THE AUTONOMY LIMITS IN PHYSICAL RESERVOIR COMPUTING

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Abstract: *Physical Reservoir Computing (PRC) has emerged as a compelling paradigm for embodied robotic control, exploiting the intrinsic dynamics of soft and compliant materials to perform real time computation without centralized processing. At the same time, the Infos framework offers a rigorous, capacity-based account of what constitutes genuine information processing agency in natural and artificial systems. This article brings these two strands together to evaluate the degree of autonomy achievable by PRC based robots. We show that individual PRC systems reliably support reactive operational self-regulation, and that collectives equipped with stigmergic external memory can achieve limited forms of adaptive tactical self-management. However, higher order capacities in the Infos hierarchy — including proactive tactical planning, strategic self-management, internal goal generation, persistent temporal memory, and self-reflective control — remain unattainable for PRC architectures. These capacities require cognitive mechanisms that cannot emerge from physical reservoir dynamics alone. We argue that future progress toward autonomous robotic systems will depend on hybrid architectures that integrate the material intelligence of physical reservoirs with higher level modules for predictive modeling, hierarchical value formation, and metacognitive regulation. The Infos framework provides a principled roadmap for assessing such developments and for clarifying the boundary between reactive embodied computation and genuine agency.*

Keywords: *Physical Reservoir Computing, Soft-Body Robotics, Infos Theory, Autonomous Systems, Self-Regulation, Stigmergy, Cognitive Robotics.*

ITHEA Keywords: *I.2 Artificial Intelligence; I.2.9 Robotics*

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1. Introduction

The pursuit of autonomous robots (machines capable of generating their own goals, adapting to unforeseen circumstances, and regulating their behavior across multiple timescales) remains a central challenge in robotics and artificial intelligence (Pfeifer & Bongard, 2006; Siciliano & Khatib, 2016). Among the approaches that have gained prominence in recent years is Physical Reservoir Computing (PRC), which leverages the intrinsic dynamics of soft materials to offload computational work from centralized processors onto the body itself (Nakajima & Fischer, 2021). PRC has demonstrated remarkable efficiency in embodied sensorimotor control, suggesting that physical substrates can serve as powerful computational resources.

In parallel, theoretical work in complex systems science has sought to clarify what it means for a system to possess genuine information processing agency. One influential account is the Infos framework, proposed by Krassimir Markov (Markov et al., 1993, 2003a, 2004, 2007, 2009).

Infos is defined as a material complex open system sustained through continuous exchange of energy and matter with its environment, and characterized by five interrelated capacities:

(1) **Reflection and Memory** — forming and retaining internal states in response to external impulses;

(2) **External Activity** — generating actions that causally affect the environment;

(3) **Self-reflection** — generating internal impulses and directing reflection inward;

(4) **Information Expectation** — anticipating future internal or external impulses;

(5) **Resolution of Information Expectation** — acting to confirm, correct, or resolve predictive states (Markov et al., 2004).

Together, these capacities provide a principled basis for understanding agency, adaptive self-regulation, and goal directed behavior in physical systems.

This article brings PRC as an engineering paradigm and Infos as a theoretical framework into direct dialogue. We argue that PRC systems, whether individual or collective, instantiate only the lowest tier of the Infos capacity hierarchy. They excel at reactive, body centric computation but lack the internal models, temporal memory, goal structures, and metacognitive mechanisms required for higher order autonomy. Clarifying precisely why this is the case, and what architectural additions would be required to transcend these limitations, offers a principled foundation for designing the next generation of autonomous robotic systems.

The remainder of the article is organized as follows. Section 2 reviews the related literature across four areas: Physical Reservoir Computing and soft-body robotics, swarm robotics and stigmergy, cognitive architectures and autonomy frameworks, and the theoretical antecedents of the Infos framework. Section 3 provides a systematic analysis of the capabilities and limits of PRC systems, first at the individual level and then at the collective level, evaluated through the lens of the Infos capacity hierarchy. Section 4 maps the findings onto a structured taxonomy of self-control levels, distinguishing reactive operational self-regulation from adaptive tactical self-management, proactive tactical planning, and strategic self-management. Section 5 discusses the implications of the analysis for the design of hybrid architectures and for the broader research program of autonomous robotics. Section 6 concludes by summarizing the main findings and identifying directions for future work.

2. Related Works

2.1 Physical Reservoir Computing

Physical Reservoir Computing (PRC) extends the reservoir computing paradigm, in which a fixed high dimensional dynamical system transforms input signals into rich spatiotemporal patterns that a simple readout layer can decode (Maass et al., 2002; Jaeger & Haas, 2004; Stepney, 2024). In classical

implementations, the reservoir is a recurrent neural network with randomly initialized and fixed internal weights; only the readout layer is trained. The computational advantage lies in the fact that the reservoir's nonlinear dynamics perform the essential signal transformation without requiring optimization.

PRC generalizes this idea by using the intrinsic physical dynamics of a real material substrate as the reservoir (Nakajima & Fischer, 2021). In soft body robotics, the deformations, vibrations, and mechanical state changes of a compliant body constitute the reservoir: incoming sensorimotor signals are continuously mapped into high dimensional state trajectories by the body's material dynamics, from which motor commands or behavioral policies can be extracted with minimal computation (Nakajima et al., 2013; Hauser et al., 2011).

This approach offers several advantages. It enables efficient local adaptation, stable self-regulation under perturbations, and a natural capacity to handle complex sensorimotor dependencies, without requiring a central processor or explicit control laws (Pfeifer et al., 2007). In a literal sense, the body itself performs the computation (Pfeifer & Bongard, 2006).

The application of reservoir computing to robotic control has expanded significantly since early demonstrations of echo state networks for motor pattern generation (Jaeger & Haas, 2004; Maass et al., 2002). A key insight was that the reservoir need not be implemented in software or silicon: any sufficiently complex dynamical system can serve as a reservoir if it exhibits high dimensionality, nonlinearity, and fading memory (Nakajima & Fischer, 2021; Stepney, 2024). This realization enabled the use of physical substrates (tensegrity structures, soft pneumatic actuators, and compliant limbs) as reservoirs for real time robotic control (Nakajima et al., 2013; Caluwaerts et al., 2014). Stepney (2021) further refined the ESN model by incorporating non instantaneous information transfer, a physically realistic constraint with direct implications for material reservoir design.

Subsequent research has shown that PRC based controllers can support stable locomotion, adaptive grasping, and robust disturbance rejection across diverse robotic platforms without centralized computation (Thuruthel et al., 2019; Urbain et al., 2017). These results have been interpreted as evidence for the viability of

body centric computation as a control paradigm (Stepney, 2024; Dale et al., 2021). However, the autonomy limitations of such systems (specifically their reliance on externally specified objectives and the absence of internal goal structures) have received comparatively little theoretical scrutiny. Addressing this gap is one of the aims of the present article.

The broader concept of morphological computation, the idea that the body's physical structure and dynamics can offload cognitive and computational work from a controller, has developed in parallel with PRC research (Pfeifer & Bongard, 2006; Pfeifer et al., 2007; Stepney, 2008). Hauser et al. (2011) provided a formal foundation for this concept, demonstrating that compliant bodies can implement nonlinear filters and short-term memory purely through passive dynamics. This work established a rigorous link between the mechanical properties of soft bodies and their computational capacities, forming a theoretical basis for PRC in robotics.

Soft robotics research has further shown that material compliance simplifies control by absorbing perturbations and enabling stable interaction with unstructured environments (Rus & Tolley, 2015; Laschi et al., 2016). Tensegrity robotics has explored how structural dynamics can simultaneously support locomotion and sensing (Caluwaerts et al., 2014). Stepney (2008) argued that such material substrates should be studied on their own computational terms rather than forced into classical Turing frameworks. A position that motivates but also constrains the PRC paradigm. While these contributions highlight the computational richness of physical dynamics, they largely set aside the question of how such systems might acquire genuine goal directedness, a question central to the present analysis.

The collective behavior of robotic swarms has been extensively studied as a means of achieving adaptive coordination that exceeds the capabilities of individual agents (Brambilla et al., 2013; Dorigo et al., 2006). Stigmergy, the indirect coordination through environmental modification, originally observed in social insects (Bonabeau et al., 1999), has been especially influential. Pheromone inspired trail formation, distributed task allocation, and self-organized construction have all been implemented in robotic systems,

demonstrating that collective intelligence can emerge from simple local rules and shared environmental cues (Dorigo & Birattari, 2007).

However, stigmergic systems remain fundamentally reactive at the individual level and lack mechanisms for proactive planning at the collective level (Theraulaz & Bonabeau, 1999; Dorigo et al., 2006). The environment serves as a distributed memory, but it encodes past states rather than anticipated future ones, and the system cannot generate novel goals independently of environmental contingencies. These limitations parallel the analysis developed in this article and highlight the need for architectural additions beyond stigmergy to achieve higher order autonomy.

The question of "what architectural features are necessary for genuine autonomy" has been explored across cognitive science, AI, and robotics. Classical cognitive architectures such as SOAR (Laird et al., 1987) and ACT R (Anderson et al., 2004) emphasize symbolic goal representation, hierarchical planning, and persistent memory. More recent work on predictive processing and active inference (Friston, 2010; Clark, 2016) frames autonomy in terms of maintaining and acting upon an internal generative model of the world - a capacity notably absent from PRC systems.

Barandiaran et al. (2009) proposed a rigorous definition of agency requiring individuality, normativity, and asymmetric causal relations between agent and environment - criteria that align naturally with the Infos capacity hierarchy. Tani (2016) explored how recurrent neural networks can develop rudimentary self-models and anticipatory behavior, suggesting a potential bridge between reactive reservoir dynamics and higher cognition. World model-based approaches such as Dreamer (Hafner et al., 2020) show that learned latent models can support temporally extended planning, though primarily in simulation. Stepney (2012) examined the broader challenge of programming unconventional computers, noting that dynamics, development, and self-reference are key properties absent from purely reactive substrates.

Taken together, these lines of work converge on the conclusion that genuine autonomy requires cognitive mechanisms far beyond what physical reservoir

dynamics alone can provide - a conclusion that the present article formalizes through the Infos framework.

2.2 The Infos Framework

The Infos Framework defines a genuine information processing agent as a material, complex open system sustained through continuous exchanges of energy and matter with its environment (Markov et al., 1993, 2007, 2009). A fully developed agent must exhibit five interconnected capacities. Their formal grounding is provided in Markov et al. (2003a), where reflection is defined as an internal structural change caused by an external impact and self-reflection as a direct or mediated self-impact generated by the agent's own internal processes.

- *Reflection and memory* denote the ability to receive external stimuli, form internal states, and maintain them over time - an essential basis for learning and experience driven adaptation (Markov et al., 2003a, 2007).

- *External activity* is the capacity to generate actions that causally influence the environment, the minimal requirement for agenthood (Barandiaran et al., 2009).

- *Self-reflection* extends reflection inward, enabling introspection and self-modeling (Legg & Hutter, 2007).

- *Information Expectation* refers to predicting future internal or external stimuli and preparing internal dynamics accordingly, consistent with predictive processing (Clark, 2016; Friston, 2010).

- *Resolution of Information Expectation* is the ability to act so as to confirm, correct, or otherwise resolve predictive states.

Together, these five capacities form the foundation of agentivity, adaptive self-regulation, and purposeful behavior (Markov et al., 2003a, 2004, 2007, 2009). The Infos definition, first introduced in Markov et al. (1993) and formalized in Markov et al. (2003a, 2004), is explicitly non biological: it applies to both natural organisms ("Infogenes") and artificial systems ("Infotrons") that instantiate the required structural properties.

The concept of Infos is far broader than that of a robot. Only a narrow subset of artificial systems, those with genuine intellectual capabilities, fall within the Infos

category. Most robots, including the physical reservoir computing systems discussed here, do not qualify because they lack internal goal generation, persistent memory, and self-reflective capacities. These capacities form a graded hierarchy: a system may possess lower-level abilities without higher level ones, and its degree of Infos-ness depends on how fully it instantiates all five.

Developed within General Information Theory (GIT) (Markov et al., 1993, 2003a, 2004, 2007, 2009), the Infos framework is rooted in the biology of living organisms while extending to artificial agents. As described in Markov et al. (2004), the concept emerged from the need to generalize the notion of an "information subject" beyond humans to all natural and artificial entities with comparable information processing capacities. First proposed verbally by Krassimir Markov in 1990, the concept was later formalized in print. In GIT, Infos represents the essential information processing characteristics shared by all living systems, from unicellular organisms to humans and social collectives, and by artificial systems designed to replicate these capacities (Markov et al., 2004).

The hierarchical nature of the framework aligns with evolutionary accounts of cognition (Llinás, 2001) and hierarchical models of cognitive control (Fuster, 2008). A bacterium may exhibit rudimentary reflection and external activity, whereas a human being expresses all five capacities at their highest development (Markov et al., 2007, 2009).

The first capacity, *Reflection and Memory*, parallels the classical multi store model of memory (Atkinson & Shiffrin, 1968), but the Infos model extends it by incorporating interoceptive and afferent signals into the formation of working memory representations (Craig, 2003; Damasio, 1994). This integration of external sensory and internal affective signals distinguishes Infos type agents from purely reactive systems.

The capacity *Information Expectation* aligns with predictive theories of cognition. Llinás (2001) argued that the brain's fundamental function is predictive anticipation. The Infos framework formalizes this insight: anticipatory structures (information expectations) guide the recognition and categorization of

sensory data. Formally, information expectation consists of free information valencies unsatisfied relational possibilities that drive the system to seek confirming or correcting contact with the environment (Markov et al., 2004). Data become information only insofar as they satisfy or violate a prior expectation (Markov et al., 2003a, 2009). This view aligns with the free energy principle (Friston, 2010) and predictive processing (Clark, 2016).

The capacity *Resolution of Expectations* captures the active dimension of information processing: the organism acts to confirm or correct its anticipatory states, forming a bidirectional loop between prediction and action (Friston, 2010; Barandiaran et al., 2009).

The capacity *Self-Reflection* introduces the interoceptive dimension of agency. In complex organisms and artificial systems, reflection, expectation, and resolution also apply to internal states. Through the integration of exteroception, proprioception, and interoception (Craig, 2003), the organism constructs a unified model of the world and of itself - Damasio's (1994) somatic self and Llinás's (2001) thalamocortical self-model. On this basis, an Infos type agent can generate its own goals and regulate behavior at operational, tactical, and strategic levels (Markov et al., 2007, 2009).

The Infos definition applies equally to biological and artificial systems. The criterion is functional, not substrate dependent: any system that instantiates all five capacities qualifies as an Infos agent (Markov et al., 2004). The formal framework in Markov et al. (2003a, 2004), grounded in set theoretic definitions of entity, impact, reflection, and information, provides the mathematical foundation for this generality. This makes Infos a powerful lens for evaluating artificial cognitive architectures, including those based on physical reservoir computing. While artificial Infoses may be considered intelligent agents, most robots, including the PRC systems examined here, fall outside the Infos category. As shown in Sections 4 and 5, current PRC systems satisfy only the lowest tier capacities of the Infos hierarchy, and achieving fuller Infos agency requires architectural components that reservoir dynamics alone cannot provide.

3. Capabilities and Limits of Physical Reservoir Computing

3.1 What PRC Systems Can Do

Evaluated through the lens of the Infos framework, PRC systems reliably satisfy the capacity *External Activity*, since they clearly generate actions that causally affect the environment. They also exhibit a limited form of the capacity *Reflection*, insofar as the material state of the reservoir retains a short-lived trace of recent inputs. This transient memory, often described as the fading memory or echo state property (Jaeger, 2001; Stepney, 2024), allows the system to respond to input sequences rather than to instantaneous stimuli alone.

These two capacities, combined with the rich nonlinear transformations afforded by physical dynamics, are sufficient to support what may be termed *reactive operational self-regulation*: maintaining stable behavior under perturbations, adapting motor responses to sensory input, and exploiting the body's mechanical intelligence for complex locomotion tasks (Nakajima et al., 2013). At this level, PRC provides an elegant solution to embodied control, achieving through passive material dynamics what would otherwise require substantial computational overhead (Hauser et al., 2011).

3.2 Fundamental Limitations

The picture changes sharply when considering the higher order capacities in the Infos hierarchy. PRC systems possess no internal world model: they maintain no representation of the environment that persists independently of current sensory input (Tani, 2016). The reservoir state reflects only recent inputs and the system's material dynamics, not a structured symbolic or sub symbolic model of the world beyond the body.

Correspondingly, PRC systems lack long-term memory in the Infos sense. The fading memory of the reservoir is inherently transient; information about events beyond a characteristic timescale determined by the reservoir's dissipative dynamics is irretrievably lost (Maass et al., 2002). This prevents the formation of

stable internal states capable of encoding goals, preferences, or records of past experience.

PRC systems also perform no causal reasoning. They cannot infer hidden causes of sensory inputs, plan multi step action sequences, or evaluate the anticipated consequences of alternative behaviors (Pearl & Mackenzie, 2018). What appears as adaptive behavior is, in fact, the execution of externally specified objectives through the physical dynamics of the reservoir. Goals remain external; the system merely provides an efficient computational substrate for achieving them.

As a result, Self-Reflection, Information Expectation in a genuinely predictive sense, and Resolution of Expectations are all absent from PRC architectures. The system cannot generate internal impulses, cannot form anticipatory states based on an internal model, and cannot act to resolve discrepancies between predictions and outcomes — because it possesses neither predictions nor models to begin with.

Table 1 summarizes the capabilities and limits of PRC.

In short, the physical reservoir excels at answering how to move, but the questions why, where, and for how long require cognitive mechanisms of an entirely different order (Tani, 2016; Clark, 2016).

Table 1. Physical Reservoir Computing: Capabilities and Limits

Strengths	Limitations
Natural Computation: Soft-body dynamics act as a physical reservoir **Real-time Adaptation:** Fast, efficient responses to sensorimotor input **Low Control Overhead:** Complex behavior emerges from material dynamics	**No World Model:** No internal representation of environment **No Internal Long-term Memory:** Only short-lived physical state dynamics **No Causal Reasoning:** Cannot infer or plan beyond immediate reactions **No Self-generated Goals:** Acts only on externally defined objectives

3.3 Collective Systems and External Memory

A natural extension of individual PRC based robots is to examine their collective behavior - colonies of robots capable of coordinated action through stigmergic communication. In social insects, pheromone trails function as a form of external memory distributed across the environment, enabling colonies to achieve adaptive tactical self-management: optimizing foraging paths, reconfiguring in response to environmental changes, and exploiting newly discovered resources (Dorigo et al., 2006; Bonabeau et al., 1999).

Robotic swarms equipped with analogous mechanisms (shared environmental markers, distributed data structures, or stigmergic communication channels) can partially replicate these achievements (Brambilla et al., 2013). At the collective level, such systems can exhibit adaptive tactical self-management that exceeds the capabilities of any individual reservoir-based robot (Dale et al., 2021).

However, these collective advantages do not overcome the fundamental limitations identified above. External memory is not equivalent to internal long-term memory in the Infos sense: it records past environmental states, not the system's own goals, values, or predictive models. Proactive tactical planning — generating novel goals, reasoning about multi step futures, selecting strategies based on hierarchical value structures — remains impossible (Dorigo et al., 2006). Strategic self-management, which requires self-model and metacognitive capacities, is equally unattainable.

4. A Taxonomy of Self-control Levels

The preceding analysis motivates a structured taxonomy of self-control levels, each corresponding to a distinct class of mechanisms and to the types of systems capable of exhibiting them. The taxonomy is summarized conceptually in Table 2.

At the first level, reactive operational self-control is achievable by individual reservoir-based robots. Their physical dynamics and sensorimotor feedback loops enable them to maintain stable behavior under perturbations and to adapt

their motor responses in real time. This form of self-control emerges directly from the reservoir's nonlinear transformations and fading memory properties.

At the second level, adaptive tactical self-management becomes partially achievable in collectives equipped with external memory mechanisms, such as pheromone like trails or other stigmergic markers. Through stigmergy and reinforcement like processes, such colonies can coordinate, reconfigure, and optimize their behavior in response to environmental changes.

At the third level, proactive tactical planning remains unattainable for all current PRC systems, whether individual or collective. This level requires temporally extended memory, internal goal generation, and the ability to evaluate alternative future action sequences. These capacities do not arise from physical reservoir dynamics.

At the fourth and highest level, strategic self-management is similarly beyond reach. Achieving this level requires a self-model, hierarchical value structures, and metacognitive capacities that allow an agent to regulate its behavior over long temporal horizons. None of these mechanisms are present in reservoir-based architectures.

Table 2. Taxonomy of Self-control Levels in Robotic Systems

Level of Self-control	System	Possible	Mechanism
Reactive operational	Individual reservoir	√	Physical dynamics + feedback
Adaptive tactical	Colony with external memory	√ partially	Stigmergy + reinforcement
Proactive tactical	Colony	x	No temporal memory
Strategic	Any of the above	x	No self-model and no metacognition

This taxonomy aligns with established hierarchical models of cognitive control in biological systems (Fuster, 2008) and with theoretical accounts of the

necessary conditions for genuine autonomy in artificial agents (Barandiaran et al., 2009).

It also resonates with the broader consensus in cognitive science that reactive behavior, however efficient or impressive, is insufficient as a foundation for full agency (Clark, 1997; Brooks, 1991).

5. Discussion

The analysis developed above carries several implications for the design of autonomous robotic systems. First, it indicates that Physical Reservoir Computing should be understood not as a pathway to full autonomy, but as a powerful and elegant solution to a specific subproblem: embodied sensorimotor control — the how of movement. Treating PRC, as more than this, risks obscuring the additional architectural layers required for genuine autonomy.

Second, the findings point toward a principled research agenda for hybrid architectures that integrate the computational efficiency of physical reservoirs with higher level cognitive modules capable of goal generation, temporal reasoning, and self-modeling. Work on hierarchical reinforcement learning (Botvinick et al., 2009), predictive coding and active inference (Friston, 2010), and world model-based planning (Hafner et al., 2020) suggests promising directions for such integration. Stepney (2024) likewise identifies the embedding of physical reservoirs within larger cognitive systems as a central open challenge for the field.

Third, the Infos framework itself merits broader recognition within robotics and AI as a principled theoretical tool for evaluating the degree of agency realized by a system. Its graded, capacity-based structure avoids the binary framing that often dominates discussions of machine autonomy, and its grounding in physical systems makes it particularly suitable for embodied robotics.

A key insight emerging from this analysis is the distinction between *computation within a situation* and *reasoning about a situation*. The reservoir computes brilliantly within the immediate sensorimotor context, but it cannot represent, evaluate, or plan beyond it. This boundary (between reactive, body centric computation and the higher order cognitive mechanisms required for autonomy)

may prove to be a productive conceptual guide for future research on autonomous systems.

6. Conclusion

This article has examined the capabilities and limitations of Physical Reservoir Computing as a paradigm for autonomous robotic control, evaluated through the theoretical lens of the Infos framework. The analysis shows that PRC enables reactive operational self-regulation at the individual level, where the material dynamics of the body efficiently substitute for centralized computation. At the collective level, swarms equipped with external memory can achieve adaptive tactical self-management through stigmergic mechanisms, partially extending the system's behavioral repertoire.

However, proactive tactical planning and strategic self-management remain unattainable for PRC based systems, whether individual or collective. These higher order capacities require internal goal generation, persistent temporal memory, hierarchical value structures, and metacognitive processes, none of which can emerge from physical reservoir dynamics alone. The reservoir transforms signals with remarkable efficiency, but it does not generate goals, construct models, or reason about future states.

Future research should therefore focus on hybrid architectures that integrate the material intelligence of physical reservoirs with higher level cognitive mechanisms capable of genuine goal directedness, predictive world modeling, and self-reflective control. Work on hierarchical reinforcement learning (Botvinick et al., 2009), predictive processing and active inference (Friston, 2010), and world model-based planning (Hafner et al., 2020) offers promising pathways for such integration. As Stepney (2024) emphasizes, embedding physical reservoirs within broader cognitive architectures is a central open challenge for the field.

The Infos framework provides a principled roadmap for evaluating progress toward these goals. By distinguishing between computation within a situation and reasoning about a situation, it clarifies the boundary between reactive embodied intelligence and the higher order cognitive capacities required for full

agency. Understanding and operationalizing this boundary may prove essential for the next generation of autonomous robotic systems.

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Bibliography

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. Psychological Review, 111(4), 1036–1060. https://doi.org/10.1037/0033-295X.111.4.1036

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In K. W. Spence & J. T. Spence (Eds.), The Psychology of Learning and Motivation (Vol. 2, pp. 89–195). Academic Press.

Barandiaran, X. E., Di Paolo, E., & Rohde, M. (2009). Defining agency: Individuality, normativity, asymmetry, and spatio-temporality in action. Adaptive Behavior, 17(5), 367–386. https://doi.org/10.1177/1059712309343819

Bonabeau, E., Dorigo, M., & Theraulaz, G. (1999). Swarm intelligence: From natural to artificial systems. Oxford University Press.

Botvinick, M. M., Niv, Y., & Barto, A. C. (2009). Hierarchically organized behavior and its neural foundations: A reinforcement learning perspective. Cognition, 113(3), 262–280. https://doi.org/10.1016/j.cognition.2008.08.011

Brambilla, M., Ferrante, E., Birattari, M., & Dorigo, M. (2013). Swarm robotics: A review from the swarm engineering perspective. Swarm Intelligence, 7(1), 1–41. https://doi.org/10.1007/s11721-012-0075-2

Brooks, R. A. (1991). Intelligence without representation. Artificial Intelligence, 47(1–3), 139–159. https://doi.org/10.1016/0004-3702(91)90053-M

Caluwaerts, K., Despraz, J., Iscen, A., Sabelhaus, A. P., Bruce, J., Schrauwen, B., & SunSpiral, V. (2014). Design and control of compliant tensegrity robots through simulation and hardware validation. Journal of the Royal Society Interface, 11(98), 20140520. https://doi.org/10.1098/rsif.2014.0520

Clark, A. (1997). Being there: Putting brain, body, and world together again. MIT Press.

Clark, A. (2016). Surfing uncertainty: Prediction, action, and the embodied mind. Oxford University Press.

Craig, A. D. (2003). Interoception: The sense of the physiological condition of the body. Current Opinion in Neurobiology, 13(4), 500–505. https://doi.org/10.1016/s0959-4388(03)00090-4

Dale, M., Evans, R. F. L., Jenkins, S., O'Keefe, S., Sebald, A., Stepney, S., Torre, F., & Trefzer, M. (2021). Reservoir Computing with Thin‐film Ferromagnetic Devices. arXiv:2101.12700.

Damasio, A. R. (1994). Descartes' error: Emotion, reason, and the human brain. Putnam.

Dorigo, M., & Birattari, M. (2007). Swarm intelligence. Scholarpedia, 2(9), 1462. https://doi.org/10.4249/scholarpedia.1462

Dorigo, M., Birattari, M., & Stutzle, T. (2006). Ant colony optimization. IEEE Computational Intelligence Magazine, 1(4), 28–39. https://doi.org/10.1109/MCI.2006.329691

Friston, K. (2010). The free-energy principle: A unified brain theory? Nature Reviews Neuroscience, 11(2), 127–138. https://doi.org/10.1038/nrn2787

Fuster, J. M. (2008). The prefrontal cortex (4th ed.). Academic Press.

Hafner, D., Lillicrap, T., Ba, J., & Norouzi, M. (2020). Dream to control: Learning behaviors by latent imagination. Proceedings of the International Conference on Learning Representations (ICLR 2020). https://doi.org/10.48550/arXiv.1912.01603

Hauser, H., Ijspeert, A. J., Füchslin, R. M., Pfeifer, R., & Maass, W. (2011). Towards a theoretical foundation for morphological computation with compliant bodies. Biological Cybernetics, 105(5–6), 355–370. https://doi.org/10.1007/s00422-012-0471-0

Jaeger, H. (2001). The "echo state" approach to analysing and training recurrent neural networks (GMD Report No. 148). German National Research Center for Information Technology.

Jaeger, H., & Haas, H. (2004). Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication. Science, 304(5667), 78–80. https://doi.org/10.1126/science.1091277

Laird, J. E., Newell, A., & Rosenbloom, P. S. (1987). Soar: An architecture for general intelligence. Artificial Intelligence, 33(1), 1–64. https://doi.org/10.1016/0004-3702(87)90050-6

Laschi, C., Mazzolai, B., & Cianchetti, M. (2016). Soft robotics: Technologies and systems pushing the boundaries of robot abilities. Science Robotics, 1(1), eaah3690. https://doi.org/10.1126/scirobotics.aah3690

Legg, S., & Hutter, M. (2007). Universal intelligence: A definition of machine intelligence. Minds and Machines, 17(4), 391–444. https://doi.org/10.1007/s11023-007-9079-x

Llinás, R. R. (2001). I of the vortex: From neurons to self. MIT Press.

Maass, W., Natschläger, T., & Markram, H. (2002). Real-time computing without stable states: A new framework for neural computation based on perturbations. Neural Computation, 14(11), 2531–2560. https://doi.org/10.1162/089976602760407955

Markov, Kr., Ivanova, Kr., & Mitov, I. (1993). Basic concepts of a general information theory. International Journal Information Theories and Applications, 1(10), 3–10.

Markov, Kr., Ivanova, Kr., & Mitov, I. (2007). Basic structure of the general information theory. International Journal Information Theories and Applications, 14(1), 5–19. http://www.foibg.com/ijita/vol14/ijita14-1-p01.pdf

Markov, Kr., Ivanova, Kr., & Mitov, I. (2009). Theory of Infos. In International Book Series "Information Science & Computing" (Book No. 13): Intelligent Information and Engineering Systems (pp. 9–16). ITHEA. http://foibg.com/ibs_isc/ibs-13/ibs-13-p01.pdf

Markov, Kr., Ivanova, Kr., Mitov, I., & Velikova-Bandova, E. (2003a). The information. International Journal Information Theories and Applications, 10(1), 5–9. http://www.foibg.com/ijita/vol10/ijita10-1-p01.pdf

Markov, Kr., Ivanova, Kr., Mitov, I., & Velikova-Bandova, E. (2004). Formal definition of the concept "Infos". International Journal Information Theories and Applications, 11(1), 16–19. http://www.foibg.com/ijita/vol11/ijita11-1-p03.pdf

Nakajima, K., & Fischer, I. (Eds.). (2021). Reservoir computing: Theory, physical implementations, and applications. Springer. https://doi.org/10.1007/978-981-13-1687-6

Nakajima, K., Hauser, H., Li, T., & Pfeifer, R. (2013). Exploiting short-term memory in soft body dynamics as a computational resource. Journal of the Royal Society Interface, 11(100), 20140437. https://doi.org/10.1098/rsif.2014.0437

Pearl, J., & Mackenzie, D. (2018). The book of why: The new science of cause and effect. Basic Books.

Pfeifer, R., & Bongard, J. (2006). How the body shapes the way we think: A new view of intelligence. MIT Press.

Pfeifer, R., Lungarella, M., & Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. Science, 318(5853), 1088–1093. https://doi.org/10.1126/science.1145803

Rus, D., & Tolley, M. T. (2015). Design, fabrication and control of soft robots. Nature, 521(7553), 467–475. https://doi.org/10.1038/nature14543

Siciliano, B., & Khatib, O. (Eds.). (2016). Springer handbook of robotics (2nd ed.). Springer. https://doi.org/10.1007/978-3-319-32552-1

Stepney, S. (2008). The neglected pillar of material computation. Physica D: Nonlinear Phenomena, 237(9), 1157–1164. https://doi.org/10.1016/j.physd.2008.01.028

Stepney, S. (2012). Programming unconventional computers: Dynamics, development, self-reference. Entropy, 14(10), 1939–1952. https://doi.org/10.3390/e14101939

Stepney, S. (2021). Non-instantaneous information transfer in physical reservoir computing. In Unconventional Computation and Natural Computation (UCNC 2021), Lecture Notes in Computer Science (Vol. 12984, pp. 164–176). Springer. https://doi.org/10.1007/978-3-030-87993-8_11

Stepney, S. (2024). Physical reservoir computing: A tutorial. Natural Computing, 23, 665–685. https://doi.org/10.1007/s11047-024-09997-y

Tani, J. (2016). Exploring robotic minds: Actions, symbols, and consciousness as self-organizing dynamic phenomena. Oxford University Press.

Theraulaz, G., & Bonabeau, E. (1999). A brief history of stigmergy. Artificial Life, 5(2), 97–116. https://doi.org/10.1162/106454699568700

Thuruthel, T. G., Ansari, Y., Falotico, E., & Laschi, C. (2019). Control strategies for soft robotic manipulators: A survey. Soft Robotics, 6(2), 149–163. https://doi.org/10.1089/soro.2018.0054

Urbain, G., Degrave, J., Carette, B., Dambre, J., & Wyffels, F. (2017). Morphological properties of mass-spring networks for optimal locomotion learning. Frontiers in Neurorobotics, 11, 16. https://doi.org/10.3389/fnbot.2017.00016

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