits of cross-timescale interactions in embodied systems is to achieve energetic efficiency while maintaining behavioral diversity. Every embodied system has its intrinsic patterns of behaviors associated with its natural dynamics, such as a walking gait of a passive dynamic walker. Because of these natural dynamics, energetic input to the system is usually minimal for this type of behavior, but additional behavioral patterns—such as different stride lengths, frequencies, or other gaits in general—require additional considerations.

Energy input is crucial in any dynamical systems in the real world to fuel the systems against dissipation. Regardless of whether they are biological or artificial, every embodied dynamical system contains mechanisms of energy supply, preservation, and dissipation, and because of their mechanical and/or chemical processes, the timescales of a system's behaviors are determined largely by the intrinsic dynamics of energy input and dissipation. Energetic consideration—also known as embodied energy (95)—is therefore fundamental for cross-timescale interactions, from which embodied systems can benefit for the improvement of autonomy and adaptability.

As exemplified by the passive dynamic walker in the previous section, legged locomotion is an interesting and important research field to systematically investigate energy efficiency. The passive dynamic walker was initially proposed as an energetically efficient locomotion system, but a series of other mechanisms were also proposed for further improvement (96). The energy efficiency of locomotion systems is typically calculated by using a metric called cost of transport (97, 98), which is defined as the amount of energy required to move a unit weight for a unit distance. In this formulation of efficiency, the cost of transport indicates lower values for efficient systems, and it decreases with increasing mass and constant power consumption at increasing speeds. Generally, passive dynamic walkers are at a disadvantage when speed and body mass increase, because their pendulum-like gait dissipates more energy when interacting with the ground (99). An alternative approach is to make use of more dynamic gait patterns, based on the so-called parallel elastic actuation mechanisms (100, 101), shown in **Figure 7c**, in which a large mass can be supported by a spring, and harmonic oscillation can be induced for hopping locomotion by actuating the system at the resonance frequency (103) (see **Figure 7f**).

Parallel elastic actuation is a scalable design method that works in a large variety of hopping locomotion systems, from small and light to large and heavy ones, because the resonance frequency can be determined by the mass and spring constant, as described in Equations 1 and 2. That said, the spring constant and mass are not completely independent, as the spring must support the mass statically, and a large-mass system requires a large spring constant. The control of the motor is another element that needs timescale matching. For the most energy-efficient locomotion, the motor can only drive oscillation at the natural frequency, as a very-low-power motor is used. As a



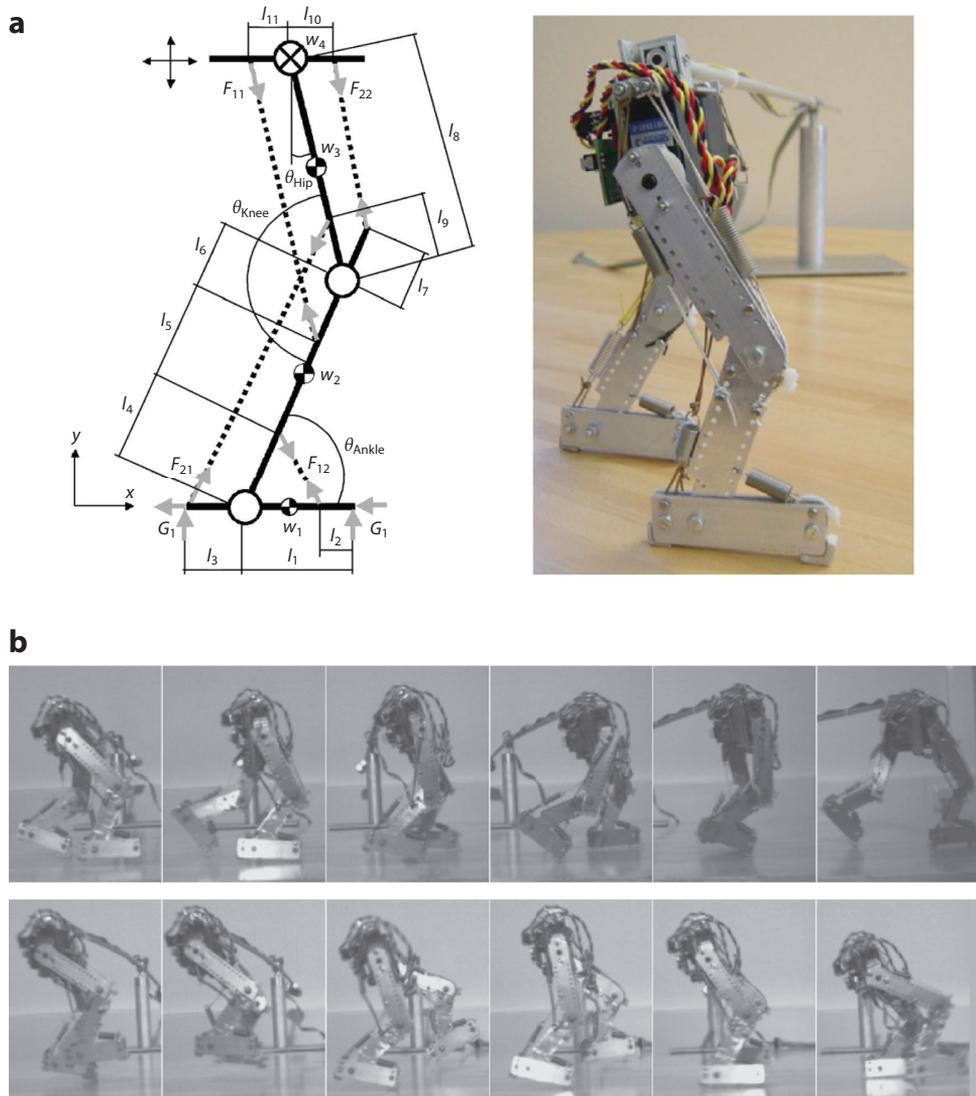
**Figure 7**

Actuation mechanisms and locomotion robots. (a–d) Schematics of (from top to bottom) a series elastic actuator, a variable-stiffness actuator, a parallel elastic actuator, and a parallel elastic actuator with a discrete coupling. (e) A linear multimodal actuator equipped with three micro discrete couplings. (f) A hopping robot that makes use of a parallel elastic actuator. (g) A hopping robot with a variable-stiffness actuator that is capable of varying its locomotion speed while maintaining energy efficiency. Abbreviation: L-MESTRAN, linear mechanism to vary stiffness via transmission angle. Panels e–g adapted with permission from References 102–104, respectively.

result, the current record of energy efficiency is a cost of transport of 0.01 for a 180-kg hopping robot actuated by a 40-W DC motor.

Intrinsic body dynamics can also be varied—for instance, by equipping systems with stiffness-adjustable mechanisms (105) (**Figure 7b**). Such a mechanism has demonstrated that energy consumption for locomotion can be kept low at various hopping frequencies and speeds if the leg stiffness can be adjusted in a hopping robot (104) (**Figure 7g**). In this context, cross-timescale separation and nontemporal sequences could introduce valuable contributions. The use of mechanical clutches in a legged robot could decouple the dynamics of springy legs from the locomotion dynamics, which could be beneficial for further improvement of locomotion efficiency and other performance metrics (102, 106) (**Figure 7d,e**).

Locomotion gait transitions in biological systems are another phenomenon in which cross-timescale interactions play a significant role (107). Four-legged animals, such as horses, dogs, and cats, are known to exhibit a large number of gait patterns, including walking, pacing, bounding, and galloping (108), and bipedal animals, such as humans, switch between walking and running depending on whether the situation calls for speed or efficiency (109). For any locomotion gait to happen, a complex coordination between neuromusculoskeletal systems is necessary, in which individual components of neurons, muscles, skeletons, tendons, and ligaments need to tune into a single timescale. While this phenomenon can be regarded as timescale matching among all of the active components involved, a timescale separation is needed to induce gait transitions. For a transition from walking to running, for example, gait patterns change from walking cycles involving single or double support legs (either one or two legs are on the ground) to running cycles of single or no support legs (either one or no legs are on the ground) (38). For these two gait patterns, two different sets of muscles need to be recruited to induce different body dynamics.



**Figure 8**

Biomimetic planar biped robot with biarticular springs. (a) Schematic (left) and photograph (right) of the robot, with four springs (indicated by dotted lines labeled  $F_{11}, F_{12}, F_{21}$ , and  $F_{22}$ ) incorporated into each leg, to mimic some of a human's leg muscles. (b) Time-series photographs of the two gait patterns of walking (top) and running (bottom). Figure adapted with permission from Reference 110.

To investigate such a gait transition mechanism, a planar biped robot (**Figure 8**) was built with four sets of mechanical springs in each leg arranged in human-like leg muscles (110). This case study explored which muscle-like springs were necessary to induce running and walking gait patterns, by adjusting the degrees of tension given in each of these springs. The investigation identified that the thigh springs (representing humans' rectus femoris muscles) are necessary for a running gait, while the calf springs (representing gastrocnemius muscles) are more important for a walking gait.

In general, energy efficiency and behavioral diversity are often a trade-off. For efficient motions, systems need to take advantage of given intrinsic dynamics, such as natural frequencies, whereas active control by adding energy is necessary to deviate from the intrinsic dynamics to achieve variations of motions. Nevertheless, the case study of gait transitions introduces a counterexample of this trade-off between energy efficiency and behavioral diversity. Two patterns of walking and running behaviors can be achieved without compromising energy efficiency if a different set of muscles can be exploited, which can be regarded as an example of timescale separation.

### 3.2. Coordination for Motion Control

Cross-timescale interactions are also an essential concept for coordinating the motions of embodied systems and their interactions with the environment through sensing and feedback control. In the previous examples of legged locomotion, we assumed perfectly smooth and rigid terrain with no need for sensing and feedback, but real-world systems usually require sensing and adaptation to the environment if it is changing or uncertain. For instance, locomotion on rigid ground requires different control than locomotion on elastic ground, and systems therefore first need to sense the environment to adjust their motor actions to maintain locomotion dynamics. As explained previously, cross-timescale matching is necessary for motor control, but another timescale-matching mechanism is also necessary for the sensing processes.

Sensory-motor coordination is a general principle of motion control in nature; that is, animals regulate their own motions to maximize sensitivity and discrimination abilities (111). A well-known example from neurophysiological experiments with rodents is the use of active whisking for environmental perception (112, 113). These animals have arrays of whiskers that can be moved back and forth, and these whisking actions are important for their sensing capabilities. Whisker-inspired sensing has been explored thoroughly in the field of robotics (114–116). In one example, shown in **Figure 6b**, a robot with whiskers was built to investigate the relationships between actions and performance in sensing the environment (66). The robot had an array of sticks, each of which had a Hall-effect magnetic sensor to detect deformation, and the sticks were actuated to mimic active whisking. The interactions between these whiskers and the environment were not trivial, but the relationship between motor actions and sensory information was clearly identified for better performance of environment classification. A similar relationship was also found in tactile discrimination tasks of a human-like finger robot with touch sensors (**Figure 6c**) interacting with textured surfaces (67), which complemented the active efforts in robotics for embodied touch sensing (117–119). Studies have demonstrated information gain and classification performance of complex tactile perception tasks (e.g., detection of abnormal human body tissues through palpation) when motions of these sensorized fingers trigger pertinent interactions with the environment (120, 121).

These case studies exemplify that the mechanical interactions with the environment through active sensing could induce timescale matching to transform physical interactions into sensory signals through mechanical designs in order to detect particular aspects of the environment. It is also worth mentioning that these interactions can separate the timescales of other environmental features through this active sensing. These mechanisms of sensor-motor coordination are conceptually similar to the coupled oscillator model introduced in Section 2.2. The oscillation frequencies of the whiskers or the sensorized fingers should match the oscillation frequencies of physical interactions of whiskers or fingers with the environment. The larger amplitude of oscillation could, in turn, induce large forces exerted on the sensory receptors. These frequency-matching behaviors can be modeled and analyzed in a similar way as the weakly coupled oscillators.

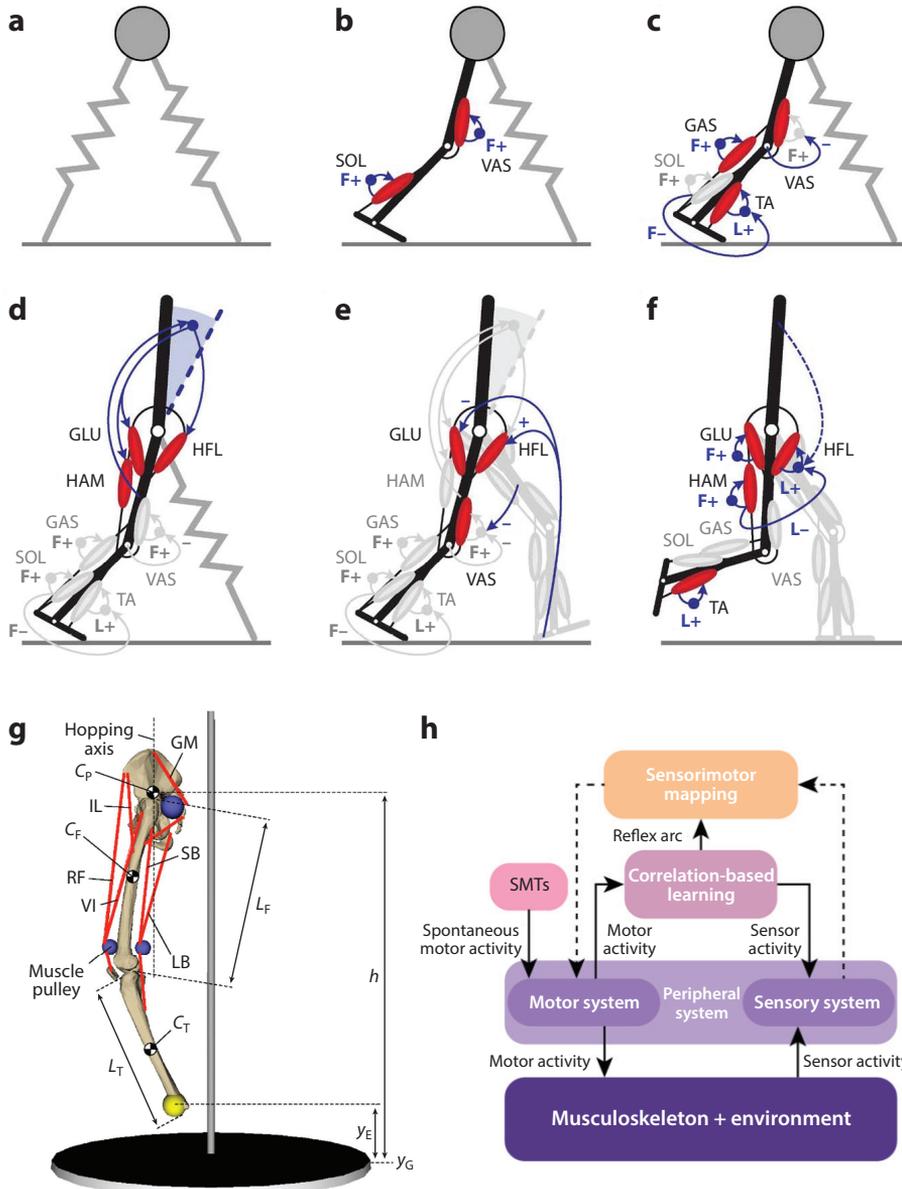
A more complex example of sensory-motor coordination was investigated in the salamander robot introduced above, which creates significantly more complex behavioral patterns by using a large number of oscillators (64). The robot has more than eight actuated joints, each of which is controlled by a neural oscillator model, but in theory, the same architecture can be extended to arbitrarily complex systems with a greater number of joints, as shown in many other robotic applications (122–125). The scalability of complex motor coordination relies on the local timescale matching of neural oscillators, and whole-body undulation motions can be generated at a different timescale, which enables swimming or walking behaviors.

The use of complex neural dynamics as generated by central pattern generators is not the only approach for coordinating complex motor behaviors in nature. An alternative approach relies on spinal reflexes (126) (**Figure 9a–f**). Spinal reflexes result from neural circuits in animals' spinal cords that have direct connections with skeletal muscles and their sensory receptors. These reflexes usually trigger a contraction of muscles upon sensory stimuli and take place on a very short timescale (on the order of 10–50 ms) compared with the timescales of neural oscillators (on the order of seconds). Reflex-based control schemes have also been heavily used in robotic systems (129–131). In one work, 30 spinal reflex circuits were incorporated in a simulated bipedal robot, and a natural walking gait was obtained as a consequence of spinal reflexes only (127). This case study is particularly interesting for two distinctive reasons from the viewpoint of cross-timescale interactions. First, it is a good example of how nontemporal sequences can generate temporal behaviors because of the interventions of embodiment. Though the triggering control signals are instantaneous, with no temporal components, a continuous sequence of complex adaptive behaviors can be generated. In fact, the underlying mechanism of this bipedal walking is not the design of spinal reflex circuits in isolation; rather, the reflexes trigger the dynamics of the musculoskeletal system (each muscle has mechanical stiffness and damping properties, for example). This nontemporal reflex control strategy suggests a useful approach to minimize control efforts by exploiting the natural dynamics. Second, another important aspect is the use of mechanical bodies for the coordination of motions. Each individual reflex circuit receives only limited information about the behaviors of local muscles at a certain point in time and does not know the behaviors of other muscles or the overall body over time. Nevertheless, the reflex circuits trigger muscle contractions with their own timescales, the consequences of which eventually propagate to the other set of surrounding muscle reflex circuits because these muscles are physically connected with and influenced by each other. This coordination of complex motor actions for walking is possible because, even though the reflexes have no temporal component, muscles and their connections through the skeletal structure provide timescale matching.

How can the complex coordination of spinal reflex circuits be programmed or automatically acquired in a self-organized fashion? A concept from the muscle twitch hypothesis has shown that basic spinal reflex circuits can be automatically obtained via random perturbations of musculoskeletal systems (128). In this framework, a simulated animal-like skeletal system has a set of muscles with integrated sensors and activation dynamics (**Figure 9g,b**). These sensors and actuators are initially connected fully, but when muscles are randomly activated individually, a Hebbian learning algorithm (132) can pick up correlations between muscle activation signals and corresponding sensor signals. These correlations can, in turn, behave like spinal reflexes, which have been used to demonstrate simple coordinated hopping behaviors. This case study shows that an additional timescale of the self-organization process involving muscle twitches and Hebbian learning can be integrated such that it is separated from practical behavioral functions such as walking and hopping.

### 3.3. Embodied Dynamics and Physical Computation

Cross-timescale interactions are important not only for generating behavioral patterns, as explained in the previous two subsections, but also for information-processing and computational purposes. Any computational process, regardless of whether it is of biological or artificial origin, is governed by some form of physical dynamics, such as arithmetic operations on silicon wafers or spike trains on neurons. Today's computer technologies are fairly generalized and modularized such that we usually do not need to think about these underlying physical dynamics; however,



(Caption appears on following page)

**Figure 9** (Figure appears on preceding page)

Coordination of reflexes in simulated legged locomotion models. (a–f) A bipedal locomotion model based on eight reflexes in each leg. Interactions with the ground trigger a series of reflexes that lead to a stable walking gait. Abbreviations: F–, negative force feedback; F+, positive force feedback; GAS, gastrocnemius; GLU, gluteus muscle group; HAM, hamstring muscle group; HFL, hip flexor; L–, negative length feedback; L+, positive length feedback; SOL, soleus; TA, tibialis anterior; VAS, vasti muscle group. (g) A three-segment skeletal model connected through two joints and six muscles (indicated by the red lines). This model is constrained by a vertical pole for a one-dimensional hopping behavior to test the muscle twitch hypothesis. Abbreviations:  $C_F$ , center of mass of the femur;  $C_P$ , center of mass of the pelvis;  $C_T$ , center of mass of the tibia; GM, gluteus maximus;  $b$ , height of the hip; IL, iliacus; LB, long biceps;  $L_F$ , length of the femur;  $L_T$ , length of the tibia; RF, rectus femoris; SB, short biceps; VI, vastus intermedius;  $y_E$ , height of the end effector;  $y_G$ , height of the ground. (h) A Hebbian-learning-based architecture to test the muscle twitch hypothesis. Biological models of sensory receptors and muscles are initially fully connected, and then the sensory-motor causalities are learned through the embodied interactions with the environment triggered by muscle twitches (indicated as spontaneous motor activities). The learned coordination can be used in a hopping behavior. Abbreviation: SMT, spontaneous motor activity. Panels a–f adapted with permission from Reference 127; panels g and h adapted with permission from Reference 128.

the computational processes and physical dynamics are intrinsically related to each other (133). While the independent nature of today's computers from the underlying physical dynamics can be beneficial in many ways, the relationships between them can be another facilitator for complex autonomous and adaptive systems. Here, we introduce a few examples of cross-timescale dynamics as a form of physical computation used for practical functions of autonomous adaptive systems.

Computational tasks can be regarded as a problem of mathematical function approximation or regression. Assuming an  $n$ -dimensional vector as input information and an  $m$ -dimensional vector as an output, the relationship between input and output can be approximated by a set of mathematical equations, or a neural network with  $n$  input nodes and  $m$  output nodes. The input/output vector can also be a time-series variable. In such a case, the equations or neural network can be more complex, with time-varying parameters, but the general characteristics of computation can be discussed in a similar manner.

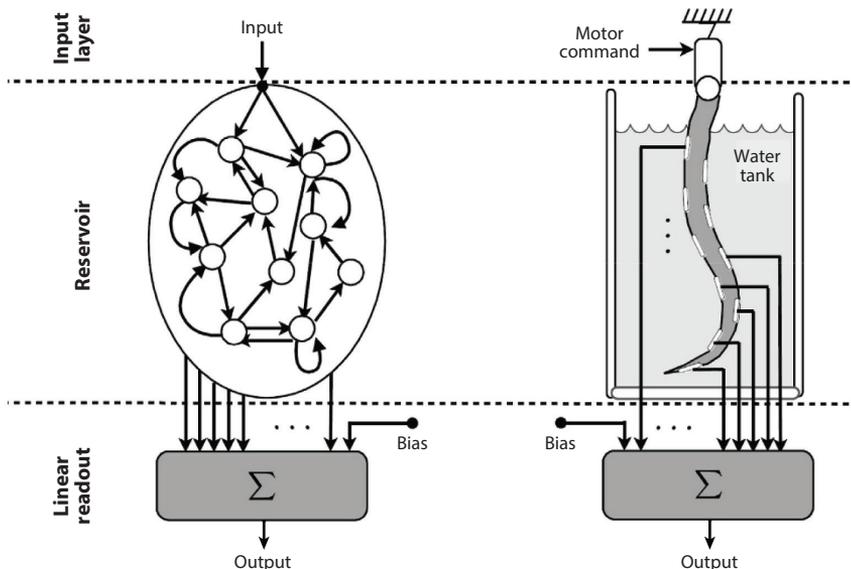
Now, physical computation can be discussed in the same context, by replacing the equation/neural network with some physical dynamics. A famous example of basic physical computation is the replacement of a proportional–differential (PD) gain controller with a spring–damper system (134). A PD controller can be mathematically represented by  $T = K_p[x(t) - x^*] + K_d[\dot{x}(t) - \dot{x}^*]$ , where  $x(t)$  and  $\dot{x}(t)$  denote the position and velocity of the system, respectively;  $*$  indicates the target position and velocity; and  $K_p$  and  $K_d$  are the gain constants. This controller is usually used to calculate the motor torque  $T$ , which asymptotically pushes the system toward the target position and velocity by setting pertinent gain constants, which are used in many feedback control systems, such as temperature control of refrigerators. When we employ physical computation, this mathematical equation can be replaced by a simple spring–damper system, where  $K_p$  and  $K_d$  can be regarded as spring and damper constants, respectively, while  $x^*$  and  $\dot{x}^*$  can be the rest length of the spring and the offset of the damper, respectively. The PD controller usually makes use of digital computations with microcontrollers and so on, but it can be replaced by a physical spring–damper system, with which we could bypass the use of position/velocity sensors and microcontrollers, thus avoiding potential issues due to measurement errors.

This concept of mechanical PD control is used by many biological systems, where it is known as a preflex (135). Here, the viscoelastic properties of biological muscle–tendon elements are often used to stabilize the motions of legs and arms, which is significantly more advantageous than motor control based on slow and expensive neural processes. On the other hand, it is necessary to have timescale matching between the overall behavior of legs/arms and the muscle–tendon elements.

The same concept has been applied to many robotic systems since the invention of series elastic actuators (136) (**Figure 7a**), which became one of the main actuation mechanisms for robots to cope with uncertain and complex interactions with their environment, such as locomotion on rough terrain (137) and coworking with humans (138).

How can we extend this concept of physical computation for more complex problems? The concept of reservoir computing provides a theoretical framework to systematically discuss this question (139, 140). The reservoir computing framework originally started as a subcategory in the field of recurrent neural networks, and it specifically considers a learning problem of readout only. Unlike the ordinary learning of recurrent neural networks, in which all of the connection weights are tuned in the learning process, the learning algorithm of reservoir computing considers only the last layer (the readout layer) of the network, and all of the other layers are assumed to have sufficiently rich connections that they do not need any further adjustment. If the main body of the network already has rich resources of computation, then the reservoir computing learning algorithm only needs to select which part of the network to connect to the readout layer. This approach turns out to be an efficient and effective way to emulate various nonlinear functions.

An interesting aspect of the reservoir computing framework from embodied intelligence research lies in the fact that the main body of the network can be replaced by any rich dynamical system, including physical dynamics. A thought-provoking case study was conducted by using a sensorized soft robotic arm mimicking an octopus tentacle as the main source of computation (141) (see **Figure 10**). This soft arm was made of deformable silicon that exhibits characteristic viscoelastic behaviors underwater when it is moved by an electric motor installed at the base. This case study used the soft arm as the reservoir, the time-series motor rotation angles as input signals to reservoir computing, and signals from the 10 deformation sensors as the readout output of reservoir computing. It showed that a standard machine learning benchmarking task—the



**Figure 10**

Physical reservoir computing. The illustration on the left shows the concept of general reservoir computing based on a recurrent neural network. The one on the right shows how a soft robotic arm (in this case, one mimicking an octopus tentacle) was used as a physical reservoir to test its computational capacity. Figure adapted with permission from Reference 139.

so-called nonlinear autoregressive moving-average system—can be successfully performed in certain conditions, and that the computation capacity is dependent on the viscoelastic property of the soft arm, which is directly related to the timescales of the dynamics. This study has ignited a stimulating discussion about how systems can use their physical bodies as a computational resource, and several robotic systems have been created to study this question (142, 143).

The case studies discussed above showed that systems' behaviors and computation do not need to be independently processed, but can be coupled to each other through embodiment. We still do not know what the benefits are of such couplings beyond the conventional approaches of computation, but there is no reason to ignore these free resources of computation. In fact, it is important to identify how much physical computation can be achieved in complex embodied systems and how much energy and other resources the systems could save through the physical computation.

## 4. CHALLENGES AND PERSPECTIVES

This article has described case studies of cross-timescale interactions in various biological and engineered systems. Based on these previous explorations, we proposed three types of cross-timescale interactions (matching, separation, and nontemporal sequences), which allow us to systematically discuss the theoretical models as well as their robotic applications. Even though each individual case study is relatively simple, a landscape of these examples in the context of cross-timescale interactions can provide insights that enable a better understanding of autonomy and adaptability in embodied systems. In this section, we extend these arguments further to discuss open challenges and future directions of research.

### 4.1. Patterns, Structures, and Complexity

Research on embodied intelligence aims to understand the principles and technologies for complex autonomous and adaptive systems. Obviously, if we wish to build a basic clock, we do not need complex dynamics, and a simple mechanical pendulum or stable quartz should be sufficient. On the other hand, if we wish to develop a system exhibiting rich dynamics in less structured and noisy environments, as exemplified by biological systems, it is necessary to investigate a new methodology, taking advantage of the insights gained from the discussions above.

As an example of a complex system, take the human body. An adult human consists of  $10^{13}$  cells and modular organs such as the brain, muscles, blood, reproductive systems, and so on (35). The number of cells is already impressive compared with our most technically advanced artificial systems (for example, the world's largest passenger aircraft, the Airbus A380, has only 4 million parts, which is seven orders of magnitude smaller than the number of cells in an adult human body). Moreover, all of these cells are continuously changing and being replaced by new ones throughout the person's life span, leading to highly dynamical systems at many different timescales.

For a systematic analysis of such complex systems, it is crucial to consider their growth processes: Each human starts as a single cell and develops into an organism of  $10^{10}$  cells at birth (144), after which the number of cells increases another 1,000-fold until it reaches  $10^{13}$  at the adult stage. To achieve such large-scale development, the growth process must be sequential, well planned, precise/repeatable, and robust against various sources of disturbances. This growth process also requires significant interactions with and involvement of the surrounding physical environment. For example, the human genome has 3 billion pairs of four nucleobases (adenine, thymine, cytosine, and guanine), representing approximately 700 MB of information—an extremely small amount compared with the overall complexity of the whole body. If this relatively small amount of information is the origin of the complex organism, then the developmental processes must involve significant embodied dynamics of physical bodies and the surrounding environment, such that a small amount of information can trigger complex developmental processes.

In this context, the discussions of cross-timescale interactions could provide an interesting avenue of research to investigate the effect of the three types of cross-timescale interactions on the origin of the large diversity of patterns and structures. This concept allows us to develop an overarching framework between systems and environment, patterns and structures, and physical and informational dynamics.

## 4.2. The Frame-of-Reference Problem

Compared with biological systems, conventional robotic systems are static and rigid. In conventional robotics, for example, motions are defined as time-series trajectories of joints, end effectors, or wheels. The complexity in such systems can be benchmarked by the number of degrees of freedom. For example, a humanoid robot with 100 joints is more complex than one with 20 joints. This approach is valid as long as the tasks can be described as a set of trajectories and the trajectories are fully controlled by the joints or wheels. If the system is underactuated, for example, then the complexity cannot be defined by the number of degrees of freedom alone; the environment must also be considered, as even for a single-joint system, if the environmental influences are nontrivial, the control of such a joint is challenging. Similarly, for problems like cleaning a messy room or rescuing a human at a disaster site, the task itself cannot be defined as the set of trajectories; the designs-for-emergence approach is necessary, as the tasks cannot be known at the stage of system designs and become known only on site.

This is a fundamental problem often referred to as the frame-of-reference problem (20): A system's internal mechanisms in isolation cannot always explain the system's behaviors, because behaviors are always the result of system-environment interactions. In other words, if the environment is known or perfectly controlled, then system design problems can be significantly simplified. On the other hand, if we have environments with dynamics and uncertainty, then we need a different approach, one that includes more redundancy, more sensing capacity, more task versatility, and less specialization.

One of the significant challenges of complex autonomous adaptive systems, therefore, is to consider the factors of the surrounding environment, in which the conventional notion of degrees of freedom is not sufficient. Studying a robot with a large number of degrees of freedom in a single environment is not sufficient to improve the autonomy and adaptability of our complex systems; we need to systematically analyze how a system can interact with various environments to maintain dynamics. From this perspective, the DARPA Robotics Challenge (145) and the Amazon Picking Challenges (146) were interesting attempts. These robot competitions defined complex tasks and environments (such as humanoid robots traversing the rough terrain of a disaster site with lots of debris and robotic picking of hundreds of unstructured items in Amazon warehouses, respectively) and asked competition participants to develop systems to solve these problems. Obviously, system designs must consider all kinds of interactions in the competitions, and sometimes they must prepare for surprise tasks. Systems' behaviors and functions are always a result of the interplay between the actions interacting with the environment (147), and thus environment-inclusive designs and analysis are essential. That said, the design processes in these competitions were still highly dependent on the human designers, which significantly restricted the autonomy and adaptability of these systems. As long as systems' performance in complex environments is dependent on human designers, their autonomy and adaptability cannot overcome the problems beyond the benchmarks.

More generally, how can we design a system if its tasks and environments are not known at the development stage? There are three basic strategies. First, we make the system as redundant as possible to improvise or learn previously unknown new tasks, by equipping the system with more than the minimum task functions to allow for creative and flexible solutions to unexpected

situations. Second, we design the system such that it could construct or modify given tasks and environments; for example, many animals make use of the so-called extended phenotype strategy (148) to construct their ecological niche. Third, we allow the system to grow over time physically and cognitively to adapt itself to changing/unknown tasks and environments, which we discuss in the following subsections.

### 4.3. Data-Driven Embodied Intelligence

Assume that a system is not completely optimized for given tasks but has some capacity for adaptation through sensory-motor learning. If the system has large degrees of sensing and motor capabilities (many sensory receptors and many motors and joints in the body), then finding motor actions at every time step is a nontrivial problem because of the combinatorial explosion.

For this problem, machine learning algorithms made a crucial contribution in the last few decades. The progress was made mainly in the approximation methods of functions describing the relationships between informational input and output. If the input–output relationships can be shown by many examples (training data), then any relationships can be approximated in theory. However, more data are required as the complexity of the input–output relationship increases.

It is important to consider that the complexity of input–output relationships can involve temporal processes determining the input and output. For example, the input signals can be time-series information, such as the sound of a piece of music or the time-series joint trajectories of a robot. In this case, the learning needs to consider temporal information, such as long short-term memory networks (149), which contain recurrent connections within the neural networks. Obviously, because of the recurrent connections in the network, the problem of function approximation is more complex than it is for those without temporal dimensions. On the other hand, if we consider the cross-timescale interactions carefully, this complex problem can be significantly simplified. As introduced in bipedal walking based on reflex circuits (in Section 3.2), for example, a complex sequence to carry out a walking motion can be achieved through a set of nontemporal reflexes, because the musculoskeletal dynamics has its own intrinsic timescales that can be triggered.

In theory, a neural network with recurrent connections can approximate any input–output relationship, including diverse timescales. However, the wider the range of timescales contained in the input–output dynamics, the more difficult it is to obtain the relationships, especially under the practical constraints of limited resources of data and computation. In this context, timescale matching and separation are the key concepts to manage the capacity of learning under restrictions. This discussion implies that timescales of machine learning cannot be arbitrarily set, but the considerations of timescales in embodied interactions are essential, especially when approximating complex input–output relationships.

The physical reservoir computing framework is particularly interesting in this context. The learning of physical reservoir computing considers only the last layer of the network (the readout connections), but the rest can remain open and flexible. The dynamics can be physical or informational and can be added or removed from the reservoir. Also, physical reservoir computing can emulate any computational task as long as it contains a sufficient diversity of dynamics with variations of timescales.

### 4.4. Material-Level Intelligence and Soft Robotics

While sensory-motor learning can certainly increase autonomy and adaptability, the remaining limitations need to be addressed by physical or mechanical adaptation of systems. If a system has a good physical design in a well-behaved physical environment, then many sensory-motor control processes can be simplified or completely eliminated, as exemplified by plants, which have no

brains. There has also been growing interest in the study of soft-material robotics, i.e., the study of deformable materials to be used for robotics applications (28). Animals' autonomy and adaptability depend largely on the deformation of the eye lens, the internal organs (such as lungs and stomachs), and the muscles in general, because controlled deformation is a powerful adaptation approach, particularly in dynamic and uncertain environments. The soft robot shown in **Figure 6a** is a crawling robot made exclusively of elastomer that is capable of multiple gait patterns, facilitated by the flexible properties of its body.

That said, deformations have significant drawbacks because soft structures cannot transmit large forces across distances. With the lack of large-force transmission, a system cannot be large, strong, fast, and precise in its motion control (150). A hybrid of soft and rigid structures is, therefore, an important design principle for complex systems, which can exploit advantages of both soft and rigid aspects of embodiment. Not only is the principle of soft–rigid hybrid structures related to size, strength, speed, and precision, but, as shown by our discussions of cross-timescale interactions, it has additional implications in terms of motor efficiency, coordination, computation, learning, and social interactions.

Increasing the size and volume of physical structures is another significant challenge. Many technological solutions have been based on 3D-printing technologies and inflatable structures, but none of them have yet considered cross-timescale interactions. Many exciting challenges exist in this line of research, such as how to perform spatial exploration through growth, how to include environment dynamics that can be exploited for structure growth (151), how structures can autonomously recover from failures and damage and possibly strengthen themselves, and how material dynamics can be exploited for autonomy and adaptability (152). The functionalization of materials with sensory, motor, and computational capabilities will also open a door for autonomy and adaptation in various timescales in this context.

#### 4.5. Physical Evolutionary and Developmental Robotics

Even though physical adaptation provides a broad spectrum of exciting opportunities in which robotic systems can significantly improve their autonomy and adaptability, it also introduces several considerable challenges because of the expansion of dimensionality. As discussed above, the design problems of autonomous and adaptive systems include an extraordinarily broad range of timescales, from very short ones (such as milliseconds) to very long ones (such as years and decades), which makes them impossible to handle in an ordinary design optimization approach—a phenomenon usually referred to as the curse of dimensionality (153). These limitations were challenged with conventional evolutionary approaches (e.g., genetic algorithms, evolutionary algorithms, and evolutionary robotics) (154), but it became apparent that these approaches can deal only with a smaller subset of the much larger parameter space. For a much more complex optimization problem that is ultimately comparable to biological evolution, we certainly need significant additional insights, where the concepts of cross-timescale interactions could be beneficial.

How could we apply the notions of cross-timescale interactions to such large-scale design optimization processes of embodied systems? In conventional genetic and evolutionary algorithms, the frameworks typically allow one to encode any design parameters and hence optimize any design features of autonomous and adaptive systems. However, this approach is obviously limited to relatively simple systems, considering the limitations on the number of trial-and-error iterations that can be performed. For a scalable optimization process, it is necessary to employ more cross-timescale solutions, such as the use of generative encoding methods (155, 156). Generative encoding methods usually consider a smaller set of design parameters that specify generative or developmental processes of larger/more complex structures, as exemplified by compositional pattern-producing networks (157). By incorporating the concept of timescales, this

approach certainly represents a significant step forward from the direct encoding of design parameters to genomes, although the processes are simplified. Similarly, the concept of cross-timescale interactions can be considered for fitness evaluation processes. The evaluation of behavioral consequences in nature does not happen on only one timescale, but across many. For example, in biological natural selection processes, behavioral changes can be observed on at least three time perspectives, such as sensory-motor learning in the here and now, body growth and adaptation in ontogenetic development, and species evolution on phylogenetic timescales. The concept of the Baldwin effect, which explains how learning capacities can develop through evolutionary process, is a good example of such cross-timescale interactions, but it has not yet been investigated in the evolution of artificial systems.

## DISCLOSURE STATEMENT

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