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Energy Constraints and Behavioral Complexity: The Case of a Robot with a Living Core

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Abstract

The new scenarios of contemporary adaptive robotics seem to suggest a transformation of the traditional methods. In the search for new approaches to the control of adaptive autonomous systems, the mind becomes a fundamental source of inspiration. In this paper we anticipate, through the use of simulation, the cognitive and behavioral properties that emerge from a recent prototype robotic platform, EcoBot, a family of bio-mechatronic symbionts provided with an 'artificial metabolism', that has been under physical development during recent years. Its energy reliance on a biological component and the consequent limitation of its supplied energy determine a special kind of dynamic coupling between the robot and its environment. Rather than just an obstacle, energetic constraints become the opportunity for the development of a rich set of behavioral and cognitive properties.

Introduction

During the last two decades, robotics has increasingly redirected much of its traditional emphasis on precision, speed and controllability towards three new objectives: adaptivity, learning and autonomy (Pfeifer, Iida, and Bongard 2005). In its initial formulation, the problem has been mapped neatly onto the traditional domain of engineering methods, in particular their natural evolution towards system and control theory (e.g. see (Brogan 1990)). After mastering the artificially protected environment of the technological factory, though, the scenario for the robots to come reveals the world in its least structured form: the exploration of inhospitable and unexplored territories, participation in search and rescue actions, and the social context in robot-robot and human-robot interactions. The uncertain, sometimes the unknown, potentially (and often) described by limited, inconsistent and unreliable information, characterizes the likely setting for most of these activities. The environment requires contingent adaptation to temporal and spatial features and, at the same time, underdetermines the appropriate robot behavior. The environmental intrinsic dynamics express an inertia that the robot has often no power to influence directly (e.g. the case of a marine tidal stream for a small robotic explorer or a hostile and non-collaborative human interlocutor for a service robot). The robot has to adapt by synchronizing to exogenous dynamics, thus operating under time pressure. Furthermore, an autonomous robot is expected to manage and provide for its own energetic needs by finding in its surroundings the means for its *energetic autonomy*, whilst operating with limited or no human intervention.

Within this complex scenario, a certain level of autonomy in the context dependent selection of the behavior might be crucial to boost performance. The search for the solution to the contemporary problem of robotics seems to suggest the need of a methodological hiatus. The attention of many researchers has moved to the one system that, to our knowledge, masters the new objectives: the (biological) mind, as an invaluable source of inspiration. Unfortunately, to date, science lacks a satisfactory theory of the mind, as we are still struggling in order to find the right perspective and set of methods to dissipate its mystery. The early cyberneticists, pioneers of this field, readily developed minimalist robotic or dynamic models that drew attention to the emergence of the mind as a complex interplay of brain, body and environment (Ashby 1960; Walter 1950; 1951; 1963; Braitenberg 1984). Despite the fact that mainstream artificial intelligence has deployed a representation-centric view of the mind, several lines of research have rejected representationalism and have renovated the original cybernetic intuition. Neurophysiologists and cognitive scientists have shown that the methods of dynamic system theory can be effectively applied to interpret and model biological cognition (Skarda and Freeman 1987; Freeman 2000; Kelso 1995; Thelen and Smith 1994; Thelen et al. 2001). The dynamic system approach to cognitive science has been explored at the theoretical level (Beer 1995; 1997; 2000; Van Gelder 1995; 1998; Chemero 2009), whilst cognitive tasks of minimal cognitive relevance have been synthesized and analyzed as robotic models (Beer 1996; Slocum, Downey, and Beer 2000; Beer 2003; Nolfi and Floreano 2000; Tani 2003; Tani and Ito 2003). Recently it has been argued that despite the fact that a metaphysical rejection of representations is hardly defensible, an epistemological analysis might reveal that dynamic system models of cognition offer a richer description and explanation of cognitive phenomena (Chemero 2009).

An embodied cognitive science, i.e. a cognitive science where the body plays a foundational cognitive role, has emerged quite naturally within this more systemic view of the mind. The body of the robotic agent is not simply a passive framework that relocates in space and time the agent's interface with its world. The body actively redefines the cognitive problem by pre- and post-processing information (Chiel and Beer 1997; Pfeifer and Bongard 2006). The mind emerges from the causal interweaving of coupled body, brain and environment (Beer 2000). Increasingly, embodied cognitive science inspires current robotics. To date, though, the role of the body in cognition has mostly been studied in terms of dynamics that take place along the surface of the body. We are starting to suspect that deep, non-neural bodily dynamics of biological cognitive agent (e.g. homeostatic bodily regulation and metabolic processes) might play a crucial role too.

In this perspective, relatively recent work revitalized William James' classical somatic theories of emotions (James 1890), in the light of neuroscientific evidence (Damasio 2000; 2003). According to Damasio, a hierarchy of bodily processes (metabolic regulation, basic reflexes, immune responses, pain and pleasure behaviors, drives and motivations), triggered by emotionally relevant stimuli, determine the constitutive substrate for emotion proper. On top of that, the conscious or unconscious perception of the bodily state dynamics determine the physical foundation for feelings. These ideas become relevant to robotics if we follow some authors who argue that the complex system of bodily processes might be a crucial key to a general understanding of biological cognition (Parisi 2004), and a powerful organizational principle for the deployment of robots with extended capacity for adaptivity and autonomy (Ziemke 2008; Ziemke and Lowe 2009).

Similarly, contemporary robotics has almost entirely neglected energy, unless as a corollary annoyance that sets a strong and undesirable constraint over the robot's autonomy. Nevertheless, the role of biological metabolism is not limited to the assimilation and synthesis of the basic material needed for the continuous organismic self-production. It also makes available a net amount of energy that can be used to supply sensory, motor and nervous activity. An experiment in evolutionary robotics, elegantly straightforward in its simplicity, has shown how energy constraints could effectively inform interesting cognitive properties and behavioral dynamics (Floreano and Mondada 1996). We can take this result as the starting point of our journey. In the remainder of this paper we will try to show how energy limitation, in parallel with its traditional role as constraint for autonomous robots, can also be interpreted as an unexpected source of behavioral diversity. First, we will introduce the prototype robotic version of a sustainable technology for energy generation, namely oxygen-diffusion cathode microbial fuel cells, and its computationally inexpensive mathematical model. This will constitute our experimental reference. Then, we will explore a number of interesting cognitive and behavioral consequences deriving from the intrinsic properties of this experimental setup.

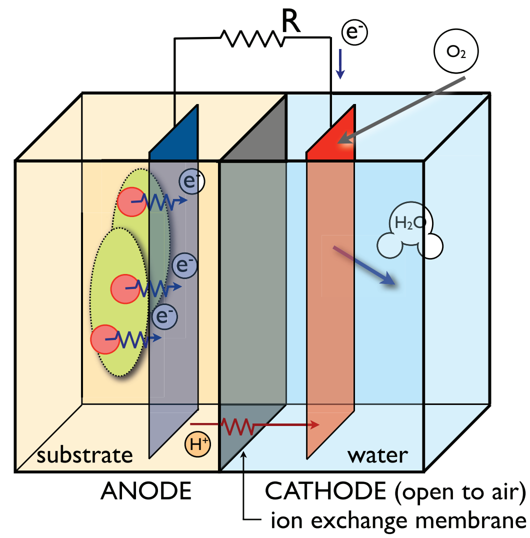

Figure 1: Schematic of an oxygen-diffusion cathode MFC.

A robot with a living core

Oxygen-diffusion cathode microbial fuel cells

During the last decade, researchers at the Bristol Robotics Laboratory have been working on the development of a peculiar family of prototype robots, EcoBot (Melhuish et al. 2006; Ieropoulos et al. 2005; 2010). Its source of power depends entirely on the availability of water and biodegradable mass. In fact the energy that is supplied for the robot's sensing, actuation and control derives from a robotic variation of the *microbial fuel cell* (hereafter MFC) technology.

In the anodic compartment of a MFC, an anodophilic population of bacteria in tight adhesion with the anodic electrode makes available electrons by oxidizing the biomass contained in a liquid substrate (Fig. 1). In MFCs that do not make use of exogenous consumables, the electron transfer from the bacterial intracellular space to the anodic electrode can take place via endogenously produced mediators, direct membrane-electrode contact or nanowires (Rabaey and Verstraete 2005; Logan et al. 2006). The anodic bacterial population, as long as provided with fresh substrate to maintain a well buffered and healthy environment, tends to reach a stationary yet metabolically active growth dynamic. The substrate can be fed by refined renewable biomass, e.g. sucrose, acetate, starch (Rabaey and Verstraete 2005; Logan et al. 2006), but also by unrefined biomass, e.g. rotten fruit, flies, green plants, wastewater (Melhuish et al. 2006).

A semipermeable membrane separates anolyte and catholyte, at the same time preventing any flux of O_2 to the anode and allowing the migration of H^+, a byproduct of oxidation in the anodic compartment, to the cathode. Since the robot prototype is intended to be an autonomous system, the (more efficient) exhaustible chemical electrolyte based cathodes, traditionally used in MFC research, have been replaced by oxygen-diffusion cathodes, partly open to the external atmosphere and, for the remaining part, filled with water. This choice translates into a self-sustained electrochemical process. Hereafter, we will specifically refer to this configuration as *oxygen-diffusion cathode microbial cell* (ODC-MFC). In an ODC-MFC (Fig. 1), H^+ ions reduce at the cathode by combining with O_2 and accepting electrons to endogenously produce a little quantity of water (normally insufficient to compensate the loss due to evaporation), thus closing the electric circuit. The presence of a continuous flow of highly oxygenated water would support the cathodic chemical dynamics, promoting optimal efficiency. As this is not an option for autonomous terrestrial robots, the instant level of water present in the cathode and of the chemical energy in the substrate are the two crucial parameters for the system.

We can conceive the ODC-MFC powered robot as a biomechatronic symbiont, where each of the two hybrid components not only benefits, but depends on the other for its own survival (Melhuish et al. 2006). To date, the power density produced by MFCs in general, and even more so by ODC-MFCs, is admittedly extremely low. Nevertheless, this technology has been proved sufficient to substantially support the energy demands of important applications, e.g. wastewater treatment and mobile robot platforms (Habermann and Pommer 1991; Wilkinson 2000; Melhuish et al. 2006; Ieropoulos et al. 2010). Both theoretical and experimental results demonstrate that MFC miniaturization might lead to higher levels of power density (Ieropoulos, Greenman, and Melhuish 2010) and that miniaturization might be pushed to microscopic levels (Kim et al. 2003). Prospectively, this indicates that MFC technologies are in principle capable of supplying the robots with a significantly higher power once a large number of miniature MFC units, in appropriate stack configurations, would be integrated on the robotic platform.

A mathematical model of ODC-MFC

We can readily anticipate the future of the ODC-MFC technological evolution in simulation. For this reason we developed a mathematical model of ODC-MFC (Montebelli et al. 2011). Differently from other models of MFC currently available in the scientific literature, its high level of abstraction, which omits the details down to the physical-chemical level, allows its use as a platform-independent plug-in that can be easily integrated within standard computer robot simulations, with extremely limited computational overhead.

We developed a simple resistance-capacitance electric model (Fig. 2). Both the electromotive force (V_0) and internal resistance (R_i) of the ODC-MFC depend on the level of hydration at the cathode and on the chemical energy in the substrate. The functional relations for these crucial parameters were identified by using energy generation data extracted from the physical ODC-MFC powered robot prototype (Montebelli et al. 2011). An external capacitance (C) transiently stores the available energy. Its presence is a design choice, due to the strong power constraints imposed by the physical sensors and actuators for robotic applications. A hysteresis cycle ensures that the tension supplied to the robot (the resistive load in Fig. 2) remains within a reasonable range. When the tension across the capacitor exceeds a given upper threshold, the accumulated energy is distributed to the robot. When a lower threshold is reached, the switch S in Fig. 2 opens and the distribution is inhibited, while the capacitor recharges its energy. The relations that mathematically describe the system parameters (V_0 and R_i) and their physical interactions, constitute the platform independent model of energy generation. To the contrary, the distribution of the available energy must be estimated on the basis of the actual robot in use. For the reader's convenience the model's equations are reported in the appendix.

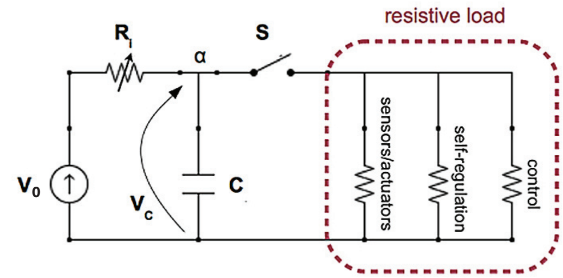

Figure 2: Model of ODC-MFC energy generation. The lumped parameters V_0, R_i and C schematically represent our platform independent model. A dashed rectangle represents the robot as a resistive load.

The levels of cathodic hydration and chemical energy in the anodic substrate determine the instant rate of energy (power) that is generated by the ODC-MFC. In other words, well hydrated and fed robots recharge faster and therefore have more energy for their actuation. A more detailed description is available in (Montebelli et al. 2011). What is important to the current discussion is that the model produces realistic ODC-MFC energy generation dynamics.

In simulation, sources of 'water' and 'food' can be easily introduced, and the desired modality of interaction between them and the robot (ranging from more realistic to heavily abstract) implemented. In principle, the implementation of analogous mechanisms for direct access to the environmental resources (although not yet implemented) are possible for the physical prototypes. Observe that both the hydration level and the chemical energy in the substrate are subject to temporal decay. This models the spontaneous evaporation from the cathode and (undesired) biochemical processes that degrade the substrate in the digester.

Behavioral and cognitive consequences

As mentioned before, by using the ODC-MFC we can readily anticipate the technological developments of the MFC technology for robotic applications, whilst maintaining realistic energy generation dynamics. Free from physical limitations, we can extend to our will the number of on-board ODC-MFCs in any arbitrary number of stack configurations. We can easily reach the point where the characteristic power limitations of ODC-MFCs cease to pester the robotic system, i.e. where the ODC-MFCs can supply the robot with any amount of power it may require over an extended period of time. Nevertheless, each level of energy constraints that we are about to explore, from the most stringent to the most relaxed, will imbue the ODC-MFC powered robotic system with characteristic properties.

At a more abstract level, the role of the ODC-MFCs in a similar setup is twofold. First, we can interpret it as an artificial metabolism that relates energy to the two crucial variables of the system (level of hydration and of chemical energy in the substrate). This provides the system with a set of metabolic signals that are directly connected to the intrinsic 'well being' of the robot. We could characterize these signals as low frequency, as compared to the the sensorimotor dynamic that typically emerges from robot's sensors and actuators during the interaction with its environment. Second, the living bacterial colony in the anode provides the system with a component that imbues a certain level of *biological causal powers* (Di Paolo 2003; Ziemke 2008). These observations have important cognitive and behavioral implications that we are about to explore.

State of the art ODC-MFCs

Current physical ODC-MFCs powered robots don't actually display surprising behavioral dynamics. The different generations of EcoBot scaled up from 8 to the current 48 on-board ODC-MFCs. Each ODC-MFC provides around 0.1 mW to its load at about 0.2 V. The energy demand of the actuation of a robot like EcoBot-III should not be overlooked. In parallel for the actuation of its motors, the available energy supplies the pumps that periodically rehydrate the cathode and recirculate the substrate from a central digester to the anodic chambers of the MFCs. Despite a careful morphological design and the use of low-power electronic solutions for the robot's actuation, sensing and control, a few seconds of activity require several minutes of recharge. Therefore, the extremely low generated power limits the robot behavior to cycles of full charge and discharge of the energy accumulated across the capacitor. Nevertheless, despite the fact that the physical prototype robot currently relies on human support, it is rather close to achieving energy autonomy, the capacity to provide for its own energetic needs with no human intervention.

A foreseeable future

Now imagine scaling up the number of ODC-MFCs units that currently power EcoBot-III by a factor 10. In simulation we can power, for example, a simple e-puck robot, whose energy demand can be estimated on the basis of the physical characteristics of its actuators (Montebelli et al. 2010). This maintains the robot in a situation of mild energy constraint while it operates under dynamical engagement with its environment. Within its environment the robot can find sources of food and water. Since the ODC-MFC system is its only source of energy, the maintenance of a high level of hydration and chemical energy in its (virtual) digester allows for a higher available power. A deficit in water and food intake (remember that both hydration and energy content in the substrate are subject to decay), entails the incapacity for further movement or to further support the anodic bacterial ecology (death).

Also imagine that the robot is controlled by an artificial neural network (ANN). Its synaptic weights can be adapted by evolutionary algorithms (Goldberg 1989). In virtue of this choice, we abandon a rigid control over the adaptive process. By doing this, we can avoid the injection of our own perception of the task and of the required steps for its solution (Nolfi and Floreano 2000). In other words, we can renounce our own ontological perspective of the problem by using a very generic fitness function to drive the evolutionary algorithm. In fact, given the constraints that are implicitly set on the possible dynamics of the system, the fitness function could be in the form: "live as long as you can". This leaves maximal freedom to the system under study to self-organize its solution to a high degree (Nolfi 1998).

Energy limitations and biological causal powers induced by the use of ODC-MFCs concur, with specific consequences, during the simulated evolutionary process:

- They promote adaptation towards behaviors that most effectively trace and exploit the environmental resources (food and water).
- In case the body morphology could also be adapted by evolutionary algorithms (Pfeifer, Iida, and Bongard 2005), this would be synergistic to the evolution of the neurocontroller.
- The variables that are essential to the viability of the system (food and water levels) work as its control parameters (Kelso 1995). In an experiment, we clamped their values and left a successfully evolved robot free to roam in its environment. By a systematic exploration of several combinations of the parameters' value, we showed how their current values reconfigured the phase space of the dynamic system constituted of the robot's body, neurocontroller and environment. This mechanism implemented a self-organized *dynamic action selection mechanism* that elicited the subset of behavioral attractors as appropriate to the current context. This constitutes a form of *motivational autonomy*, the agent's capacity to independently select the behavior that is functional to its own viability (McFarland 2008). In a simplified setup, where energy is the only control parameter, we classified a set of 8 behavioral attractors, and we demonstrated their distribution as a function of the energy level (Montebelli, Herrera, and Ziemke 2008). A simplified illustration of this distribution is exemplified in Fig. 3. Three 'exploratory' behaviors were selected to find energy sources in the environment when the robot was in the condition of energy deficit (type A behaviors); four were local behaviors, typically selected to remain close to the potential energy source for high levels of energy (type C); finally, two were hybrid behaviors, at the same time sharing characteristic with both exploratory and local behaviors and selected for intermediate levels of energy (type B). The selection of the particular behavioral attractor followed the normal laws of dynamic systems: falling on one behavioral attractor rather than another depended on the robot's starting position and on the integrated effects of noise. In a more recent and preliminary experiment, with both hydration level and energy in the substrate as control parameters,

we found a similar mechanism (Montebelli et al. 2010). In this case, water and food areas were the focus of two basins of attraction. In clamped conditions, the control parameters modulated the ratio of access to water with respect to food resources, i.e. the probability of a transition from one to the other basin of attraction.

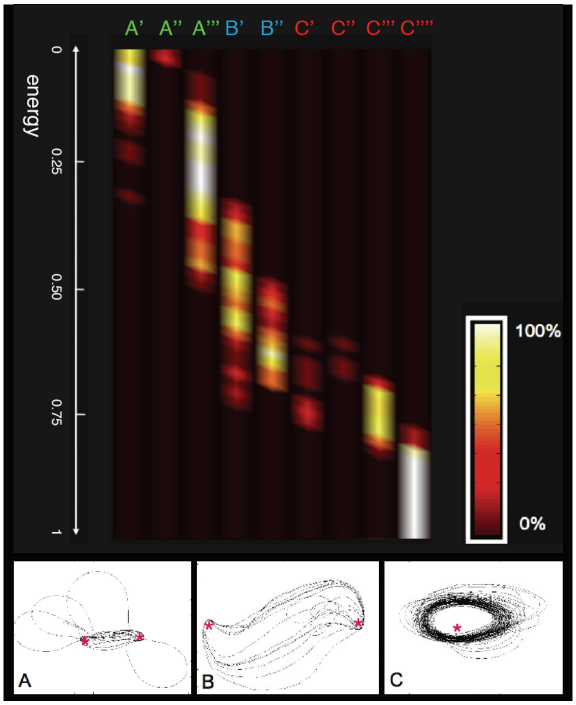

Figure 3: *Lower panels*: Sample spatial trajectories for the three classes of behaviors observed in clamped conditions after transient exhaustion. Exploratory behaviors (panel A), local behaviors (panel C) and hybrid forms (panel B). Potential energy rechargers (i.e. the position of the light sources) are indicated by red stars. For a better resolution, the icons representing each class of trajectories zoom on the area of main interest surrounding the light sources. *Top panel*: The intensity of the pixels for each column (corresponding to attractors belonging to classes A-C, as specified by their labels on the top row) represents the relative frequency of the behavioral attractor as a function of the energy level. For example, an energy level of 0.7 leads to the expression of attractor C''' (in 70% of the replications), C' (20%) or B' (10%). For energy levels in the interval [0.0, 0.4] we can observe a clear dominance of attractors in class A. A similar dominance in the energy interval [0.7, 1.0] is shown by attractors in class C. The hybrid forms in class B characterize intermediate energy levels. Adapted from (Montebelli, Herrera, and Ziemke 2008).

- The interaction of more complex controllers and morphologies tends to develop energy efficient behaviors. For example, a less energetically demanding ocular actuation might be selected for an initial screening of the environment before a direct engagement in action (Lowe et al. 2010). A similar strategy might involve abstract planning

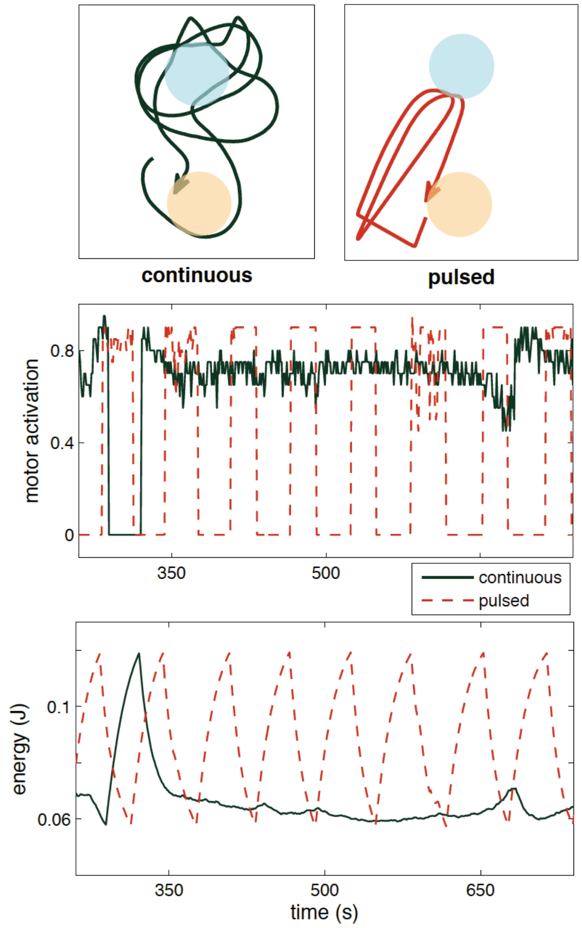

Figure 4: *Top panels*: examples of continuous (green) and pulsed (red) robot trajectories. In each panel, on entering the higher/lower circle the robot receives hydration/fresh substrate. *Lower panels*: motor activation (top) and energy level (bottom) for continuous (continuous green plot) and pulsed (dotted red plot) behavior. Adapted from (Montebelli et al. 2010).

and thought.

- Depending on the environmental conditions, the viable robot could rely on bursts of maximal power activation, leading to cycles of full energy recharge and distribution, or on more conservative, sub-maximal motor activation that would tend to maintain an instant balance between the generated and utilized power. In other words, pulsing and continuous actuation would be two qualitative behavioral options in front of an identical quantitative energy balance. This result, reminiscent of the different behavioral strategies of wolves and cheetahs (where the former tend to cover very long distances at low speed during their daily roaming and the latter can run at surprisingly high speed for a few seconds, but need a few hours of recovery afterwards), is clearly demonstrated in (Montebelli et al. 2010), and reported here in Fig. 4.

- More sophisticated sets of sensors (e.g. electronic noses) might integrate the robot design for an elementary chemical analysis of the available resources. The robot might consequently classify the potential food on the basis of preferences, related to the energy content of the available resources.
- The substrate that is periodically excreted from the anodic chamber in order to be substituted with fresh substrate from the digester is expected to have fertilizing properties. The robot might learn how to spatially organize areas dedicated to its foraging and excretions, and temporally rotate them in order to achieve more prosperous harvests.
- The meaning of the labels 'water' and 'food' is grounded in the viable dynamics of the robot. Following Varela: "There is no food significance in sucrose except when a bacteria swims upgradient and its metabolism uses the molecule in a way that allows its identity to continue." (Varela 1997)

A long-term prospective

Finally, imagine increasing the number of on-board ODC-MFCs further, so that they could promptly cover virtually any power demand by the robot they serve. Under these conditions, would the described system differ in any significant way from robots powered by more conventional sources of energy? We could answer by pointing to the intrinsic thermodynamic irreversibility of, for example, common rechargeable batteries. On the other hand, in principle, the bacterial colony in the MFCs' anode constitutes a rather robust and dynamically self-sustained system. Furthermore, and most importantly, consider a population of ODC-MFCs powered robots. Each member of the population still crucially depends on the resources at hand in its environment. It is viable as long as its behavior promotes a balanced and sustained relationship with its environment within the space-time horizon of this robotic species. Behaviors that are disruptive of the ecological balance would be irreconcilable with its collective long-term viability. In other words, the viable robot would be ecologically grounded in its environment and their specific form of autonomy would be constrained by the maintenance of its ecological balance. By *ecological autonomy* we mean a collective form of energy and motivational autonomy that is crucially constrained by the demands of the agent's viable integration in its natural environment over time.

Conclusions

In the present paper we have presented a robotic system subject to energetic limitation that can capitalize on this restriction in order to develop, through its adaptive process, a rich behavioral diversity. The simulated agent in our experiments constitutes a bio-mechatronic hybrid. A conventional e-puck robot derives the energy for its actuation from a stack of ODC-MFCs, mathematically modeled on the basis of an actual physical prototype. In our simulated robotic setup, the ODC-MFC energy generation system represents a basic abstraction of a metabolic system, thus allowing the study of the interaction between sensorimotor and deep bodily dynamics. The use of simulation offers the opportunity for the systematic study of different scenarios, where the energy constraints can be increased or relaxed at will. The living bacterial colony in the ODC-MFC cathode endows the system with biological causal powers that are unprecedented in robotics.

Energy restriction and biological causal powers play a fundamental role during the robot's adaptation and endow the robot with characteristic and peculiar properties. They create a powerful pressure that tends to select effective (in the sense of viable) energy-efficient behaviors and morphologies. They determine the conditions for a rich collection of behaviors and behavioral strategies. The metabolic signals, directly connected to the basic needs for the viability of the system, can be readily interpreted as its control parameters, the crucial variables that dynamically select the subset of behaviors that are appropriate to the specific context. In particular, the biological causal powers, due to the living component of the system, constrain the robot's autonomy to behaviors that promote an ecologically balanced integration in its environment and the grounding of meaning, relatively to the aspects of the environment that are most salient to the robot viability.

Under a cognitive perspective, the importance of the simple metabolic system implemented in our simulations should not be overlooked. Indeed, the relatively high-frequency sensorimotor signals that characterize the agent-environment interaction constitute a solid basis for the study of perception and action. Nevertheless, low -frequency metabolic signals associate the contingent sensorimotor flow with the non-negotiable essence of adaptivity: the agent's well being. Blindness to this primary fact amounts to pursuing a myopic perspective on cognitive science, trapped in contingent and local dynamics, whilst ignoring that cognition amounts to nothing but the deployment of a sophisticated strategy for survival.

Appendix: Equations of the ODC-MFC model

We report below the set of equations for the ODC-MFC model, as throughly described in (Montebelli et al. 2011). The values for the parameters that appear in the equations are reported in Table 1. Observe that the form of the model used in (Montebelli et al. 2010) differers from the one described here. The former model can be interpreted as the local linearization of the following equations.

a) Electric charge balance With reference to node α in Fig. 2:

$$\frac{V_0 - V_C}{R_i} = C\frac{dV_C}{dt} \tag{1}$$

b) Dependence on substrate

$$subst = 1 - \frac{t_s}{\tau_s} \tag{2}$$

where *subst* represents the current level of biochemical energy in the anodic substrate and t_s is the time from the last replenishment of the anodic chamber with fresh substrate.

parameter	equation	numeric value	physical dimension
C	1;8	0.0282	F
τ_s	2	60000	min
q_{V_0}	3	3.2	V
m_{V_0}	3	-0.00000667	V/min
q_{R_i}	4	550	Ω
m_{R_i}	4	0.0442	Ω/min
β	5	0.2	-
α_p	5	1.9	-
α_n	5	0.85	-
γ_p	5	0.0055	$1/min$
γ_n	5	0.031	$1/min$
δ_p	5	710	min
δ_n	5	600	min
α_{V_0}	6	0.18	V
α_{R_i}	7	320	Ω

Table 1: Suggested values for the parameters.

$$V_{0_{max}} = q_{V_0} + m_{V_0} t_s \tag{3}$$

$$R_{i_{min}} = q_{R_i} + m_{R_i} t_s. \tag{4}$$

c) Relation time-hydration

$$hyd = \beta + \frac{\alpha_p}{1 + e^{\gamma_p (t_h - \delta_p)}} - \frac{\alpha_n}{1 + e^{\gamma_n (t_h - \delta_n)}} \tag{5}$$

where *hyd* represents the current level of hydration in the cathode and t_h is the time from the last hydration.

d) Relation hydration-R_i and hydration-V_0

$$V_0 = V_{0_{max}} - \alpha_{V_0} + \frac{\alpha_{V_0}}{1 - hyd^*}(hyd - hyd^*) \tag{6}$$

$$R_i = R_{i_{min}} + \frac{\alpha_{R_i}}{1 - hyd^*}(1 - hyd). \tag{7}$$

e) Energy stored in the capacitor

$$\varepsilon = \frac{1}{2} C V_C^2. \tag{8}$$

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