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BODILY PROCESSING: WHAT PROGRESS HAS BEEN MADE IN UNDERSTANDING THE EMBODIMENT OF COMPUTING SYSTEMS?

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ABSTRACT. In this article I will address the issue of the embodiment of computing systems from the point of view distinctive of the so-called Unconventional Computation, focusing on the paradigm known as Morphological Computation. As a first step, I will contextualize Morphological Computation within the disciplinary field of Embodied Artificial Intelligence: broadly conceived, Embodied Artificial Intelligence may be characterized as embracing both conventional and unconventional approaches to the artificial emulation of natural intelligence. Morphological Computation stands out from other paradigms of unconventional Embodied Artificial Intelligence in that it discloses a new, closer kind of connection between embodiment and computation. I will further my investigation by briefly reviewing the state-of-the-art in Morphological Computation: attention will be given to a very recent trend, whose core concept is that of "organic reconfigurability". In this direction, as a final step, two advanced cases of study of organic or living morphological computers will be presented and discussed. The prospect is to shed some light on our title question: what progress has been made in understanding the embodiment of computing systems?

Keywords: Embodied Artificial Intelligence; Morphological Computation; Reservoir Computing Systems; Organic Reconfigurability; 3D Bio-Printed Synthetic Corneas; Xenobots

1. Introduction

To raise the question of the embodiment of computing systems clearly implies the assumption of a particular point of view, the one distinctive of so-called Embodied Artificial Intelligence (EAI). EAI is a flourishing research field. Its origin dates back to the last decades of the XX century and namely when the strong criticism towards classical AI began and was raised by philosophers and cognitive scientists, such as Dreyfus, Searle, and Harnad.[1] In contrast to scholars working in the field of classical

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[1] H.L. Dreyfus, *What Computers Can't Do. New York*, MIT Press, New York (NY), 1972; J.R. Searle, "Minds, Brains, and Programs", in *Behavioral and Brain Sciences*, vol. 3/1980, pp. 417-457; S. Harnad, "The Symbol Grounding Problem", in *Physica D*, vol. 42/1990, pp. 335-346.

AI, who almost exclusively concentrated their efforts on the artificial emulation of knowledge – interpreted as overlapping with intelligence itself –, EAI proponents focus, instead, on building artificial agents that are able to inhabit the real world through some kind of intelligent behavior that mimic the one performed by natural agents.[2] In this context, "behavior" refers to the regularity observed in the agent-environment adaptive dynamics, with both the agent and the environment that are expected to be complex entities. Accordingly, the assumption underpinning the shift in interest and approach at the origin of EAI is a new scientific interpretation of intelligence.[3] The classical symbol system hypothesis, according to which intelligence overlaps with centralized information processing of abstract and observer-dependent descriptions (i.e., knowledge), is rejected. Intelligence is seen as the process of enacting multiple-sourced, concrete and environment-dependent information. In other terms, intelligence is equated with meaning-making processes emerging from sensory-motor behavioral structures.[4] To quote Bryson and Theodorou: « [Intelligence is] The property of an agent that allows that agent to change its world in response to contexts, opportunities and challenges».[5]

EAI scholars look at embodiment as a core condition for intelligent behavior. Here, "embodiment" typically refers to the property of having a robotic body.[6] As observed by Steels, classical AI systems «do not include a physical body, sensing, or acting. If intelligent robots have been considered, sensing and action has been delegated to subsystems that are assumed to deliver symbolic descriptions to the central planning and decision-making modules».[7] In contrast, standard EAI systems have behavior-based architectures, the so-called subsumption architectures,[8] which are implemented in reactive robots able to perform intelligent behavior – at least that is the

[2] In particular, the behavior of simple organisms in adherence with an evolutionary stance. Indeed, as observed by the MIT roboticist Rodney Brook, a pioneer of EAI, «human level intelligence did not suddenly leap onto the scene. There were precursors and foundations throughout the lineage to humans» (R. Brooks, "Intelligence Without Reason", in J.P Mylopoulos and R. Reiter (Eds.), *IJCAI' 91: Proceedings of the 12th International Joint Conference on Artificial intelligence*, Kaufmann, San Francisco (CA) 1991, pp. 569-595, p. 567).

[3] R. Brook, "Elephants Don't Play Chess", in *Robotics and Autonomous Systems*, vol. 6/1990, pp. 3-15.

[4] R. Pfeifer and J. Bongard, *How the Body Shapes the Way We Think. A New View of Intelligence*, MIT Press, Cambridge (MA), 2007.

[5] J.J. Bryson and A. Theodorou, "How Society can Maintain Human-Centric Artificial Intelligence", in M. Toivonen-Noro and E. Saari (Eds.), *Human-Centered Digitalization and Services*, Springer, Singapore 2019, pp. 305-323.

[6] T. Ziemke, "The Body of Knowledge: On the Role of the Living Body in Grounding Embodied Cognition, in *Biosystems*, vol. 48/2016, pp. 4-11.

[7] L. Steels, "The 'Artificial Life' Route to 'Artificial Intelligence'", in C.G. Langton (Ed.), *Artificial Life: An Overview,* The MIT Press, Cambridge (MA), 1995, pp. 75-110, p. 78.

[8] Subsumption architectures are networks of finite state machines augmented with timing elements and fed by behavior language groups.

hope of their human builders.[9] Nonetheless, this standard version of EAI was criticized by theorists of embodied (artificial) intelligence themselves for iterating basic assumptions of classical AI. More specifically, a mechanistic conception of the body, which would imply a radical form of internalism in the understanding of intelligence.[10]

To overcome this impasse, novel versions of EAI, such as the so-called enactive EAI,[11] among others, are currently promoting a biology-inspired interpretation of artificial embodiment, focused on engineering the self-preserving structures of the natural body, namely homeostasis and allostasis, through layered/nested architectures. The idea is to ascribe meaning-making processes to minimal forms of online intelligence derived from the complex causal interactions of the body-environment system, according to a radical externalism that stands up to the radical internalism ascribed to classical EAI. References are made to Maturana and Varela's theory of autopoiesis,[12] Christensen and Hooker's autonomy theory,[13] and the so-called somatic theories of emotional intelligence, such as those of Damasio, Panksepp, and Prinze.[14] Reviews in the field show that coexistence among classical and novel approaches is not without consequences for the identity of EAI.[15] Other than the self-portrait provided in negative terms of «what it is *against*, i.e. traditional AI»,[16] EAI is still looking for a positive self-characterisation. The elaboration of new disciplinary frameworks is thus required, which are able to account for the coexistence of standard and novel approaches to EAI.

In this article I will address the issue of the embodiment of computing systems from the point of view distinctive of an emerging disciplinary framework for EAI, i.e., unconventional

9 Well-known examples are provided by the MIT Mobile Robots developed by Brook and associates.

10 As observed by Dreyfus, «what AI researchers have to face and understand is not only why our everyday coping couldn't be understood in terms of inferences from symbolic representations […], but also why it can't be understood in terms of responses caused by fixed features of the environment, as in Brooks' empiricist model. AI researchers need to consider the possibility that embodied beings like us take as input energy from the physical universe, and respond in such a way as to open themselves to a world organized in terms of their needs, interests, and bodily capacities without their brains converting stimulus input into reflex responses, as in Brooks's animats» (H.L. Dreyfus, "Why Heideggerian AI Failed and How Fixing It Would Require Making It More Heideggerian", in *Artificial Intelligence*, vol. 71/2007, pp. 1137-1160, p. 1142).

11 T. Froese and T. Ziemke, "Enactive Artificial Intelligence: Investigating the Systemic Organization of Life and Mind", in *Artificial Intelligence*, vol. 173/2009, pp. 466-500.

12 H.R. Maturana and F.J. Varela, *Autopoiesis and Cognition*, Reidel, Dordrecht, 1980.

13 W.D. Christensen and C.A. Hooker, "Autonomy and the Emergence of Intelligence: Organised Interactive Construction", in *Communication and Cognition-Artificial Intelligence,* vol. 17/2000, pp. 133-157.

14 T. Ziemke, *The Body of Knowledge*, cit.

15 T. Ziemke, "Embodied AI as Science: Models of Embodied Cognition, Embodied Models of Cognition, or Both?", in F. Iida, R. Pfeifer, L. Steels and Y. Kuniyoshi (Eds.), *Embodied Artificial Intelligence. Lecture Notes in Computer Science,* Springer, Berlin-Heidelberg, 2004, pp. 27-36.

16 *Ivi,* p. 30, italics original.

EAI, based on the so-called unconventional approach to the artificial emulation of natural intelligence. Attention will be given to the paradigm of unconventional EAI known as Morphological Computation (MC). I will briefly review the state-of-the-art in MC with a focus on a very recent trend, whose core concept is that of "organic reconfigurability" (§ 2). In this direction, two advanced cases of study of so-called organic or living morphological computers will be presented and discussed (§ 3). The prospect is to shed some light on our title question: what progress has been made in understanding the embodiment of computing systems? (§ 4).

2. MC: A Brief Review of the State-of-the-Art

Information theorists usually distinguish between the concept of computing and that of computation.[17] The first typically refers to the use or study of the digital computer as a tool for storing and processing information, namely structured data, whereas the second more generally refers to any activity regarding information, whether it is obtained by a digital computer or not. During the last decades the aforesaid distinction has gained a growing interest. This has occurred to the simultaneous decline of Turing Computability, a theory that postulates that all kinds of computation can be described in terms of computing, i.e., digital computation.[18] In this context, the research area of Unconventional Computation (UC) has emerged to provide an alternative to Turing Computability together with the connected approach to the physics of computation.[19]

UC covers huge amounts of models, techniques, and technologies. Of particular relevance are those known as Natural Computation (NC).[20] NC includes neuro- and bio-inspired computation and quantum computation. Its core idea is to exploit patterns of complex dynamics, which are available in nature, as an intrinsic computational resource (to nature).[21] MC stands out from other paradigms of NC in that it discloses a new, closer kind of connection between embodiment and computation. It focuses, indeed, on the direct use of the body in computational tasks.[22] This is mainly achieved through a functional interpretation of body morphology, which is seen as overlapping with the function of shaping the information exchanges embodied in the

[17] C.S. Calude, "Unconventional Computing: A Brief Subjective History", in *CDMTCS Report*, vol. 480/2015, pp. 1-10.

[18] J.M. Shalf and R.M. Leland, "Computing Beyond Moore's Law", in *Computer*, vol. 48/2015, pp. 14-23.

[19] A. Adamatzky et al., "East-west Paths to Unconventional Computing", in *Progress in Biophysics and Molecular Biology,* vol. 131/2017, pp. 469-493.

[20] K. Rozenberg, T Bäck and J.N. Kok, *Handbook of Natural Computing*, Springer, Berlin-Heidelberg, 2012.

[21] Measures of spontaneous organisation are generally referred to as structural complexity. Intrinsic computation may be defined as structural complexity expressed in non-analytical terms. See: J.P. Crutchfield, "The Calculi of Emergence: Computation, Dynamics, and Induction", in *Physica D,* vol. 75/1994, pp. 11-54.

[22] P.R. Nowakowski, "Bodily Processing: The Role of Morphological Computation", in *Entropy*, vol. 19/2017, 295.

matter-energy exchanges of the physical bodies.[23]

From a technical point of view, MC is based on a family of recursive neural networks, called physical reservoir systems. Reservoir systems allow for complex temporal computations, i.e., transformations of non-linear input sequences into spatiotemporal patterns, through an abstract dynamic system called reservoir (cf. **Figure 1a**). A reservoir maps inputs onto spaces of high-dimensional state, analogously to what is performed by a kernel in Machine Learning. Spatiotemporal patterns are read by a readout mechanism trained with (a combination of) simple methods, such as linear regression/classification, local learning rules and synaptic plasticity. When the reservoir describes the dynamics (either physical, chemical or biological) of a natural system, it is called physical reservoir.[24] A physical reservoir has three main properties:

- High dimensionality: this property allows to separate inputs for classification tasks and to readout spatiotemporal patterns in prediction tasks.
- Non-linearity: this property transforms non-linearly to linearly separable inputs in classification tasks and extracts non-linear dependencies in prediction tasks.
- Fading memory: this property ensures that the reservoir state is dependent only on recent-past inputs in sequential data representation tasks.

Reservoir computing systems consisting of an input mechanism, a physical reservoir and a readout mechanism are called physical reservoir systems (cf. **Figure 1b**).

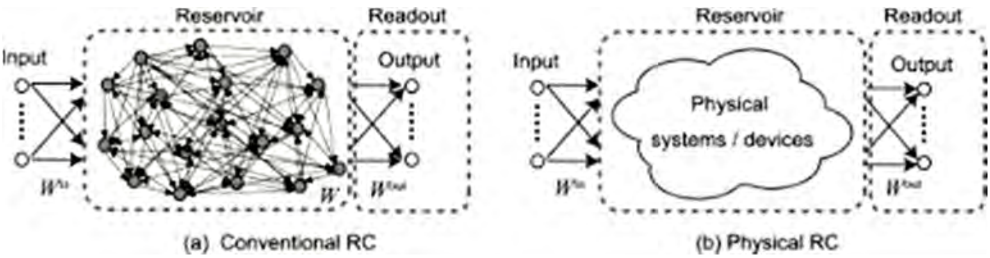

Figure 1: Conventional and physical approaches to reservoir computing systems. (a) In conventional reservoir systems the reservoir is an artificial recursive neural network. (b) In physical reservoir systems the reservoir describes a natural system or a device. See: Tanaka et al., *Recent Advances,* cit., p. 3.

[23] G. Dodig-Crnkovic and R. von Haugwitz, "Reality Construction in Cognitive Agents through Processes of Info-Computation", in G. Dodig-Crnkovic and R. Giovagnoli (Eds.), *Representation and Reality in Humans, Animals and Machines*, Springer, Cham, 2017, pp. 211-234.

[24] Tanaka, G. et al. (2018). Recent Advances in Physical Reservoir Computing: A Review, in *arXiv* [cs.ET]. https://arxiv.org/abs/1808.04962. Accessed 16 February 2019.

Standard applications of MC are discussed in the paper of Müller and Hoffmann.[25] For example, the octopus robotic arm developed by Nakajima, Hauser and Pfeifer,[26] and modelled as a reservoir by Nakajima, Hauser, Li and Pfeifer (cf. **Figure 2**).[27] Other examples are the bio-inspired robots based on masse-spring systems described with linear feedback loops and trained to emulate output streams that correspond to motor patterns, e.g., quadruped gaits.[28]

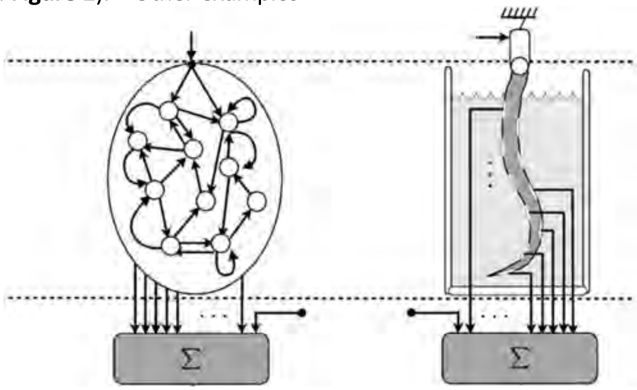

Figure 2: Analogy between a reservoir computing system and the octopus robotic arm modelled as a physical reservoir computing system by Nakajima, Hauser, Li and Pfeifer. The units of the physical reservoir are sensors coupled through a soft silicone material. See: K. Nakajima, H. Hauser, T. Li and R. Pfeifer, *Information Processing*, cit., p. 3.

However, a new generation of physical reservoir robots and robotic devices is currently under investigation. The rationale is that traditional physical reservoir technologies are made from synthetic materials which degrade over time and can produce harmful ecological and health side effects. It would thus be useful to build physical reservoir technologies using self-renewing and biocompatible materials, of which the ideal candidates are living systems themselves ("organic reconfigurability"): the concept of organic reconfigurability means to exploit the intrinsic computational capacity of living systems.[29] This, in turns, implies advancements in the modelling of both the input and the readout mechanism obtained by emulating aspects of the living systems

[25] V.C. Müller and M. Hoffmann, "What Is Morphological Computation?", in *Artificial Life*, vol. 23/2017, pp. 1-24.

[26] K. Nakajima, H. Hauser and R. Pfeifer, "Exploiting Short-Term Memory in Soft Body Dynamics as a Computational Resource", in *Journal of the Royal Society Interface*, vol. 11/2014, 20140437.

[27] K. Nakajima, H. Hauser, T. Li and R. Pfeifer, "Information Processing via Physical Soft Body", in *Scientific Reports*, vol. 5/2015, 10487.

[28] V.C. Müller and M. Hoffmann, *What Is Morphological Computation*, cit., pp. 5-7.

[29] S. Kriegman, D. Blackiston, M. Levin and J. Bongard, "A Scalable Pipeline for Designing Reconfigurable Organisms", in *PNAS,* vol. 117/2020, pp. 1853-1859.

that are not described by the reservoir. I will refer to these kinds of mechanisms inspired by nature as "support-based",[30] so as to highlight the contrast with traditional mechanisms, which are abstractly modelled. In the following paragraph I will present and discuss two advanced cases of study of organic or living morphological computers, where artificially induced complex anatomies are obtained by virtue of the intrinsic computational capacity of cells to function in novel morphologies.

3. Two Advanced Cases of Study

For the first time ever, in 2018 the research group led by Prof. Connon at the Institute of Genetic Medicine of Newcastle University was successful in printing, by using an advanced 3D bio-printing technique, perfectly synthetic corneal prosthetic implants, which were suitable for translation into the clinic in patients affected by the loss of corneal function.[31] After the corneal microstructures were printed by utilizing bio-inks that comprised corneal stroma cells of a healthy donor together with collagen and alginate, a highly organized and functional corneal tissue was created using only the curved shape of the plastic template of the bio-printed cornea. This was possible by covering the plastic template with a very thin adhesive film of enzyme-sensitive Peptide amphiphiles (PA). The physicochemical environment that has been created, variable over time, induced the corneal keratocytes, specialized fibroblasts residing in the corneal stroma, to adhere to the template, migrate towards its center, proliferate, align and finally, autonomously deposit large amounts of collagen and alginate fibrils, according to a uniform self-assembled organization equivalent to the latex structure of the natural tissue (cf. **Figure 3**).

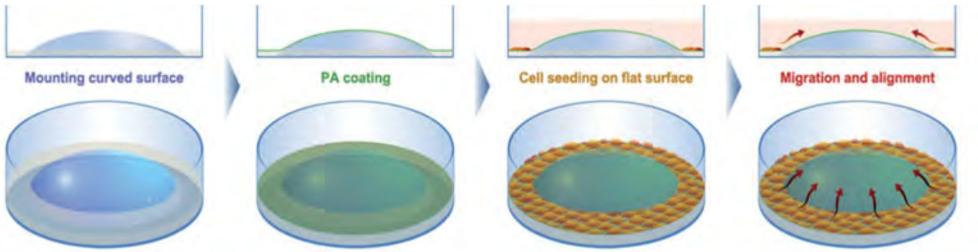

Figure 3: Adhesion and migration of human corneal stromal cells on the curved plastic templates. Cells seeded onto the flat surface at the periphery of the wells were allowed to adhere and then migrate up toward the center of the templates. Templates comprising planar surfaces only (different geometry) or curved surfaces left uncoated (different bioactivity) were used as negative controls. See: A. Isaacson, S. Swioklo and C.J. Connon, *3D Bioprinting*, cit., p. 192.

[30] R. Pfeifer and F. Iida, "Embodied Artificial Intelligence: Trends and Challenges", in F. Iida, R. Pfeifer, L. Steels and Y. Kuniyoshi (Eds.), *Embodied Artificial Intelligence*, Springer, Berlin-Heidelberg, pp. 1-26.

[31] A. Isaacson, S. Swioklo and C.J. Connon, "3D Bioprinting of a Corneal Stroma Equivalent", in *Experimental Eye Research*, vol. 173/2018, pp. 188-193.

What I just briefly described is a strategy of generating complex patterns without external direction (i.e., self-assembly) in which the morphology of the cell body is used to perform the intrinsic computations required to calculate the control actions that corneal keratocytes perform, in particular, in autonomously depositing the extracellular matrix. Modelled as physical reservoirs, corneal keratocytes implement motor programs in their body morphology. The input and readout mechanisms are support-based, in the sense that they are specified by the time-varying physicochemical exchanges that corneal keratocytes establish with the curved shape of the plastic-coated PA template. The cell reservoirs, together with the input and readout mechanisms, are used as morphological computers to predict simple classifications: working as classifiers, they separate different physicochemical inputs, i.e., collagen and alginate fibrils from (the other) corneal keratocytes. It should be noted how researchers play an active role in the self-assembly process of the synthetic corneal stroma, although limited to predisposing the physicochemical conditions of the cellular environment and, above all, to setting the overarching goal of living morphological computers.

A more invasive design intervention is put into play in our second case of study, i.e., the xenobots recently realized by researchers of the University of Vermont, Tufts University and Harvard University.[32] They developed, indeed, a scalable pipeline for designing morphological computers able to perform four different behavioral goals: locomotion, object manipulation, object transport and collective behavior. This scalable pipeline is organized as a generators-and-filters architecture. The first generator is an evolutionary algorithm used to find the best performant designs starting from biological building blocks and a certain behavioral goal. Discrepancies between in silico and in vivo behavior are returned to the algorithm in the form of constraints on the kinds of designs that can evolve during subsequent design-manufacture cycles. The steps towards manufacture, and hence towards in vivo behavior, are provided by a robustness filter, which only allows passage of designs that sustain the desired behavior in the face of noise, and a transferability filter, which only allows passage of designs that are buildable and scalable. A second generator is the so-called realizability generator: the designs that successfully pass through the transferability filter are then built out of living tissues.

At this stage, pluripotent stem cells are first harvested from blastula stage *Xenopus laevis* embryos, dissociated, and pooled to achieve the desired number of cells. Following an incubation period, the aggregated tissue is then manually shaped by subtraction producing a morphological computer which is an organic or living approximation of the simulated design. Further, contractile tissues are layered into the organism through the harvesting and the embedding of *Xenopus* cardiac progenitor cells, an embryonically derived cell type which naturally develops into cardiomyocytes (heart muscle) and produces contractile waves at specific locations in the resultant shaped form

32 S. Kriegman, D. Blackiston, M. Levin and J. Bongard, *A Scalable Pipeline*, cit.

(cf. **Figure 4**). The final product of this procedure is a more complex morphological computer, i.e., the xenobot as an organic or living approximation of the evolved design, which possesses the ability to self-locomote and explore an aqueous environment for a period of days or weeks (cf. **Figures 5-6**).

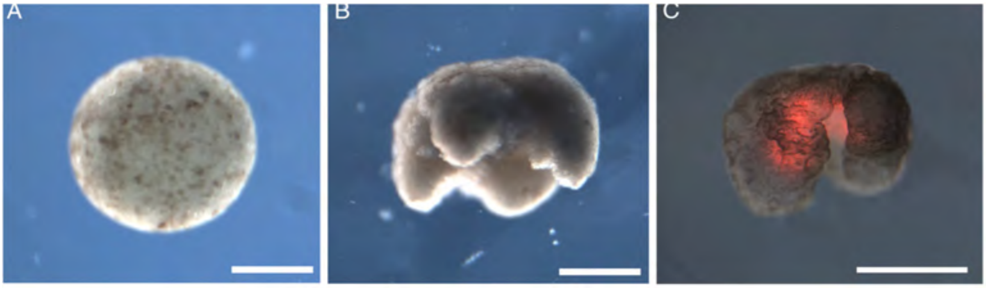

Figure 4: Manufacturing reconfigurable organisms. (A) Aggregation of pluripotent blastula cells harvested from *Xenopus laevis* embryos. (B) Shaping results in 3D representations of the evolved in silico designs. (C) Layering of cardiac progenitor cells results in contractile cardiomyocyte tissue at specific locations, visualized by red fluorescent lineage tracer. See: S. Kriegman, D. Blackiston, M. Levin and J. Bongard, *A Scalable Pipeline*, cit., p. 1857.

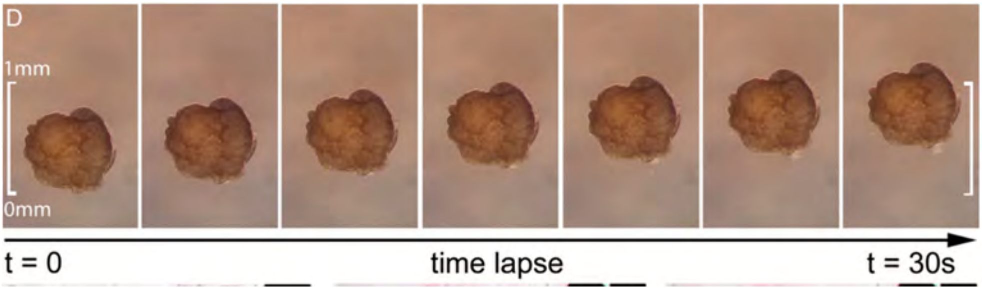

Figure 5: Emergent behavior by an individual xenobot. See: S. Kriegman, D. Blackiston, M. Levin and J. Bongard, *A Scalable Pipeline*, cit., p. 1857.

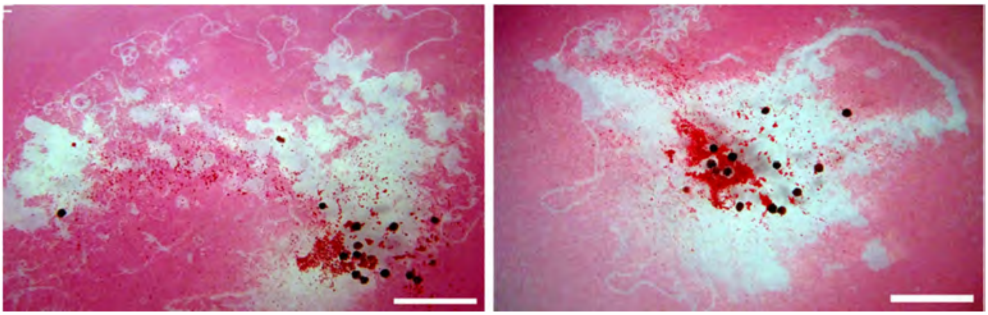

Figure 6: Emergent behavior by a group of xenobots. See: S. Kriegman, D. Blackiston, M. Levin and J. Bongard, *A Scalable Pipeline*, cit., p. 1857.

4. Conclusion

To conclude this article, I would like to summarize the results obtained in order to attempt an answer to our title question: what progress has been made in understanding the embodiment of computing systems? First of all, in briefly reconstructing the evolution internal to EAI, attention was drawn to emerging frameworks for this research field, particularly to frameworks based on UC such as the one inspired by MC. MC discloses a new, closer connection between embodiment and computation in virtue of a functional interpretation of the body morphology. An overview of the state-of-the-art in MC was provided with the prospect of presenting two advanced cases of study in the context of the emerging generation of living morphological computers grounded on the concept of organic reconfigurability. After having had a closer look at their current design and manufacture, I would speculate that some relevant progress has been made in the direction of understanding the embodiment of computing systems. In particular, complex anatomies may be artificially induced by exploiting the intrinsic computational capacity of cellular morphologies, which benefit of guided cellular self-assembly and/or emergence processes.