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Body Machinery and Intelligence

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Resumen

Este trabajo tiene un propósito que podría calificarse de artificioso. Por una parte, puede entenderse como una revisión de los recientes avances en robótica, computación neuromórfica, control morfológico e inteligencia artificial (IA) corporeizada que han reavivado el interés en la relación entre la estructura física y el comportamiento inteligente, recogiendo una tradición postergada. Por otra parte, se utiliza este caso para ilustrar una práctica cada vez más frecuente en el ámbito académico: el uso de herramientas de IA en sustitución de la lectura atenta y concienzuda de la literatura pertinente para alcanzar los fundamentos de una materia, y del esfuerzo por obtener eficiencia y claridad en la expresión. Dando a ChatGPT documentos seleccionados sobre los fundamentos históricos y las propuestas actuales de los asuntos mencionados, la máquina los sintetiza y concluye proponiendo una arquitectura por capas para futuros robots. En el apéndice se discuten algunos aspectos del resultado obtenido.

Palabras clave: Computación morfológica, IA corporeizada, IA física, robótica blanda, control neuromórfico, homeostasis, robótica adaptativa, ChatGPT.

Body Machinery and Intelligence

Abstract

This work has a purpose that could be described as somewhat contrived. On the one hand, it can be understood as a review of recent advances in robotics, neuromorphic computing, morphological control, and embodied artificial intelligence (AI) that have revived interest in the relationship between physical structure and intelligent behavior, thus reviving a long-neglected tradition. On the other hand, this case is used to illustrate an increasingly common practice in academia: the use of AI tools as a substitute for the careful and thorough reading of relevant literature to grasp the fundamentals of a subject, and for the effort to achieve efficiency and clarity of expression. By providing ChatGPT with selected documents on the historical foundations and current proposals of the aforementioned topics, the machine synthesizes them and concludes by proposing a layered architecture for future robots. Some aspects of the obtained result are discussed in the appendix.

Keywords: Morphological computation, embodied AI, Physical AI, soft robotics, neuromorphic control, homeostasis, adaptive robotics, ChatGPT.

1. Introduction

Artificial intelligence has traditionally been developed around symbolic computation and centralized information processing. Classical artificial intelligence AI systems generally separate software from hardware and treat the body as a passive execution mechanism. However, biological organisms demonstrate that intelligence emerges through continuous interaction among body, brain, and environment. This observation has motivated increasing interest in embodied intelligence and morphological computation.

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Morphological computation refers to the exploitation of body dynamics, material properties, and environmental interactions to simplify computation and control tasks (Füchslin et al., 2013). Füchslin et al. define morphological computation as the use of physical dynamics to facilitate computational processes and control behavior. Their work emphasizes that morphology includes not only shape but also material properties such as elasticity, friction, and compliance. These properties allow physical systems to outsource computational tasks to their own bodies.

Soft robotics extends this principle by employing compliant materials and nonlinear body dynamics (H. Hauser and Forni, 2023). Unlike conventional rigid robots, soft robots can adapt naturally to uncertain environments and safely interact with humans. Hauser et al. argue that morphological computation transforms the complex nonlinear dynamics of soft materials from a control problem into a computational resource.

In parallel, neuromorphic engineering investigates how biological nervous systems exploit mixed feedback structures and distributed computation (Ribar and Sepulchre, 2021). Neuromorphic control architectures emulate neural excitability and adaptive modulation through analog-digital circuits operating across multiple time scales.

Recent developments in physical AI further unify these ideas by proposing that intelligence emerges from embodied interaction, physical sensing, and adaptive behavior rather than abstract symbolic manipulation alone (Salehi, 2025). Physical AI frameworks emphasize embodiment, sensory perception, motor action, learning, autonomy, and context sensitivity as fundamental principles.

This paper synthesizes these perspectives into a unified framework for adaptive embodied intelligence. We first review the theoretical foundations of morphological computation and embodied cognition. We then discuss soft robotics, neuromorphic control, and homeostatic machines as implementations of physical intelligence. Finally, we propose an integrated architecture for future adaptive robotic systems.

2. Historical Foundations of Embodied Intelligence

2.1. *From Turing to Embodied Cognition*

The modern debate on machine intelligence can be traced to Alan Turing's seminal 1950 paper "Computing Machinery and Intelligence" (Turing, 1950). Turing reformulated the question "Can machines think?" into the imitation game, now known as the Turing Test. His approach emphasized observable intelligent behavior rather than metaphysical definitions of thought.

Although Turing's framework focused on symbolic communication, later researchers recognized that intelligence cannot be fully separated from embodiment. Brooks and Stein argued that intelligence arises from bodily interaction with the world rather than abstract internal representations (Brooks and Stein, 1994). Their "Building Brains for Bodies" project proposed that autonomous robots should learn through sensory-motor experiences embedded in physical environments.

Brooks rejected purely symbolic AI approaches and emphasized behavior-based robotics. According to this perspective, cognition is grounded in physical interaction and emerges incrementally through layered behavioral architectures. This marked a major transition from disembodied symbolic reasoning toward embodied intelligence.

2.2. *Embodiment as a Computational Principle*

Embodied cognition proposes that cognition depends fundamentally on the structure and dynamics of the body. Rather than acting as a peripheral actuator, the body contributes directly to information processing.

Morphological computation formalizes this insight (Füchslin et al., 2013). Physical structures can perform computational functions by exploiting mechanical dynamics and environmental coupling. For example, passive dynamic walkers achieve stable locomotion with minimal centralized control by leveraging gravity and mechanical design.

The significance of embodiment extends beyond robotics. Biological organisms continuously exploit compliant tissues, distributed sensing, and adaptive morphology to simplify control and increase robustness. These principles provide important guidance for the development of next-generation intelligent systems.

3. Morphological Computation and Soft Robotics

3.1. *Definition of Morphological Computation*

Morphological computation describes the use of physical morphology to perform computational or control-related functions. Füchslin et al. distinguish between computation and control while emphasizing that morphology can facilitate both processes.

In classical robotic systems, control is typically centralized and model-based. Sensors gather information, controllers compute actions, and actuators execute commands. Morphological computation modifies this architecture by allowing body dynamics to participate directly in computation.

This outsourcing of computation provides several advantages:

- Reduction in centralized computational requirements.
- Increased energy efficiency.
- Improved adaptability to uncertain environments.
- Robustness through physical compliance.
- Simplification of control architectures.

Morphological computation does not replace digital computation entirely. Instead, it redistributes computation across body, environment, and controller.

3.2. *Soft Robotics as Embodied Computation*

Soft robotics provides one of the most important practical applications of morphological computation. Traditional rigid robots excel in structured industrial environments but struggle in uncertain or dynamic settings. Soft robots employ compliant materials that naturally absorb impacts, adapt to surfaces, and safely interact with humans.

Hauser et al. describe soft robotics as a paradigm inspired by biological organisms (H. Hauser and Forni, 2023). Biological systems outperform conventional robots in open-world scenarios because they exploit flexible bodies and nonlinear dynamics.

The nonlinear properties of soft materials create challenges for conventional control methods because precise modeling becomes difficult. However, morphological computation reframes these nonlinearities as useful computational resources.

For example, octopus-inspired soft manipulators exploit passive body compliance to grasp irregular objects without detailed geometric modeling. Similarly, soft locomotion systems use elastic energy storage and body resonance to reduce control complexity.

3.3. Tradeoffs and Challenges

While morphological computation offers significant advantages, it also introduces important tradeoffs.

First, exploiting body dynamics may reduce precision and predictability. Soft systems are often difficult to model mathematically because they exhibit high-dimensional nonlinear behavior.

Second, there exists a balance between morphological adaptation and centralized control. Excessive reliance on body dynamics may reduce controllability, while excessive centralized control undermines the benefits of embodiment.

Third, designing effective morphologies remains difficult. Unlike conventional software engineering, morphology design requires interdisciplinary integration of materials science, mechanics, control theory, and AI.

Nevertheless, advances in simulation, machine learning, and materials engineering are gradually addressing these challenges.

4. Neuromorphic Control and Biological Inspiration

4.1. Mixed Feedback Architectures

Neuromorphic engineering seeks to emulate the computational principles of biological nervous systems. Ribar and Sepulchre emphasize that biological neurons operate through concurrent positive and negative feedback loops distributed across multiple temporal and spatial scales (Ribar and Sepulchre, 2021).

Unlike conventional digital controllers, neuromorphic systems employ analog-digital mixed architectures inspired by biological excitability. These architectures are robust to uncertainty and component variability.

Biological nervous systems achieve adaptive behavior despite noisy components and uncertain environments. Neuromorphic control attempts to replicate this robustness by exploiting distributed feedback and local adaptation.

4.2. Excitability and Embodied Regulation

A key principle in neuromorphic control is excitability. Biological neurons exhibit all-or-none responses to stimuli, producing spikes when activation thresholds are exceeded.

This behavior emerges from the interaction of ionic currents, membrane dynamics, and feedback regulation. Neuromorphic circuits emulate these dynamics through hardware architectures capable of local positive and negative feedback.

Importantly, neuromorphic control does not treat computation as purely symbolic processing. Instead, it integrates sensing, memory, and actuation into physically embodied dynamic systems.

4.3. Distributed Adaptation

Neuromorphic systems also support distributed adaptation and learning. Rather than relying exclusively on centralized optimization, local circuit properties can adapt continuously through modulation and feedback.

This distributed architecture mirrors biological nervous systems and offers several benefits:

- Fault tolerance.
- Energy efficiency.
- Real-time responsiveness.
- Scalability.
- Robustness to uncertainty.

These characteristics are especially important for autonomous robots operating in complex real-world environments.

5. Homeostasis and Physical AI

5.1. Homeostatic Machines

Man and Damasio propose a radically different perspective on intelligent machines by introducing the concept of homeostatic robotics (Man and Damasio, 2019). Their approach argues that intelligence should emerge from systems capable of regulating their own viability.

Traditional AI systems optimize externally defined reward functions. Homeostatic machines instead maintain internal states within viable ranges. This introduces what the authors call “risk-to-self”.

In biological organisms, homeostasis underlies survival, adaptation, and emotional regulation. Feelings emerge from the monitoring of bodily states and guide behavior toward survival.

Homeostatic robots attempt to emulate this principle by embedding vulnerability and self-regulation into physical systems.

5.2. Meaning Through Embodiment

One of the most important claims of homeostatic robotics is that meaningful behavior emerges only when information processing affects the continued viability of the system.

This contrasts with purely symbolic AI systems that manipulate abstract representations without intrinsic meaning. In homeostatic systems, information becomes meaningful because it directly influences survival-related regulation.

For example, a robot monitoring internal energy reserves, structural stress, and thermal conditions develops behavior tied to self-preservation. This creates intrinsic motivation rather than externally imposed optimization.

5.3. Physical AI Frameworks

Recent physical AI frameworks extend these ideas into broader theories of embodied intelligence.

Salehi identifies six foundational principles of physical AI (Salehi, 2025):

1. Embodiment.
2. Sensory perception.
3. Motor action.
4. Learning.
5. Autonomy.
6. Context sensitivity.

These principles form a closed-loop system in which energy, information, control, and environment continuously interact.

Unlike classical AI systems that rely on static datasets, Physical AI systems learn through physical interaction and structural adaptation. Intelligence becomes an emergent property of embodied experience.

6. Toward an Integrated Framework for Adaptive Robotics

6.1. Layered Embodied Architecture

Based on the reviewed literature, we propose a layered framework for adaptive embodied robotics.

The framework consists of four interacting layers:

1. Morphological layer.
2. Sensory-motor layer.
3. Neuromorphic control layer.
4. Cognitive adaptation layer.

The morphological layer includes physical structure, compliance, materials, and passive dynamics. This layer performs part of the computational workload through mechanical interaction.

The sensory-motor layer integrates distributed sensing and low-level action. Physical interaction continuously updates the robot's state.

The neuromorphic layer regulates adaptive behavior through mixed feedback structures inspired by biological nervous systems.

The cognitive adaptation layer performs high-level planning, contextual learning, and goal management.

6.2. Embodied Learning

A central feature of this framework is embodied learning. Instead of relying solely on offline datasets, robots learn through interaction with the physical world.

Embodied learning integrates:

- Sensory feedback.
- Environmental resistance.
- Physical constraints.
- Contextual adaptation.
- Homeostatic regulation.

This approach enables robots to adapt continuously to uncertain environments.

6.3. Applications

Potential applications of adaptive embodied robotics include:

1. Healthcare robotics: Rehabilitation robots with compliant joints can adapt safely to patient movement and physical limitations.
2. Industrial automation: Soft manipulators can handle fragile or irregular objects without extensive programming.
3. Search and rescue: Embodied robots can navigate unpredictable terrains using passive adaptation.
4. Human-robot interaction: Physically compliant systems improve safety and social interaction.
5. Autonomous exploration: Embodied intelligence improves resilience in uncertain environments such as space exploration.

7. Discussion

The convergence of morphological computation, soft robotics, neuromorphic engineering, and physical AI signals a major shift in the understanding of intelligence.

Traditional AI approaches emphasized centralized symbolic reasoning detached from physical embodiment. In contrast, embodied approaches argue that intelligence emerges through interaction among body, environment, and control systems.

This transition parallels developments in biology and neuroscience, where cognition is increasingly understood as distributed, adaptive, and physically grounded.

However, significant open challenges remain:

- Developing rigorous mathematical frameworks for morphological computation.
- Designing scalable embodied learning architectures.
- Integrating physical adaptation with symbolic reasoning.
- Ensuring safety and interpretability in autonomous systems.
- Creating efficient hardware for neuromorphic and embodied computation.

Future research must integrate robotics, control theory, neuroscience, materials science, and AI into unified interdisciplinary frameworks.

8. Conclusion

This paper reviewed the theoretical and practical foundations of embodied intelligence, morphological computation, soft robotics, neuromorphic control, homeostatic machines, and physical AI (Turing, 1950; Brooks and Stein, 1994; Füchslin et al., 2013; H. Hauser and Forni, 2023; Ribar and Sepulchre, 2021; Man and Damasio, 2019; Salehi, 2025; Vinagre, 2023).

Morphological computation demonstrates that physical bodies can perform computational functions by exploiting material properties and environmental interactions. Soft robotics extends this principle through compliant materials that naturally adapt to uncertain environments.

Neuromorphic control introduces distributed adaptive regulation inspired by biological nervous systems, while homeostatic robotics emphasizes intrinsic self-regulation and meaningful behavior grounded in viability.

Physical AI unifies these concepts into a broader theory of embodied intelligence in which cognition emerges from continuous interaction among body, environment, and adaptive control.

The future of intelligent robotics may therefore depend not only on more powerful algorithms, but also on the design of bodies capable of sensing, adapting, learning, and regulating themselves within dynamic environments.

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Apéndice

Cómo se ha hecho este artículo

Para hacer este artículo se han seguido los siguientes pasos:

1. Seleccionar, entre la literatura estudiada con relación al tema tratado, un conjunto mínimo de referencias que cumplieran alguno de los siguientes requisitos:
   - Haber sentado las bases de una visión consolidada a lo largo de los años (véase (Turing, 1950)).
   - Haber propuesto una alternativa al paradigma dominante (véase (Brooks and Stein, 1994)).
   - Explorar rutas abandonadas dándoles un interés renovado (véanse (Füchslin et al., 2013), (Man and Damasio, 2019) o (Salehi, 2025)).
   - Dar contenido actual y concreto a alguna de las ideas destacadas en los items anteriores (véase (H. Hauser and Forni, 2023) o (Ribar and Sepulchre, 2021)).
   - Ofrecer una visión de conjunto del asunto tratado (véase (Vinagre, 2023))
2. Introducir en ChatGPT, versión básica, los siguientes prompts de manera secuencial:

   * By using latex, write a 2 column 6 pages paper with the following documents as references

   * traduce a español de España el texto generado

   * haz un mapa conceptual basado en el texto
3. Revisar y corregir errores de terminología (e.g.: retroalimentación/realimentación).

Lo ganado y lo perdido

Es evidente que el tiempo de escritura propiamente dicha se ha eliminado, y solo se ha realizado un trabajo de edición. Este ahorro de tiempo es especialmente destacable a la hora de confeccionar el mapa conceptual de la Figura 1. Mas para llegar al resultado final, tenga éste el valor que tenga, ha sido indespensable un conocimento de la literatura que se ha dado como alimento a la máquina.

Una vez revisado el texto se pueden constatar algunos hechos fundamentales. En primer lugar, y como es lógico, la máquina no tiene más información que la que se le ha dado y, como un circuito combinacional, da como salida el resultado bruto de sus entradas. En este caso, es notable la ausencia de alusiones a contemporáneos de Alan M. Turing que fueron precursores de la inteligencia emergente de la estructura corporal defendida por R. Brooks, como William R. Ashby ((Ashby, 1949), (Ashby, 1958)) o W. Grey Walter ((Walter, 1950), (Walter, 1981)), o continuadores que restablecieron esas bases, como (Pfeifer and Bongard, 2007). La máquina no tiene ni la más vaga idea de la tradición.

En segundo lugar, tanto el texto como la estructura son simples y poco elegantes manifestando así la ausencia de una visión de conjunto, tanto a nivel local (párrafo) como global (artículo). También de ideas, analogías o metáforas que ayuden a la comprensión o inviten a la reflexión, como, por ejemplo:

> Después de poner los fundamentos de la teoría computacional de la mente en 1937 con su máquina universal, esa especie de idea platónica de la que han bebido todos lo productos realizables de las ciencias de la computación, Turing publicó en 1950 *Computing Machinery and Intelligence*, trabajo de enormes repercusiones al que éste rinde homenaje, aunque solo sea en el título.

Ted Chiang, informático y escritor de ciencia ficción, publicaba en agosto de 2024 un artículo en *The New Yorker* títulado “Why A.I. isn’t going to make art”, en el que escribía lo siguiente:

> art is something that results from making a lot of choices. This might be easiest to explain if we use fiction writing as an example. When you are writing fiction, you are —consciously or unconsciously— making a choice about almost every word you type; [...] When you give a generative-A.I. program a prompt, you are making very few

choices; if you supply a hundred-word prompt, you have made on the order of a hundred choices.

If an A.I. generates a ten-thousand-word story based on your prompt, it has to fill in for all of the choices that you are not making. There are various ways it can do this. One is to take an average of the choices that other writers have made, as represented by text found on the Internet; that average is equivalent to the least interesting choices possible, which is why A.I.-generated text is often really bland. Another is to instruct the program to engage in style mimicry, emulating the choices made by a specific writer, which produces a highly derivative story. In neither case is it creating interesting art.

Se asume que escribir un artículo científico o técnico no es un arte, y tal vez podamos pedirle a la máquina que se alimente con todo el pasado para no dejar nada por consutar, ninguna elección por hacer. No está claro cómo evitar que el resultado sea *mediocridad o delirio*[1].

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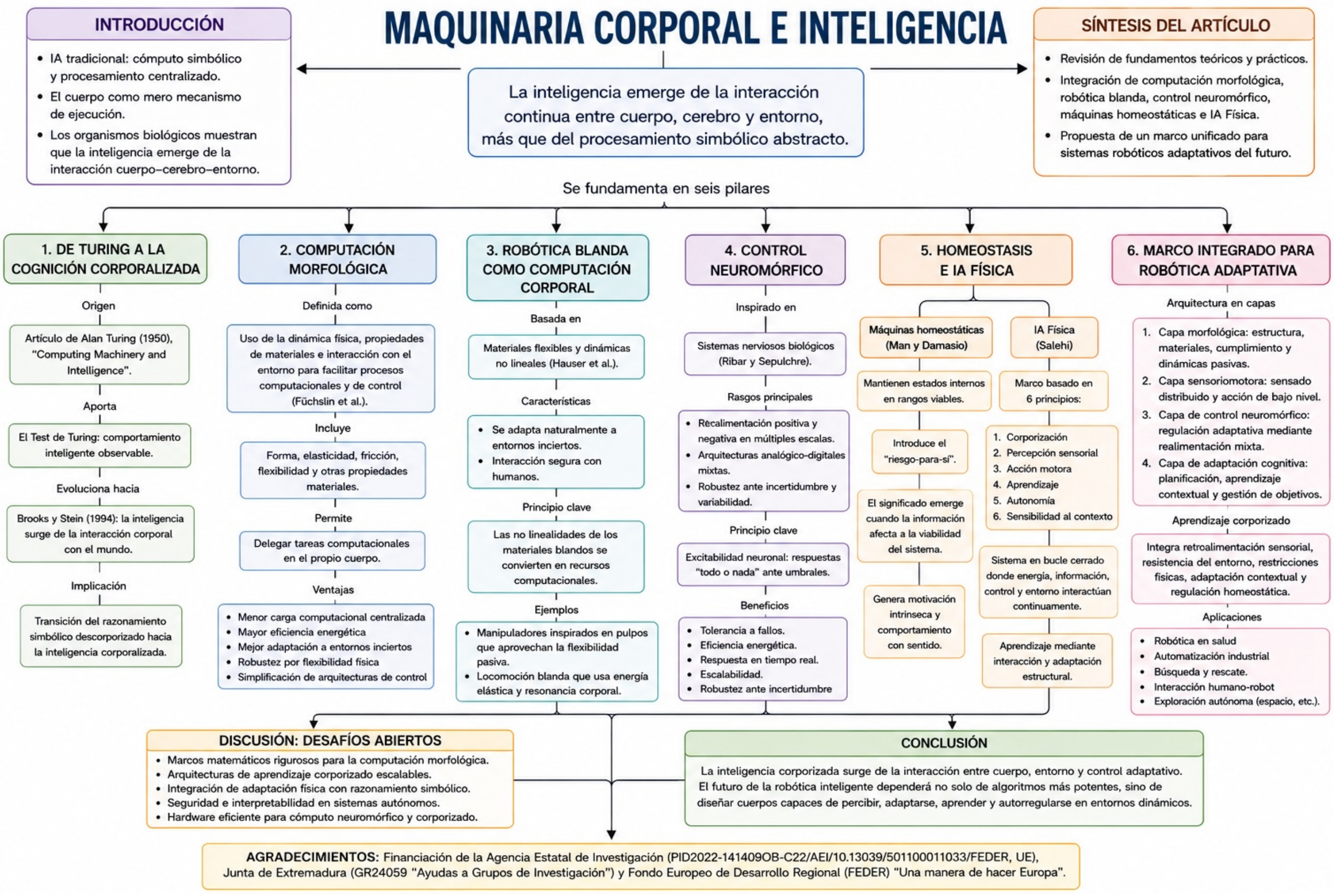

Figura 1: Mapa conceptual del contenido del artículo.

[1] Hans Magnus Enzensberger, *Mediocridad y delirio*, Anagrama 1991. El ensayo "Sobre la ignorancia" es especialmente interesante para lo aquí tratado.