BioSystems 124 (2014) e7–e20

Contents lists available at ScienceDirect

BioSystems

journal homepage: www.elsevier.com/locate/biosystems

Review

How simple autonomous decisions evolve into robust behaviours?: A review from neurorobotics, cognitive, self-organized and artificial immune systems fields

Jose A. Fernandez-Leon [a,*], Gerardo G. Acosta [b,c], Alejandro Rozenfeld [b,d]

[a] Centre for Computational Neuroscience and Robotics (CCNR), Informatics, University of Sussex, United Kingdom
[b] INTELYMEC-CIFICEN-CONICET, Engineering Faculty, Universidad Nacional del Centro de la Prov. de Buenos Aires and CONICET, Olavarría,Argentina
[c] GEE – Department of Physics, Universitat de les Illes Balears, Palma de Mallorca, Spain
[d] Rui Nabeiro Biodiversity Chair, CIBIO, University of Évora, Évora, Portugal

ARTICLE INFO

Article history:
Received 21 March 2014
Received in revised form 13 August 2014
Accepted 15 August 2014
Available online 19 August 2014

Keywords:
Adaptation
Robustness
Learning
Autonomous mobile robots
Evolutionary robotics

ABSTRACT

Researchers in diverse fields, such as in neuroscience, systems biology and autonomous robotics, have been intrigued by the origin and mechanisms for biological robustness. Darwinian evolution, in general, has suggested that adaptive mechanisms as a way of reaching robustness, could evolve by natural selection acting successively on numerous heritable variations. However, is this understanding enough for realizing how biological systems remain robust during their interactions with the surroundings? Here, we describe selected studies of bio-inspired systems that show behavioral robustness. From neurorobotics, cognitive, self-organizing and artificial immune system perspectives, our discussions focus mainly on how robust behaviors evolve or emerge in these systems, having the capacity of interacting with their surroundings. These descriptions are twofold. Initially, we introduce examples from autonomous robotics to illustrate how the process of designing robust control can be idealized in complex environments for autonomous navigation in terrain and underwater vehicles. We also include descriptions of bio-inspired self-organizing systems. Then, we introduce other studies that contextualize experimental evolution with simulated organisms and physical robots to exemplify how the process of natural selection can lead to the evolution of robustness by means of adaptive behaviors.

Contents

* Corresponding author. Present address: Department of Neurobiology and Anatomy, University of Texas, Houston Medical School, Houston, TX 77030, USA.
E-mail addresses: jafphd@gmail.com, gerardo.acosta@ieee.org (G.G. Acosta), alejandro.rozenfeld@gmail.com (A. Rozenfeld).

http://dx.doi.org/10.1016/j.biosystems.2014.08.003
0303-2647/

1. Introduction

Organisms' surroundings certainly play an important role in shaping actions, while behavior is by no means solely defined internally. The responses to particular situations in the environment (e.g., the presence of poisoned food where the organism cannot sense the involved risk of eating it), for instance, cannot be explained only in terms of stimuli involved or internal structure. The very same living being may behave in completely different ways when presented with seemingly identical stimuli at two different moments or places (Beer, 2004). In one case, the food may be hungrily consumed, while in a different moment the organism may avoid the food because it has learned the risk involved (Beer and Chiel, 1990). As these authors indicate, to account for those differences, behavioral scientists hypothesize internal states or drive which change an organism's response to its environment. Maturana and Varela (1987) also point out that the ability of an organism to draw distinctions through its selective response to perturbations is a hallmark of cognitive behavior. From an engineering standpoint, this cognitive behavior may be seen as a dynamic system that adapts the information flow between the perception part and the executive part of the system (Haykin et al., 2012). In effect, as presented in Martius et al., (2013), information theory is a powerful tool to express the principles to drive autonomous systems because it is domain invariant, and it allows intuitive interpretation. The purpose of this paper is to look for and discuss similarities between living organism's features (including human beings) and robot design from a dynamical perspective.

Automatons, machines and living organisms share common features. In general, a machine can be defined as an entity capable of mechanical behavior, i.e., processing matter and energy. An automaton instead can be understood as an entity capable of processing information in a robust manner from diverse and changing surroundings. A robot, also generally speaking, can be thought as a mechanical automaton, i.e., an entity capable of pursuing both mechanical and informational behavior in its environment (Beni and Wang, 1989). More importantly, because of a robotic organism is not just an assembly of components defining a static structure, rather than an interactive system, this work consequently proposes that the study of organism–environment dynamical couplings may have an impact on future theories on how biological systems reach robustness. Robustness as a concept refers to the capacity of a system to maintain its functionalities despite perturbations (further develop in next sections; see also (Fernandez-Leon, 2013)).

This effort is different from other works in cognitive systems and theoretical biology in that it promotes a change of perspective on robustness from being solely internally generated (i.e., a property of the internal structure of organisms) towards a dynamical phenomenon. More specifically, this work mainly focuses on the dynamical coupling between an organism's modeled central nervous system (in terms of cybernetics, the robot's control systems) within bodies (the robot's mechanical support) and the environments under the effects of internal and external factors (perturbations) disturbing the organism's behaviors. The aim of this work is consequently to understand behaviors that greatly outlast any initiating stimulus by means of processes that arise from organism–environment interactional level (Fernandez-Leon, 2012). The purpose of this understanding is to examine how desired behaviors emerge and how we can control them in order to give light through synthetic experiments to build more robust and bio-inspired systems and robots. Such behaviors are understood as desired actions of a single robot as well as a group of autonomous robots. As application case studies, this work describes the authors' experiences in developing trajectory generation systems for autonomous robots using artificial intelligence (AI) and computational intelligence (CI) methodologies. The article is organized as follows: the next Section describes classical approaches for autonomous robot navigation, the running concepts, a couple of cases study, and how, in our perspective, the limitations of these approaches result in open questions. Next, the cognitive neurorobotics approach is analyzed in Section 4 following the same scheme than in Section 3. Section 5 introduces concepts from dynamical systems theory associated to transient dynamics for behaviors. Section 6 presents some ideas from intelligent collective behavior, with the description of a DCOP approach case study for multiple robots. At the end of the paper, final discussions and conclusions are given.

2. Classical approaches for autonomous navigation

2.1. Running concepts

Generating paths to an autonomous mobile robot, being it terrestrial, aerial or aquatic, is a task that involves some basic building blocks from the very beginning. One essential feature needed consists on on-board sensory systems to have perception of the world and the robot's presence in the environment. Note that the sensory systems (also called navigation systems) may exceed the perception system that the robot needs to fulfill a mission, in what Haykin et al. call the information gap (Haykin et al., 2012). To deepen further about perception systems in robot engineering, the reader is referred to (Antonelli et al., 2001; Conte et al., 1994; Borenstein and Koren, 1991; Warren, 1999; Yoerger et al., 1996; Hyland and Taylor, 1993; Panait and Luke, 2005; Villar et al., 2013). Another necessary building block is a low-level trajectory generator from the next target position and the robot's current position, referred to as the guidance system. Finally, the lowest level feedback loops allowing the robot to describe a trajectory as close as possible to the proposed path named the control system (Fossen, 2002; Meystel, 1991).

Usually robustness is entrusted to control system designers, due to its vast antecedents on building stable and robust controllers, like for instance adaptive controllers based on the adaptation of internal parameters from environmental measurements (Aström and Wittenmarck, 1995). These kinds of controllers are nonlinear just because of its adaptation strategies. It is also well known that nonlinearities and uncertainties are easily managed by computational intelligence approaches like fuzzy logic, artificial neural networks or neurofuzzy controllers. A great deal of work on this was done in the past three decades, as reflected in the profuse literature about it. The interested reader is referred to Harris et al. (1993); Antsaklis and Passino (1993); Miller et al. (1995). Even when robustness is associated with adaptation, it is not yet clear if it is also linked to learning capabilities. Note that it is not the same to adjust previous defined parameters of a model or a controller from measurements of the environment than to define new parameters or neglect existing ones from the robot–environment interaction.

A fourth necessary building block for an autonomous robot is a top hierarchy module, which is responsible of generating the next target positions for the mobile robot as well as tasks to be carried out by the it in order to fulfill its mission. This module is called in this work, the mission planner. It varies according to the mobile robot application domain. A piece of the mission plan is given beforehand (static planning). However, the plan can be changed on-line as the robot movement progresses in the real world (adaptive planning or re-planning). Mission re-planning is the robot's response to the changing environment (e.g., obstacle avoidance, changes in mission objectives priorities, and others). This building block is responsible to maintain an updated world model from the perception system to yield smart responses to this dynamic surrounding. Hence, from the standpoint of engineering design, the mission planner system may be considered as a supervisory control layer giving appropriate set points to the lower level layer of guidance and control systems in a clear hierarchical structured control (Acosta et al., 2001).

The mission planner, sometimes also referred as task and path planner in a task decomposition perspective, has to face a complex problem: the trajectory generation for the mobile robots. Indeed, autonomous operation of mobile robots in real environments presents serious difficulties to classical planning and control methods. Usually, the environment is poorly known, sensor readings are noisy and vehicle dynamics is fairly complex and non-linear. There is a gap between robot's perception, its own world model and a final smart decision, which can be tackled doing a mimic of human or mammals cognitive reasoning, as pointed out by Haykin. Since this represents a difficult problem to solve due to the great amount of data required to take a decision in an effective time, it has attracted for years the AI community. Three main lines of activity arose in those days: planning-based systems, behavior-based systems, and hybrid systems. Starting with the intention of emulating partially some features of human intelligence and biological processes, AI as well as CI based control techniques were adopted to shorten the gap. The first two application examples in path planning, explained in Section 2.2, belong to this stage of maturity of these concepts. Further engineering implementation details of these building blocks can be found in Acosta et al. (2009).

2.2. Classical CI and AI case studies

A traditional design of a robot with a central world model to achieve path planning is analyzed firstly. The practical problem consists on the autonomous guidance and control of a terrestrial vehicle in a completely unknown environment. The autonomous guided vehicle (AGV) of Fig. 1 was used as the non-holonomic experimental platform. The proposed approach combines optimum path planning techniques with fuzzy logic to avoid obstacles and to determine the shortest path towards its goal. The technique computes the potential surface using Dijkstra's algorithm in a moving window, updating the cost map as it moves with the information of obstacles and target obtained by the ultrasonic sensor, responsible of the navigation module. A fuzzy logic controller (FLC) controls the wheels of a differential drive robot to the angle of minimum potential. This ensures a smooth trajectory towards the objective. A second FLC controls the average speed of the platform.

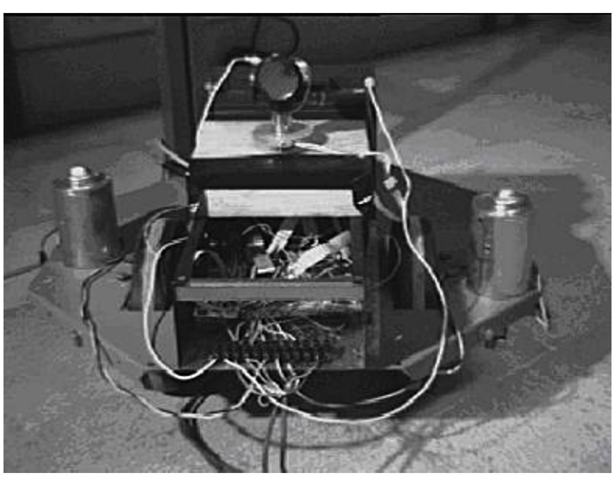


Fig. 1. Autonomous guiding vehicle with a planning module based on Dijkstra's algorithm, and fuzzy logic based guidance and control systems. This is a classical approach without self organizing possibilities and then with a poor environmental adaptation to exhibit robust behaviors (Calvo et al., 1999).

To minimize calculations, a grid was defined and the cost and potential functions were computed only considering points on the grid. A sliding window covered a few cells within the grid in the neighborhood of the vehicle. To compute the Dijkstra's algorithm, the local goal was established in the intersection of the line drawn from the actual position to the global goal, with the border of the active window. Experiments with a 13×8 cm window and a 20×20 cm grid were carried out with the robot's position fixed with respect to the window. Sometimes the objective may fall in an obstacle but when the windows moved, this local objective changed. If the final objective was really occupied by an obstacle, a trap situation occurred. Previsions in the algorithm should have been taken to cope with those situations, as well as wrong trajectories generation due to the application of such a sub-optimal method. Later, cost map was placed on the active window based on the information obtained by the sensors. With this partial cost map, Dijkstra's algorithm was computed for the window. Firstly, the actual position of the vehicle was taken as the ground node and later, the local destination was used as the reference node. Potentials were added to obtain single potential surfaces that hold the optimum path. Then, a new iteration follows: the window was moved one-step in the grid and the previous procedure was recursively repeated until the local objective matches the global one. The obstacle configuration was changed with good results in most of the cases. A comparison was also made with the virtual force field technique (VFF) (Borenstein and Koren, 1991) giving shortest and smoothest trajectories but with longer computing times. More details can be found in Calvo et al., (1999).

With this traditional path planning, the robot performed good enough to face autonomous displacement in real world. However, the robot's ability to move avoiding obstacles was constraint to the previous robot user's programming skills. In addition, the navigation scenario was glimpsed beforehand with no possibility of smart reaction to a new moving obstacle or a change in the target point. The main reason of these limitations is that the robot had no ability to learn from its own experience.

A second example to analyze is the desired trajectory generation of an autonomous underwater vehicle (AUV) devoted to pipeline inspections, developed within the EU funded Autotracker Project. In this case, the path planner is an instance of a dynamic mission planner (DMP) built from the experience of remote operated vehicles (ROV) human operators. This experience was compiled as a production system of forward chained rules. The experimental vehicle was the Geosub constructed by Subsea7, an improved commercial version of the Autosub (Southampton University, UK), shown in Fig. 2. It was robust enough to allow surveys up to 3000 m depths. A main goal of this research and development was to evaluate experimentally if that technology (by the year 2004) was able to face autonomous inspections in deep water, practically with minimum human intervention. The expert system called EN4AUV (Expert Navigator for Autonomous Underwater Vehicle) (Acosta et al., 2003, 2005).

The Autotracker's perception system included navigation sensors like a GPS giving an absolute position in global coordinates, a depth sensor and an inertial navigation system based on gyroscopes that gives a relative position when the AUV is submerged. For the inspection task, data was acquired with a multi-beam echo sounder (MBE). Raw data from this MBE is

Fig. 2. Autonomous underwater vehicle with a replanning module based on an expert system (EN4AUV) and classical approaches for guidance, control and navigation systems. It showed a smart behavior reacting to unforeseen scenarios due to the presence of the expert system to make decisions. However, the interaction robot-environment was not taken into account to perform robust behaviors yet (Acosta et al., 2005).

processed by the MBE Tracer module, which can also generate a predicted target trajectory, using image-processing techniques (Tena Ruiz et al., 2003). Position and direction of the target under inspection was estimated within this tracer, together with a priori information about the lay down of the pipeline or cable, called legacy data, and a magnetic sensor (MAG). They are combined through a sensor fusion module (SFM). Using the information from the SFM and a priori information, the DMP module, decided the path to follow on the different situations. The obstacle avoidance system (OAS) took the trajectories proposed by the EN4AUV expert system and validated or modify them using the information coming from the forward looking sonar and the exclusion zones in legacy data. Then both, the EN4AUV and the OAS are the main components of the DMP. The guidance system was a line of sight and the control system consisted of the classic controllers of the Autosub (McPhail and Pebody, 1997).

When doing the underwater inspections, complex situations might appear (like the sudden appearance of a fishing net, a complex pattern of more than one pipeline over the seabed, or a detour due to an obstacle detection, and many others). These situations were coded as possible scenarios, in about fifty rules. As the knowledge about different situations increases, the knowledge base (KB) describing new scenarios may be simply and naturally completed and updated, yielding an incremental KB growth. Each scenario triggers different searching or tracking pattern of trajectory (search, back-to-start, skip, and track). Scenarios were described considering two main concepts: the survey types and the AUV status as regards to the inspected target. The type of survey is defined a priori in the mission settings to establish the number of pipelines/cables to be tracked, the navigation depth, and other mission features. The AUV status changes when the SFM updates its sensors and classify the situation as target seen, target lost, target seen intermittently, and avoiding obstacles. The KB conceptualization is presented in Fig. 3. Note that the two main concepts for scenario building refer to the environment (survey type) and the robot itself (AUV status).

The scenarios developed for the sea trials during 2004 were diverse (14 in total). Some examples are: 1st scenario: the AUV is tracking an exposed pipeline, navigating on top, at a fixed offset smaller or equal than 5 m. Both the MBE and the MAG detect it. 2nd scenario: the AUV is tracking a buried pipeline on top, at a fixed offset smaller or equal than 5 m. The MBE may not be able to detect it, but the MAG can track it anyway. 3rd scenario: The AUV is tracking an intermittent (intermittently exposed and buried) pipeline at a fixed offset. This is a sequence of alternative appearance of scenarios number 1 and 2. The preliminary sea trials performed in the North Sea near Scotland in August/September 2004 and November 2005, in which showed promising results with that traditional AI approaches. Despite that autonomous underwater inspection was possible (Acosta et al., 2005), the scenarios description was predefined and static, and nothing similar to learning from environment interaction was present in these experiments with the robot.

2.3. Partial epitome and open questions

Previous examples, as well as the prior and contemporary work of several other researchers and practitioners, showed that robots were able to operate autonomously with minimum human intervention. They could also carry out complex tasks successfully, like pipeline inspections or take samples of the water under the poles ices. However, they were still unable to learn autonomously from their own experience. They shared the adaptation capability foreseen by their human constructors and programmers. Next generation of autonomous robots necessarily had to have this skill of autonomous learning to exhibit a more robust behavior in real environments. In our opinion, this was an inflection point in robot's development.

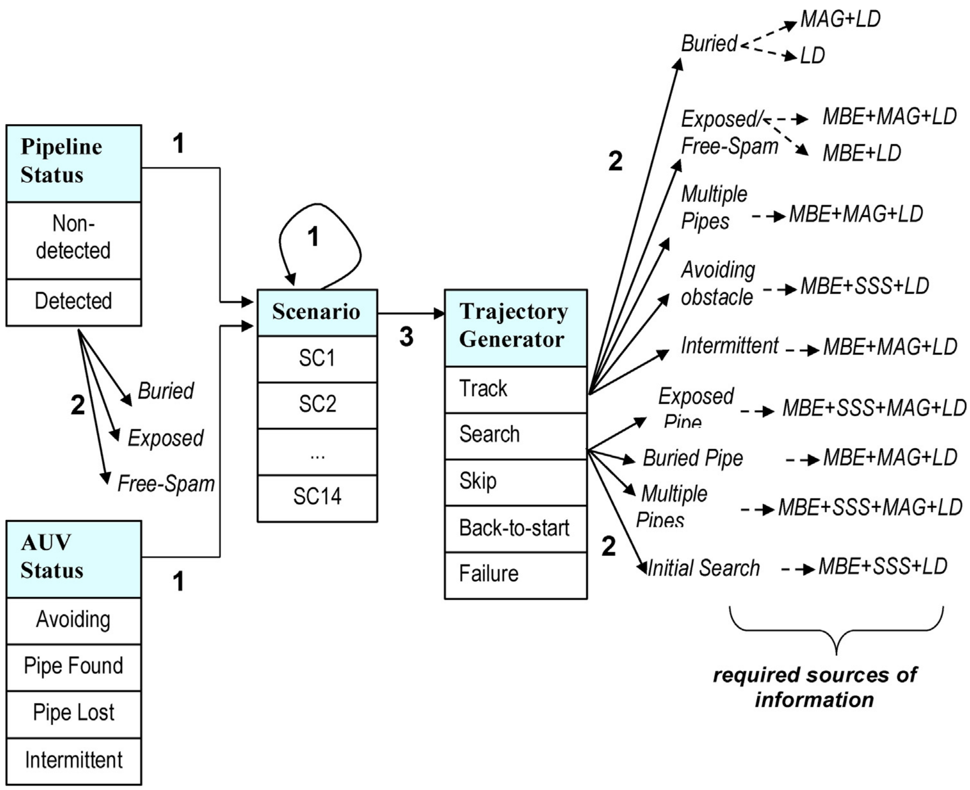
The most promising methodologies to achieve this robot ability seemed to be the ones provided by ER. Researchers in that fields try to emulate natural or bio-inspired behaviors and mainly biological adaptation. As Bongard proposes (Bongard, 2013) (p. 74), "To date, the only force known to be capable of producing fully autonomous as well as adaptive machines is biological evolution", this focus seems to be correct. Furthermore, they have the additional attractive feature of facilitating robots interaction, enabling multiple robots problem solving approaches. Then, the next step to gain robustness was to answer simple questions like: What if behavioral robustness is related to a gradual, but relatively fast, adaptation to the environment? Was this adaptation only confined to dote the robot (or agents in general) with learning capabilities? Should have the robot adapted all along its operational life or it should have learned until an optimum functional target was reached? Was it be possible to exchange their acquired knowledge about environment interaction from one robot to another?

In this context, such an adaptation refers to a gradual development or evolution of the nervous system of an organism (i.e., robot's replanning and adaptive control systems) during its lifetime, from a simple form to a more complex one. Moreover, the knowledge interchange among artificial organisms refers to the communication capabilities among them to share more than data but also their own experience coded as knowledge.

3. The cognitive neurorobotics and hybrid approaches

3.1. Running concepts

More recent streams of research and technological implementations are going towards the use of bio-inspired techniques (Vargas et al., 2013a; Bongard, 2013). Particularly in robotics, the research community is trying to take advantage not only of human beings' problem solving paradigms as part of the nature, but also from other natural systems. A great deal of activity currently growing is coming from evolutionary (Vargas et al., 2013b) and immune systems (Tripp et al., 2013; Lau et al., 2013; Raza and Fernandez, 2012; Infantino and Rizzo, 2013). In effect, several researchers and practitioners addressed the question of how biological systems adapt and interact with the environment (Abbott and Regehr, 2004; Forde et al., 2004). Especially, they are



Ref.	Relation	Inverse	Type
1	determines	is-determined-by	one-to-multiple
2	generalization-for	type-of	one-to-one
3	selects	is-selected-by	one-to-multiple

Fig. 3. Knowledge base conceptualization to build the dynamic mission planner devoted to the robot's skill to generate new plans. This is also known as replanning task.

interested in understanding and synthesizing complex behaviors in the context of autonomous behaviors. Artificial evolution was proposed as a suitable technique for the study of physical and biological adaptation and their harnessing. In Nolfi and Floreano, (2000), dynamic modular hierarchies of neurocontrollers are shown to face stability and scalability issues, in what they called ER. Scaling up in ER refers to the creation of complex behaviors from simple ones.

ER is a sub-field of Behavior-Based Robotics (BBR) (Arkin, 1998) related to the use of evolutionary computing methods in the area of autonomous robot control. One of the central goals of ER is the development of automated methods to evolve complex behavior-based control strategies (Nolfi and Floreano, 2000; Nelson et al., 2004). Another central goal of ER is to design morphological models. Some examples of these works comprises evolutionary design (Bentley, 1999), evolution of robot morphologies (Lipson and Pollack, 2000), and complete structures emerging from simple elements (Hornby and Pollack, 2001; Rieffel and Pollack, 2005).

The sequential and hierarchical organization of a complex activity in systems with many behaviors, such as robot's path generation (Fernandez-Leon et al., 2004; Maaref and Barref, 2002; Nelson et al., 2004), remains one of the main issues to investigate for biologically inspired robotics. It is expected that understanding such systems in a robotic context will also shed some light into their natural counterparts, giving for instance a better understanding of human motor capabilities, their neural and embodied underpinnings, and their adaptive properties. In particular, it is being a statement that stability and scalability in robot's behavior can be addressed by studying natural behavior (e.g., theories of evolutionary learning, skill acquisition, and behavior emergence (Dopazo et al., 2003)).

In the context of this paper, ER concepts can be used to obtain controllers that adapt robot's behaviors according to its sensory input, focusing on scalability during the path generation task in an unknown environment. A strategy to implement the scaling up of behaviors is the layered evolution (LE) (Togelius, 2003), among other approaches. It provides satisfying results in cases where some of traditional methodologies failed. Based on a comparison between incremental evolution (Urzelai and Floreano, 1991) and modularized evolution (Calabretta et al., 2000; Nolfi, 1997), LE uses the concept of subsumption architecture in the evolutionary process (Brooks, 1986; Téllez and Angulo, 2004; Togelius, 2004). Key concepts in LE are modularity (Nolfi and Floreano, 2000), adaptability (Di Paolo, 2000, 2003) and multiplicity. All of these concepts are associated, somehow, with the understanding of how biological systems reach robustness (see for example (Krakauer, 2005)).

The next case studies show the progress from traditional AI and CI approaches to bio-inspired ones.

3.2. Evolutive robotics case study

In order to develop an architecture for autonomous navigation based on ER, a control strategy over a Khepera robot was implemented in Fernandez-Leon et al. (2009). The control strategy actuated directly over the robot's wheels, taking into account the sensor measurements and the mission objectives. It was based on the generation of independent behavioral modules supported by neurocontrollers, and a coordination structure. The evolutionary approach adopted in this case study gave guidance and progressive control once a target position was determined. In this sense, the mission planner was static. However, if one of the simple behaviors to be scaled-up was obstacle avoidance, or the target was a moving point, the final complex behavior after the scaling-up process could exhibit features of a dynamic mission planner. In effect, as an obstacle appeared, the target positions changed dynamically online as the robot moved. The following working conditions were assumed: (a) the robot moved on a flat ground; (b) inertial effects, as well as non-holonomic characteristics of the mobile robot, were not taken into account; (c) the robot moved without slipping; (d) the environment was structured but unknown, with some elements fixed (e.g., walls, corridors, passages, doors, etc.) while others, like goal position references (light sources) and obstacles, were modified for each run; (e) environment variable conditions (e.g., light influence from other sources) were not managed directly but considered as perturbations to the controller.

A set of genotypes represented a first population of neurocontrollers. These genotypes were made of a constant number of chromosomes. Individual neurocontrollers were implemented for each simple behavior using feed-forward recurrent neural networks, without recurrence in any level and with a fixed number of neurons. Adaptation in each neurocontroller was achieved through a genetic algorithm based on Harvey's proposal (Harvey, 1992), in the following way. The chromosomes of the genotype included the sign and the weight strength for each synapse. Then, each genotype representing a specific neurocontroller was awarded according to its observed performance through a fitness measurement that was used as a comparison parameter, establishing a ranking (see (Nelson et al., 2009)). After that, those genotypes situated at the lower part of this scale (lower half) were discarded as individuals in the next generation. Copies of the individuals at the upper part replaced these individuals.

The selected simple behaviors were scaled-up to obtain a more complex behavior. Simple behaviors included phototaxis: the robot's ability to reach a light source as a target position point; obstacle avoidance: the robot's skill to avoid obstacles, when going towards a particular point; wall following: robot's abilities to follow a wall; and learning: the ability of the robot to approach to one of two possible light sources (targets). The more complex behavior that emerged was robot's path generation towards a certain light source in a small closed environment avoiding obstacles.

The coordination among behaviors was done in a first approach using another feed-forward neuronal network (FFNN) taking the outputs of the behavioral modules and sensors as inputs. Once behaviors were implemented, tests were carried out on a physical Khepera robot. Overall the prototype performed very well avoiding concave and convex obstacles, phototaxis, and wall seeking behaviors and hence emerging a sophisticated path generation behavior learned from its own experience. Further details are given in Fernandez-Leon et al. (2004, 2005).

This methodology then demonstrated desired conditions to face real-world problems in an efficient way. From a pure evolutionary perspective, however, it must be quoted that this methodology was still too much dependent on the designer's previous knowledge on the problem to solve. In fact, such an evolution was done from a rigid and prescribed framework. Subdivision in atomic tasks, individual fitness functions and coordination rules were strongly user dependent, leaving small chance for self-organization and feature discovering. Other interesting work is Urzelai and Floreano (1991) in which it is proposed that the encoding of information from the environment generates systems that can solve more complex tasks and are more robust to unpredictable sources of change. They also show that when the genetic encoding is left free to evolve, artificial evolution will select to exploit mechanisms of self-organization. However, a generalization of scalability to closely emulating biological systems, in the sense of self-organization, was still an open subject.

3.3. Distributed cognition within evolutionary robotics

Despite the emphasis on coupled agent–environment interactions in general, ER has paid relatively little attention to work on distributed cognition (Ziemke et al., 2004; Trianni and Nolfi, 2012). Instead, ER has derived much of its inspiration from Brooksian behavior-based AI, following principally an anti-representationalism, computational, and minimalist bottom-up approach (Beer, 1990, 1995, 2003).

Current work on embodied, situated, and distributed cognition has rediscovered some aspects of the interaction between agents and their environments (Beer, 2014, in press) as central to the emergence of distributed cognitive processes. From a distributed cognition viewpoint, in Ziemke et al. (2004) the authors present some simple initial experiments that should be taken as a fruitful starting point to discuss the use of the environment to produce cognitive behaviors. Their studies mainly focus on the so-called 'road sign problem' (Thieme and Ziemke, 2002) illustrating how the evolution of environmental adaptation, at evolutionary and individual time-scales, can serve to provide cognitive scaffolding that simplifies the tasks for individual agents. They demonstrated that even purely reactive agents can solve the T-maze navigation task satisfactorily, where a robot should 'remember' to what side it must turn after a rightward or leftward beam of light, see Fig. 4. The robot should move across the first corridor and then shift to one side at the junction to reach the goal (final position at right or left junction corridor). Interestingly, they observed that reactive agents (without internal states) produce the appropriate behavior by 'using' a wall all the way to the goal in relation to the side that the beam of light was initially presented. More interestingly, agents could use their own position with respect to the wall as an external memory. Thieme and Ziemke have argued that such use of walls as environmental (external) knowledge is an example of distributed cognition sustaining behaviors.

Ziemke et al.'s lessons are similar to those of (Jakobi, 1998) in experiments with a Khepera robot in a T-maze (Fig. 5). In Jakobi's experiments, he employs a neurocontroller evolved using the ER technique. This experiment is an example of how agents can exploit opportunities from the environment in order to solve a particular task under the ER methodology. Jakobi indicated that the observed behavior involves both a behavioral control that avoids touching the sides and control that negotiates the junction at the end of the first corridor (simple reactive behaviors both), combined with the presence of an internal state for producing the appropriate turning at the junction. Ziemke et al. (2004, p. 340) have called this situation a delayed response task.

3.4. Artificial immune system case study

Studies on self-organizing systems have emerged as a major part of the biological-inspired approach in response to challenges introduced by control systems in physical problems (Nolfi and Floreano, 2000). Due to its distributed characteristic, the main ideas of self-organizing design are the use of principles in nature to develop and control complex adaptive systems. This organization tends to be robust enough to face perturbations (Jacobi, 1997). Examples of complex adaptive systems are the immune system (Timmis et al., 2004; Roitt, 1997), the self-organized artificial neural system (Haykin,

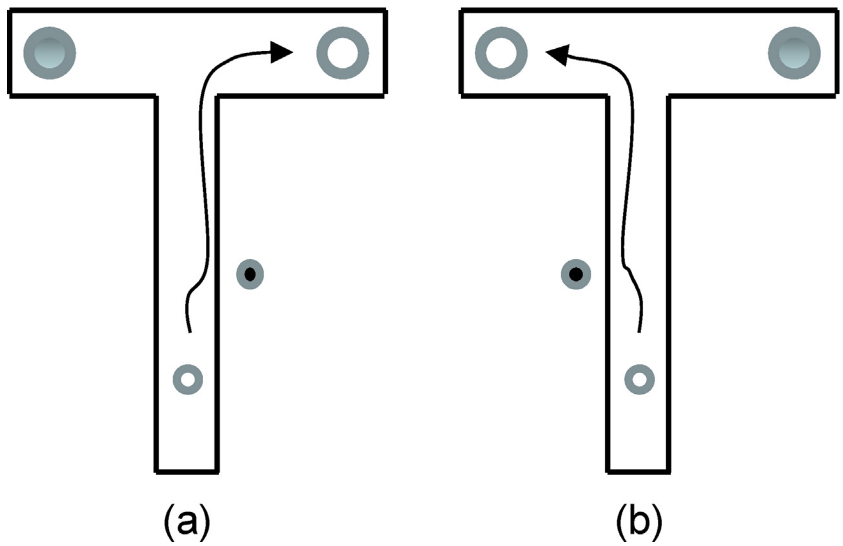


Fig. 4. Representation of the T-maze for a road sign problem exhibited by a purely reactive agent. The agent starts at the foot of the main corridor. The agent encounters a light source on the (a) right- or (b) left-side, and after a delay period, it has to turn toward the same side at the T-maze conjunction toward the large empty circles. Agents solve this behavior by using the respective wall all the time to the goal. Plots taken from (Ziemke et al., 2004).

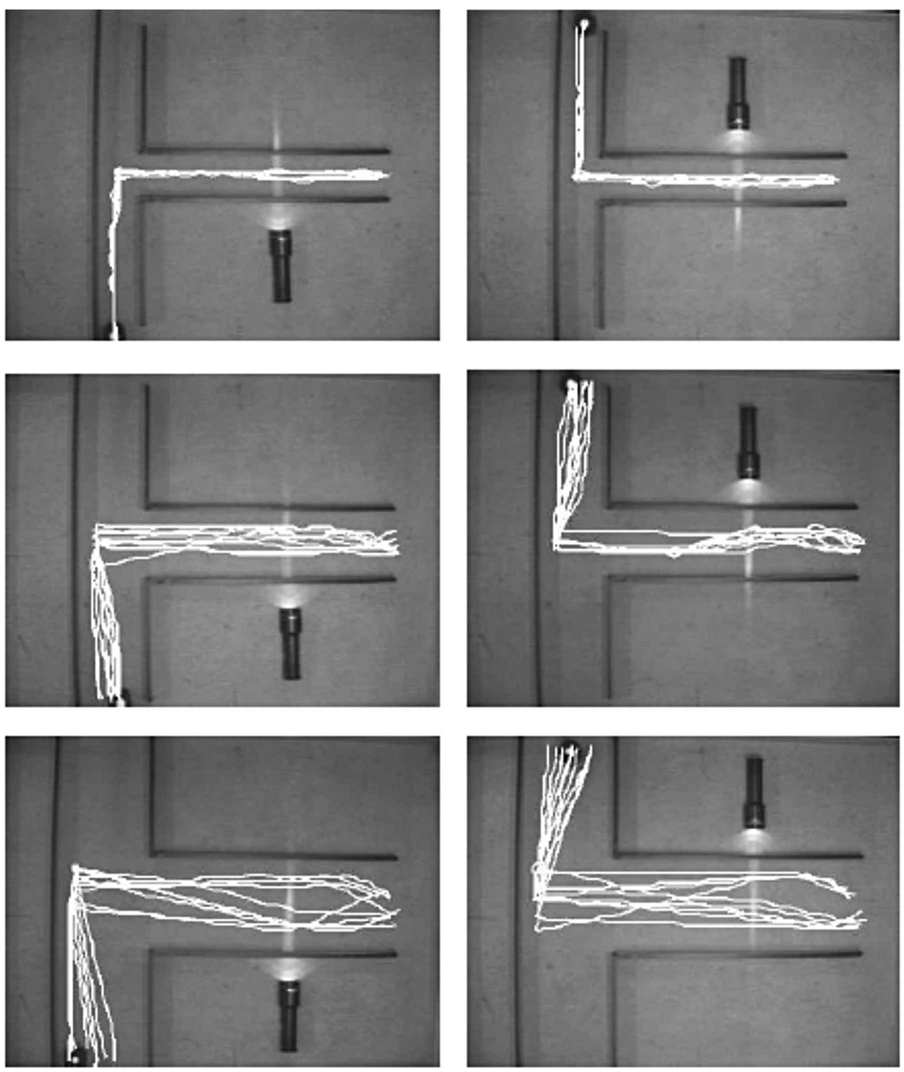


Fig. 5. Example of the paths taken by a Khepera robot in six consecutive trials. The robot should perform T-maze navigation considering a right- or left-ward source of light. Figures taken from (Jakobi, 1998).

1999), and the artificial evolution (Nolfi and Floreano, 2000). In particular, coordination and behavior integration are also central topics in the study of self-organizing collective behaviors in nature (Baldassarre et al., 2002). As stated in Nolfi (2005), the interaction among simple behavioral rules followed by each system component might lead to rather complex collective behaviors.

The objective of this section is to describe a feasible technique for behaviors coordination based on the artificial immune system metaphor (Fernandez-Leon et al., 2011). The proposed behavior coordination, based on previous works of Vargas et al. (2003); Ishiguro et al. (1996) had a dynamic process of decision making defining a network structure of conditions-action-restrictions items. The incoming information provided by each input of a system (i.e., robotic sensors) was considered in as an 'antigen', meanwhile the robot as an 'organism'. The antigen represented the current state of the environment as proposed in Vargas et al. (2003). The robot contained 'antibodies' in a network organization to recognize the antigens and to perform immune responses. Thus, the condition-action behavior of the robot could be related with the antigen–antibody response of the immune system. In this case study, we developed an AIS-based system for behavior coordination to solve the problem of tracking a target (i.e., a black line in the floor or a pipeline in the seabed). The immune network dynamics was modeled through Farmer's model (Farmer et al., 1986), selecting the most appropriate antibody to deal with external information. The concentration of an antibody may stimulate or suppress other antibodies of the network, and it may depend on the concentration of other antibodies through network links. Based on the resulting concentration level, an antibody was selected using a ranking algorithm, choosing those with higher concentrations. Only one antibody was chosen at a time to control the robot. The autonomous navigation was then obtained from the changing process of antibodies involved in antigen recognition. For demonstration purposes, we used a Khepera robot with its light and proximity sensors. The antigens refer to the direction of light sources, direction of the obstacles, and the proximity of them with respect to the robot body. During robot evaluation, the network of antibodies tried to recognize antigens, and the network dynamics determined the action (behavior) to be taken.

The antigens coding corresponded to possible situations that activated under certain conditions (e.g., an obstacle was near, or a light source was placed on the far-right-front side). Antibodies represented actions like, for example, turn left, turn right, go forward, avoid obstacle, or do phototaxis. The experiments carried out contrast with Vargas et al.'s work in that an evolutionary adjustment mechanism was not used, instead the immune 'idiotopes' (restrictions to antibody execution) were evolved using genetic algorithms. This difference was done on purpose just to find out if it was possible to evolve controllers using lifetime adaptation without human intervention. Another difference with Vargas et al.'s work was that behaviors could relate with evolved neural networks, instead of simple rules for controlling robots. The use of evolved neural networks to hold behaviors enhanced the robot robustness when performing tasks like path generation in real world, due to its intrinsic robust characteristics (Nolfi and Floreano, 2000).

A conceptual comparison among different behavior coordination approaches is always necessary to analyze their scopes, possibilities and applicability ranges. However, in engineering areas it also needs an exhaustive comparison among techniques within a specific domain of application. Although this section is far from being such exhaustive analysis, it pretends to report some results using computer simulations as promising techniques for behavior coordination within ER. These techniques are the layered evolution coordination and the AIS-based behavior coordination.

We performed some experiments with the AIS-based behavior coordination. The experimental settings were similar than the ones presented in the previous ER experimental section, with Khepera-based simulated robots (see (Fernandez-Leon et al., 2011)). The robot had the ability to sense obstacles (e.g., walls and objects) and to sense the proximity to the target (light source). The final aim was to dote a terrestrial mobile robot prototype with capabilities to navigate safely in unknown environments, programming simple behaviors that coordinated might give rise to emergent more sophisticated behavior. Similar experiment settings were proposed also in Whitbrook (2005); Vargas et al. (2003); Ishiguro et al. (1996). The task consisted on passing through a gate in a small-simulated arena (Fig. 6).

As it may be seen, the problem is difficult because the dimensions of the environment required a high degree of precision to steer towards the center of a small gate and the robot needed to be able to reach the goal in a safe way. It was found that the performance of the behavior coordination depends on the correct choice of the following parameters:

- *D*: the distance between the robot an obstacles (when it is small, there were more frequent collisions with walls and obstacles and then frequent trapped situations tend to appear);
- *S*: the scope of sensor readings, mainly those related with obstacle avoidance;
- *B*: the simple behaviors implemented to emerge a more complex behavior.

A trial and error procedure was used to determine these parameters in order to obtain acceptable results in previous experiments, because there was not a straightforward method for determining them. Although adequate parameter selection was not relevant to this research, it is an important issue in mobile robotics. In fact, Krautmacher and Dilger (2004) found that AIS code was dependent on the choice of free parameter used.

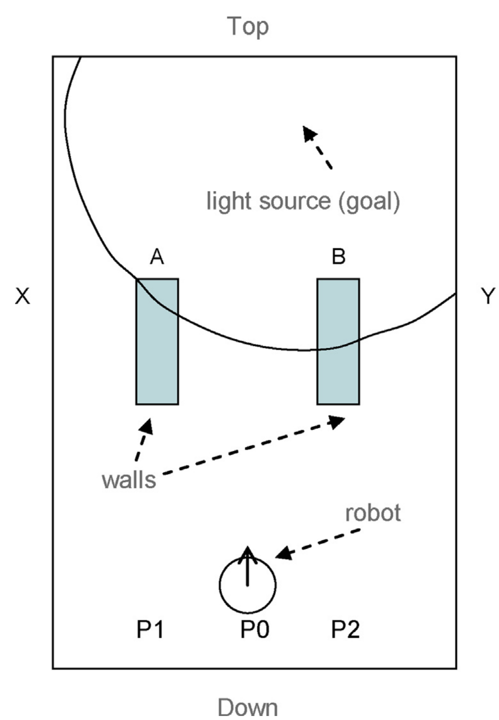


Fig. 6. Experimental settings for comparison between layered evolution and AIS based behavior coordination (Fernandez-Leon et al., 2011).

These preliminary experiments demonstrated the feasibility of this immune-based approach, even when dealing with perturbations (see (Fernandez-Leon et al., 2011)).

In summary, results show that the AIS-based coordination could deal with the expected robot performance. The robot was capable to develop all its dedicated tasks, without risk of collision. The observed problems for the AIS coordination were related to reaching the target through the narrow corridors. This difficulty could be solved with slower movements. Then, changes in simple behavior to be coordinated (like an adaptation of simple behaviors) caused changes in the coordination method itself.

3.5. Partial epitome and open questions

Comparisons between ER and AIS approaches of behavior coordination showed no significant differences in terms of behavioral adaptation capacities. In fact, these systems are basically able to learn autonomously from their own experience, rather than by their human designers. However, further experiments must be planned to test the long-term tracking problem where adaptation is essential. In these cases, the rule-based coordination seems to be less adequate than the AIS one. An improvement in the emergent overall behavior may also appear if simple behavior modules are constructed by adaptive mechanisms in a noisy and an uncertain environment before they are coordinated (Fernandez-Leon and Di Paolo, 2008). These systems also could have the additional attractive feature of facilitating adaptive robots interaction. Consequently, a next step might be to answer the question: What would happen if internal coordination extends from inside the individual to outside the agent? In this context, such an extension refers to dynamical processes that distribute between internal controls, the organism's body and the environment, including other agents or robots (Fernandez-Leon, 2011). This perspective highlights consequently the importance of the relational phenomenon through the agent–environment coupling (Fernandez-Leon, 2013). Note that this understanding of coordination does not rely exclusively on a particular inner structure ensuring robust behavior, but depends essentially on the agent–body–environment domain, and then robustness is a dynamical and relational phenomenon.

Although a common mechanism enabling behavioral robustness is still unknown, our observations suggest that the most plausible candidate for understanding behavioral robustness is dynamical integration rooted on internal control, body and environment dynamics (Fernandez-Leon, 2012, 2013). We understand that this integration can be obtained through the distribution of behavioral mechanisms in a single system that evolves, and in a group of systems or agents learning from their cooperative interaction with an environment (both ideas are introduced in next Sections). This collective behavior may be implemented and analyzed, for instance, in multiple robot teams. In this respect, the development of a comprehensive research program to investigate such ideas can be seen as an important milestone for both natural and bio-inspired robust systems research.

4. Transient dynamics for behavior generation

Biological control systems, in general, can be seen as complicated dynamical entities. Dynamic laws of neurobehavioral coordination are believed as unique in its characteristics in that are repeatable from one system to another and emerge from microscopic dynamics but may not (even in principle) be deductible from them (Kelso et al., 2013). Due to that complexity, we only know properties of some simplest cases. Just to give an example, in Rabinovich et al. (2006) it is discussed that "experimental neuroscience is often based on the implicit premise that the neural mechanisms underlying sensation, perception, and cognition are well approximated by steady-state measurements (of neuron activity) or by models in which the behavior of the network is simple (steady state or periodic)". The idea behind this observation is that after receiving an input signal, a model neural network acting as a control system settles into one pattern of activated nodes (neurons) commonly called an 'attractor state'. These attractors represent stable equilibriums in which there is not a significant change in certain variables of interest (i.e., neural activities). When a network is not at one stable attractor, it is in a transient state in which no stable equilibrium is reached. The network is able to create associations between properties of the network that were learned or memorized and the attractor state during the evolution of the system. Thus, the network acting as a control system uses these associations when necessary for behaviors.

Fig. 7(left) shows a representation of two simple dynamics that can describe a simple control system. In the right plot, a current state of an internal control can be modified by small or big

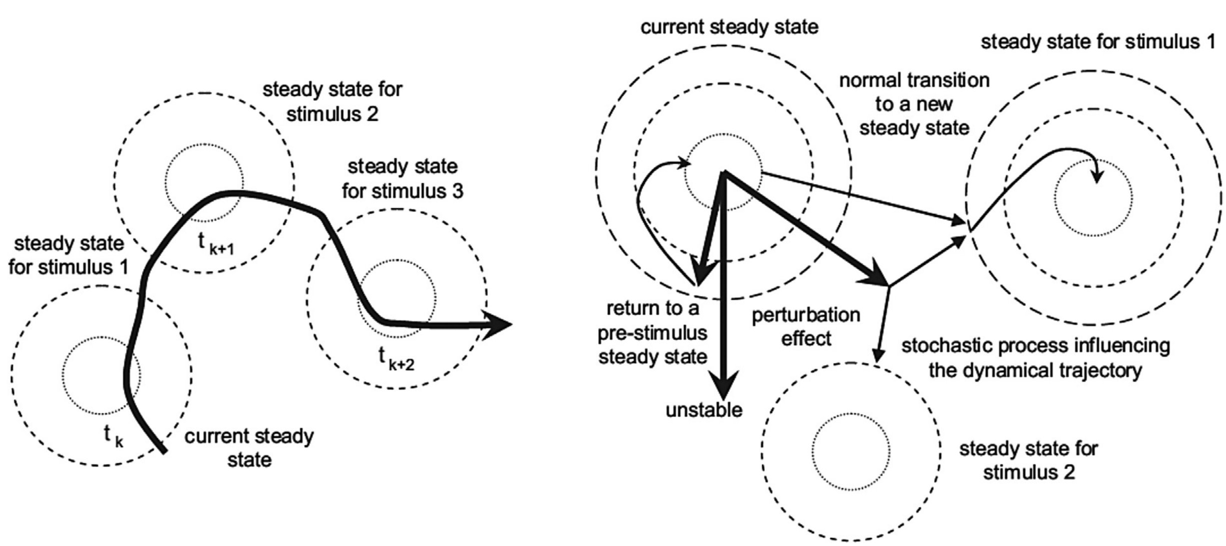


Fig. 7. Illustration of (left) a system showing dynamically determinacy and (right) a system without it. Left and right plots are adapted from (Rabinovich et al., 2006) and (Kitano, 2004), respectively. See main text.

perturbations pushing the agent–internal dynamics within the current boundary of attraction or far from it. Perturbations may produce a dynamical return to pre-perturbation state, dynamical changes toward different steady states, or push current dynamics toward an unstable region (from which the dynamics will eventually return if possible). In the left plot of Fig. 7, the transient dynamics can be affected by perturbations, but showing trajectories toward a unique attractor at each time step that maintain the system functional. The attractor can move in an input-dependent manner. For both cases, when an organism with such dynamics remains functional, the changes of regions can be part of the robust response needed to reach stability.

The proposed approach and experiments in Fernandez-Leon (2012, 2013) suggest us a common dynamical phenomenon associated to a particular control regime for robust behavior called 'dynamical determinacy', i.e., the continuous presence of a unique dynamical attractor that must be chased during behavior (Fig. 7-left). This sequence of flexible transitions between multiple states can be seen as a metastable phenomenon (see also (Kelso, 2012)).

For instance, let us assume having two dynamically different organisms. Firstly, a simple control system can be defined based on dynamical trajectories toward one of the two-fixed point attractors (Fig. 7-right). Dynamically reaching one of these attractors chiefly determines movements of the organism to the right or to the left enabling avoiding and approaching behaviors in response to an input signal. Consequently, this simple organism can be seen as a bistable agent. Secondly, a second organism's control system can be globally controlled by a monostable regime (i.e., only one attractor) enabling the agent similar avoiding and approaching behaviors, but in this case its control system returns to its unique attractor in the absence of stimuli. In brief, the bistable agent can switch its dynamical state after sensing an avoiding object showing two simultaneous attractors for some sensory input. The monostable agent can only show therefore dynamical determinacy, but the bistable ones does not. Its behavior is possible given the generated dynamical trajectories toward a unique attractor in each moment of time that is also another example of dynamical determinacy. This agent shows dynamical states that are definitely and unequivocally characterized for coherent actions via transient dynamics toward a unique attractor at neural level. The dynamical understanding presented here is a simple explanation of the observed dynamics that have emerged in agents after their evolution in silico (see (Fernandez-Leon, 2011a)).

While the current interpretation from systems biology of how simple biological organisms reach robustness depends essentially on the presence of internal structures like modularity and redundancy, among others (Krakauer, 2005), the alternative approach described here makes no assumption about the control structure for robustness. The general observation here is that the emerged common phenomenon observed in computational models of simulated agents (Fernandez-Leon, 2011a) and is associated to dynamical attractors that move in phase space in an input-specific way to maintain the system functional. In other words, a significant change in the incoming signals that an agent must process creates a change in phase space in the dynamical conditions that sustain functional behaviors. However, the emerged dynamics do not necessarily take place from the trajectories close enough to one or a set of fixed point attractors, but from the transient dynamics toward non-simultaneous attractors that move in state space (e.g., fixed point ones). This idea of transient dynamics for behavioral robustness provides an attractive and biologically plausible account of the dynamics that can emerge in some biological systems coupling with their environments.

Have we evidenced biologically conceivable robustness? A novel aspect of the introduced approach in this section may be found in how the scheme of coupled, controller–body–environment dynamics could come to terms with the continuous presence of a unique dynamical attractor that must be chased during behaviors. The overall observation is that by introducing as few assumptions as possible about the nature of robust behaviors, experiments with agents that evolve show us a common dynamical control through models rooted on the emergence of a unique attractor for coherent behavior. Note again that in principle the place where an attractor can appear in a moment of time is not static in state space, yet it can move due to significant sensory changes throughout the lifetime of the system. The structure of these movements emerges from the evolution of internal control as response to sensory incomings in non-perturbed situations.

Theoretically, the presence of a unique attractor is one of the many likely possibilities that can emerge after the interaction of an organism and its environment. Another can be multistability in the face of multiple (functionally similar) simultaneous attractors. From an engineering design standpoint, an alternative is also to predefine a particular internal dynamical control as part of the controller definition, which certainly can be difficult to conceptualize. In other words, it is one thing to design an agent (or robot) that can chase a sort of dynamical attractors during its ongoing behaviors, and quite another to prove whether a 'unique, mobile attractor' is reached in each time step. This simple observation provides examples about how we can induce the emergence of behavioral robustness in agents that evolve and refute or defend our working hypotheses by demonstrating an existence proof for robustness given conditions we have supposed are necessary.

This section highlights the importance of dynamical analyses in agent–environment couplings having some theoretical implications in the way that robustness can emerge in biological organisms (i.e., dynamics working in transient during behaviors). Even if these exact mechanisms are not observed in the biological realm, we have the opportunity to develop practical tools to guide theoreticians in the understanding of behavioral robustness as an emergent process in biological systems that evolve.

5. Paving the road toward further distributed robust systems

The concept of distributed robustness is gaining awareness in biology and other research fields (Wimsatt, 2007; Calcott, 2011) in that interactions of multiple parts each with a different role can compensate for the effects of perturbations by means of 'degeneracy' (Wagner, 2005; Felix and Wagner, 2008). This concept refers to the ability of elements that are structurally different to perform the same function (Tononi et al., 1999; Edelman and Gally, 2001). Despite the importance of degeneracy in explaining distributed robustness (Wagner, 2005), degeneracy deserves further investigation mainly because it conveys intrinsic complexity of information flow. For example, biological neural networks working as control systems are highly robust to removal of synapses or neurons regardless of populations of neurons having different roles (Amit, 1989; Beer, 1995; Clark and Chalmers, 1998; Gallagher, 2005). The distributed processing is consequently an integrated set of functionalities that are commonly performed by multiple, semiautonomous units or groups of them (McClelland, 1989). More importantly, the relationship between the distributed flow of information and the effect of perturbation on such flow is still not easy to comprehend or replicate.

Behavioral mechanisms that distribute across the brain–body–environment might be thought of as an additional protection against changes that threaten crucial biological functions (cf. Wagner, 2005; Macía and Sole, 2008). For example, in the context of adaptive behaviour, Chiel and Beer (1997) and Chiel et al. (2009) stated that the nervous system cannot process information not transduced by the body. The converse idea suggests that properties of the body may simplify complex neural processing by using different body dynamics and sensorimotor information. For example, to keep our torso stable and conserve energy, we swing our arms backwards and forwards and engage in a swing/stance cycle of our legs while walking based on foot and equilibrium feedbacks. Similar ideas can be seen in the interactions of multiple components (such as autonomous robotic agents).

Some studies in collective robotics have discussed the dynamical role of groups of interacting part of a system (e.g., robots) as part of the sensed environment, rather than concentrating on the control system, or its parts, as the sole behavior producer (see (Pfeifer and Bongard, 2006)). For example, in Rozenfeld et al., (2013), it was presented the formation control of multiple underactuated surface vessels considered as an application of a robot formation control, showing a collective emergent behavior. A distributed cooperative control using the relative information among neighboring vehicles was proposed such that the flock of multiple vehicles forms a desired geometric formation pattern that center moves along a desired trajectory. The cohesion and navigation component of the proposed controller was implemented combining consensus protocol and optimal control design for trajectory. In order to guarantee safe flock navigation and interaction of vehicles with the environment, we proposed to extend the designed formation tracking controller to more sophisticated algorithm that prevent the vehicles from colliding with environmental obstacles with unknown sizes and locations. The solutions for this given problem was basically built upon a decentralized constrained optimizing problem (DCOP) to give more flexibility to change the formation shape of the flock whenever the fleet is subject to some constrained, unknown environment. The mentioned DCOP protocol relies mainly on a novel decentralized Dijkstra's algorithm. Because of a flow of local communications between neighbor robots, they self-organize into a hierarchical minimum spanning tree. Then, robots with lower position in the hierarchy follow their parents. Fig. 8 shows snapshots of the resulting dynamics on a flock of robots after applying the mentioned DCOP algorithm. Immediately after one of the robots detects the presence of a tunnel in the path, they self-organize the formation into a line to traverse the tunnel.

It seems appropriate therefore to understand a swarm of robots as simple interacting components with decentralized control, but exhibiting a cooperative behavior. Consequently, from the collective behavior of a group of dumb robots attending to the emergence of ordered structures, unexpected behaviors can emerge from the interactions of robots (see (Nolfi and Floreano, 2000; Bongard, 2013)). This emergence can be seen as rooted on the cooperative local interactions among robots and the environment (including other robots). This emergent behavior could be produced through coordination and self-organization, and should not be in principle seen as a function of the number of units used in the system (Camazine et al., 2001). In fact, control strategies relevant to swarms are scalable, from a few units to thousands or millions of units. Swarm

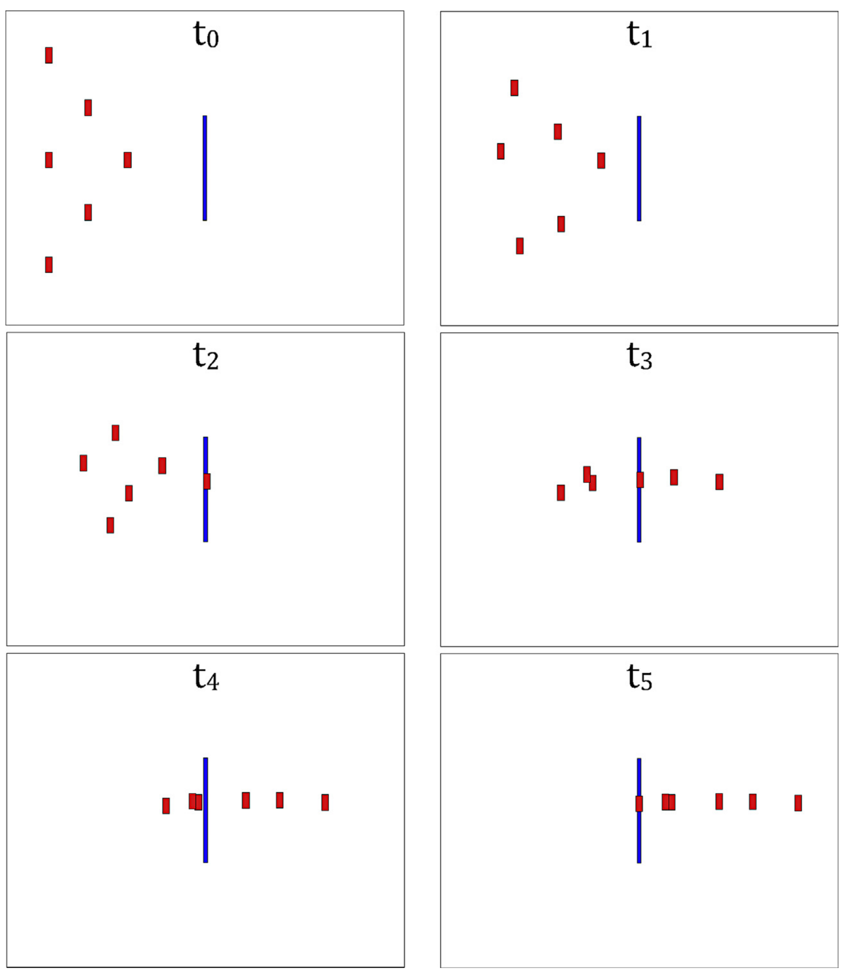


Fig. 8. Snapshots of the self-organizing dynamics across time (from t_0 to t_5) taking place in the flock of robots (small red dots), to transform the formation pattern into a line and path through a tunnel (vertical blue line). The approach to negotiate this self-organizing strategy for this computer simulation experiments, was DCOP (Rozenfeld et al., 2013). Axes represent arbitrary distances.

robotics can also be thought of as acting like a massive parallel, decentralized and scalable computational system performing tasks with a complexity beyond the capabilities of a single robot or a centralized controlled group of robots (Werfel et al., 2014).

6. Conclusions

Bio-inspired techniques in general, and ER in particular, are emerging key tools to obtain self-organized adaptive systems, as the ones required in autonomous organisms, like agents, systems or robots interacting with the real world. ER and AIS approaches to behavior coordination share many similarities. In the authors' opinion, the challenge to obtain a bio-inspired robot control within ER is to deepen in the way the emergent behavior is achieved.

In the previously described case studies of ER, it was shown that genetic algorithms obtained 'fittest' behaviors for each task (e.g., phototaxis, obstacle avoidance, and others). In this way, this means that evolutionary algorithms are suitable for optimizing the solution space in proposed problems, which besides is not new. The immediate question is about the suitability of AIS as optimization methods. According to de Castro and Von Zuben (2002) and Aickelin and Dasgupta (2005), AIS are probably more suited as an optimizer where multiple solutions are of benefit. AIS can be made into more focused optimizers by adding hill-climbing or other functions that exploit local or problem-specific knowledge. AIS can exploit its potential either when some concept of 'matching' is needed. In some sense, AIS works as algorithms that adapt their solution space during test time meaning that they are suitable for problems that change over time and need to be several times with some degree of variability.

When AIS is compared with hand-design ruled-based and fittest evolutionary coordination systems, it has the potential benefit of an adaptive pool of antibodies that can produce adaptive and robust coordination. Therefore, the benefits of this computation can be used to tackle the problem of dealing with changing or noisy environments. In this robot control context AIS-based behavior coordination is useful because it does not optimize a path; i.e., in finding the best match for a planned path in a priori unknown environment. Instead, AIS require a set of antibodies that are a close match, but which are at the same time distinct from each other for successful environmental situation recognition. This is the main interest around most of AIS implementations in literature and from our own experience, because the designer can implement different autonomous methods for path generation. AIS only require positive examples. In addition, the patterns that it has learned can be explicitly examined (see (de Castro and Von Zuben, 2002)). Besides, AIS, as well as the majority of other heuristics that require parameters to operate, has the drawback of parameter settings that are domain dependent. Universal values for them are not available, not even imaginable.

The introduction of fuzziness within the AIS properties (see (De Castro and Timmis, 2002)) in antigenic recognition, suggests that fuzzy logic might be appropriate to model several aspects and mechanisms of the immune system, particularly to combine the multiple responses of simultaneous immune network outcome. In self-organized adaptive systems, some interesting questions remain open, like how a bio-inspired system reacts to discover new optima solutions, or how hybrid solutions can enhance behavioral coordination by mean of adding other computational intelligence techniques. For example, AIS could be combined with GA for discovering more suitable immune networks for a specific problem. This could correspond to the primary response of the AIS and to the convergence phase with an immune network based on GAs. Therefore, this combination could exploit further adaptations that are precisely what GAs is lacking (Gaspar and Collard, 1999).

From a strictly theoretical point of view, the adaptive nature of behaviors has several consequences that are not well understood yet. For instance, motor actions partially determine sensor patterns in an autonomous sensory-motor loop. Therefore, on-line coordination between sensors and actuators can enhance adaptively the robot ability to achieve its goal, as suggested in Nolfi, (2005). This agent–environment coupled dynamics resembles the natural adaptation of animals to interact with their surroundings. Even further, doting the organism with learning capabilities (as a way of enabling adaptation), to take into account the dynamic environment, in a similar architecture like the one proposed in Haykin et al. (2012) seems to be the necessary path to obtain more robust and better adapted robots. Another interesting discussion to face is if reinforced learning (like in mammals) is the best way to add learning skills to organisms, and hence robustness. How to induce further dependence on the environment to achieve more robustness is still a research topic.

The most plausible candidate for increasing behavioral robustness seems to be the 'dynamical integration rooted on internal-control, body and environment dynamics' (Fernandez-Leon 2012, 2013). This integration can be induced at behavioral mechanisms 'that evolve' in the following way. Firstly, we can induce dependence by using external (environmental) sensed factors for behaviors, where sensory environmental dependence is further developed via the simplest required control dynamics (i.e., restricting the number of functional steady states to the minimum possible; see (Fernandez-Leon, 2011a)). In this way, we can induce a sequence of states in state space that internal control must reach during behaviors. Secondly, to enhance the use of feedback from the agents' body that is processed at internal control level, where such a distribution can be enlarged using sensory offsets (i.e., evolutionary-defined biases that modify incoming body signal (Macinnes and Di Paolo, 2006)) and sensorimotor noise during the evolution of the internal control (see (Fernandez-Leon, 2010)). Finally, to incorporate different dynamical dependencies for agent-to-agent dynamical interactions, where environmental dependence is further induced via relatively stable to noise, but sensitive to stimuli, internal dynamics (as an example, heteroclinic dynamics are investigated in Fernandez-Leon, (2011b)). All of these are cutting-edge research topics in bio-inspired mobile robots and in neurorobotics.

From an engineering viewpoint, a deterministic behavior is still difficult to be designed straightforward, as an emergent behavior, within ER. In addition, this case is similar when learning capabilities, with strong environment dependence, are left free all along the organisms' useful life. In terms of control systems, just only think about stability analysis. The evolution of simple autonomous decisions include a necessary learning process in which the rules governing the organism–environment interactions are progressively assigned, modified through a process of random variation, and refined during its lifetime as a part of the adaptive process. This process allows discovering and retaining useful properties emerging from such interactions without the need to identify the relation between rules governing the interactions and the resulting behaviors. Difficulties arise when trying to optimize a merit figure, engineers' obsession, like minimum energy consumption, shortest path and others. In such cases, the proper selection of a fitness function may be more an art than a prescribed method. Another perceptible drawback of ER is the need of a learning period before the task development with a certain degree of success. This training can be carried out off-line or on-line. The on-line learning as in the case of humans, has involved the risk of non-stabilities and the impossibility to assure a complete convergent algorithm.

In spite of these apparent disadvantages of ER in contrast to other more traditional techniques, it seems to be the future research in autonomous (adaptive) robotics and the source for next generation of more robust bio-inspired robots, for isolated and/or social individuals. It is also being demonstrated that it not only can contribute to solve real engineering problems, but also in spreading light to cognitive and bio-inspired sciences like biology and neurosciences in the understanding of open problems. The combination of ER and cognitive control as a set of design tool to obtain the appropriate dynamics for control bio-inspired real time systems will have a great deal of activity in the next years.

Acknowledgments

The authors thank the collaboration of Dr. Calvo (RIP) and Dr. Picos from the GEE–UIB, Spain, in the research and implementation of many autonomous robots prototypes. Thanks to Dr. Gary B. Fogel, editor-in-chief of BioSystems, for his kind invitation to JAFL to submit this review. Also, thanks to anonymous reviewers for their support and insightful comments on the paper.

References

Abbott, L.F., Regehr, W.G., 2004. Synaptic computation. Nature 431, 796–803.
Acosta, G.G., Alonso, C.B., Pulido, B., 2001. Basic tasks for knowledge based supervision in process control. Eng. Appl. Artif. Intell. 14 (4), 441–455 Elsevier Science Ltd./IFAC.
Acosta, G.G., Curti, H., Calvo Ibáñez, O., Rossi, S., 2009. Some issues on the design of a low-cost autonomous underwater vehicle with an intelligent dynamic mission planner for pipeline and cable tracking, chapter I in underwater vehicles. In: Inzartsev, A. (Ed.), I-Tech Online Books, Robotics Series. I-Tech Education and Publishing KG, Viena, Austria, pp. 1–18 (open access: http://books.i-techonline.com/).
Acosta, G.G., Curti, H.J., Calvo, O.A., 2005. Autonomous underwater pipeline inspection in AUTOTRACKER PROJECT: the navigation module. Proceedings of the IEEE/Oceans'05 Europe Conference, Brest, France, June 21–23, 2005 pp. 389–394..
Acosta, G.G., Curti, H.J., Calvo, O.A., Mochnacs, J., 2003. An expert navigator for an autonomous underwater vehicle. Proceedings of SADIO/Argentine Symposium on Artificial Intelligence ASAI '03, Buenos Aires, Argentina, Sept. 3–5 2003 in CD.
Aickelin, U., Dasgupta, D., 2005. Artificial immune systems tutorial. In: Burke, E., Keandall, G. (Eds.), Search Methodologies – Introduction Tutorials in Optimization and Decision Support Techniques. Kluwer, pp. 375–399.
Amit, D., 1989. Modeling brain function. The World of Attractor Neural Networks. Cambridge University Press, Cambridge.
Antonelli, G., Chiaverini, S., Finotello, R., Schiavon, R., 2001. Real-time path planning and obstacle avoidance for RAIS: an autonomous underwater vehicle. IEEE J. Oceanic Eng. 26 (2), 216–227.
Antsaklis, P.J., Passino, K.M., 1993. An Introduction to Intelligent and Autonomous Control. Kluwer Academic Publishers, Boston, Dordrecht, London.
Arkin, R.C., 1998. Behaviour-Based Robotics. The MIT Press, Cambridge, Massachusetts.
Aström, K.J., Wittenmarck, B., 1995. Adaptive Control. Prentice-Hall, Englewood Cliffs, NJ.
Baldassarre, G., Nolfi, S., Parisi, D., 2002. Evolving mobile robots able to display collective behaviour. In: Helmelrijk, C.K. (Ed.), International Workshop on Self-Organization and Evolution of Social Behaviour. Swiss Federal Institute of Technology, Zurich, pp. 11–22.
Beer, R., 1990. Intelligence as Adaptive Behavior, An Experiment in Computational Neuroethology. Academic Press, New York.
Beer, R., 1995. A dynamical systems perspective on agent-environment interaction. Artif. Intell. 72, 173–215.
Beer, R., 2003. The dynamics of active categorical perception in an evolved model agent. Adapt. Behav. 11 (4), 209–243.
Beer, R., 2004. Autopoiesis and cognition in the game of life. Artif. Life 10 (3), 309–326.
Beer, R., Chiel, H., 1990. Neural implementation of motivated behavior: feeding in an artificial insect. In: Touretzky, D.S. (Ed.), Advances in Neural Information Processing Systems 2. Morgan Kaufmann, pp. 44–51.
Beer, R.D., 2014. Dynamical systems and embedded cognition. In: Frankish, K., Ramsey, W. (Eds.), The Cambridge Handbook of Artificial Intelligence. Cambridge University Press, pp. 128–148.
Beni, G., Wang, J., 1989. Swarm intelligence in cellular robotic systems. Proceedings NATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy, June 26–30.
Bentley, P.J., 1999. Evolutionary Design by Computers. Morgan Kaufmann, San Francisco.
Bongard, J., 2013. Evolutionary robotics. Commun. ACM 56 (8), 74–85.
Borenstein, J., Koren, Y., 1991. The vector field histogram-fast obstacle avoidance for mobile robots. IEEE Trans. Rob. Autom. 7 (3), 278–288.
Brooks, R.A., 1986. A robust layered control system for a mobile robot. IEEE J. Rob. Autom. 14–23.
Calabretta, R., Nolfi, S., Parisi, D., Wagner, G.P., 2000. Duplication of modules facilitates functional specialization. Artif. Life 6 (1), 69–84.
Calcott, B., 2011. Wimsatt and the robustness family: review of Wimsatt's reengineering philosophy for limited beings. J. Biol. Philos. Rev. Essay 26 (2), 281–293.
Calvo, O., Rodríguez, G., Picos, R., 1999. Real time navigation of autonomous robot with fuzzy controller and ultrasonic sensors. Proceedings of the European Society of Fuzzy Logic and Technology Symposium EUSFLAT-ESTYLF99, Palma de Mallorca, Spain pp. 95–98.
Camazine, S., Deneubourg, J.L., Franks, N., Sneyd, J., Theraulaz, G., Bonabeau, E., 2001. Self-Organisation in Biological Systems. Princeton University Press, NJ, USA.
Chiel, H., Beer, R., 1997. The brain has a body: adaptive behavior emerges from interactions of nervous system: body and environment. Trends Neurosci. 20, 553–557.
Chiel, H., Ting, L., Ekeberg, O., Hartmann, M., 2009. The brain in its body: motor control and sensing in a biomechanical context. J. Neurosci. 29 (41), 12807–12814.
Clark, A., Chalmers, D., 1998. The extended mind. Analysis 58, 7–19.
Conte, G., Zanoli, S., Perdon, A., Radicioni, A., 1994. A system for the automatic survey of underwater structures. Brest, France, 13–16 SeptemberProceedings of OCEANS' 94, 2. pp. 92–95.
De Castro, L., Timmis, J., 2002. Artificial Immune Systems: A New Computational Intelligence Approach. Springer-Verlag.
Di Paolo, E., 2000. Homeostatic adaptation to inversion of the visual field sensorimotor disruptions. Proceedings of SAB, 2000, MIT Press.
Di Paolo, E., 2003. Evolving spike-timing dependent plasticity for single-trial learning in robots. Phil. Trans. R. Soc. A 361, 2299–2319.
Dopazo, H., Gordon, M.B., Perazzo, R.S., Risau-Gusman, S.A., 2003. Model for the emergence of adaptive subsystems. Bull. Math. Biol. 65, 27–56.
Edelman, G., Gally, J., 2001. Degeneracy and complexity in biological systems. Proc. Natl. Acad. Sci. U. S. A. 98, 763–768.
Farmer, J., Packard, N., Perelson, A., 1986. The immune system, adaptation and machine learning. Phys. D 1986, 187–204.
Felix, M., Wagner, A., 2008. Robustness and evolution: concepts: insights and challenges from a developmental model system. Heredity 100, 132–140.
Fernandez-Leon, J.A., 2011. Behavioural robustness: a link between distributed mechanisms and coupled transient dynamics. Biosystems 105, 49–61.
Fernandez-Leon, J.A., 2011a. Evolving cognitive-behavioural dependencies in situated agents for behavioural robustness. Biosystems 106, 94–110.
Fernandez-Leon, J.A., 2011b. Behavioural robustness: a link between distributed mechanisms and coupled transient dynamics. Biosystems 105, 49–61.
Fernandez-Leon, J.A., 2012. Behavioral robustness: an emergent phenomenon by means of distributed mechanisms and neurodynamics determinacy. Biosystems 107 (1), 34–51.
Fernandez-Leon, J.A., 2013. Robustness as a non-localizable relational phenomenon. Biol. Rev doi:http://dx.doi.org/10.1111/brv.12067.
Fernandez-Leon, J.A., Di Paolo, E., 2008. Neural noise induces the evolution of robust behaviour by avoiding non-functional bifurcations. In: Asada, M., Hallam, J.C.T., Meyer, J.-A., Tani, J. (Eds.), From Animals to Animats 10: 10th International Conference on the Simulation of Adaptive Behavior SAB. Osaka, Japan, July 7-12, 2008Springer, pp. 32–41.
Fernandez-Leon, J.A., 2010. Evolving experience-dependent robust behaviour in embodied agents. Biosystems 103 (1), 45–56.
Fernandez-Leon, J.A., Acosta, G., Mayosky, M., 2009. Behavioral control through evolutionary neurocontrollers for autonomous mobile robot navigation. J. Rob. Auton. Syst. 57 (4), 411–419.
Fernandez-Leon, J.A., Acosta, G., Mayosky, M., 2011. From network-to-antibody robustness in a bio-inspired immune system. Biosystems 104 (2–3), 109–117.
Fernandez-Leon, J.A., Tosini, M., Acosta, G.G., 2004. Evolutionary reactive behaviour for mobile robots navigation. Proceedings of the 2004 IEEE Conference on Cybernetics and Intelligent Systems (CIS04), Singapore, December 1–3 2004 pp. 532–537.
Forde, S.E., Thompson, J., Bohannan, B.J.M., 2004. Adaptation varies through space and time in a coevolving host-parasitoid interaction. Nature 431.
Fossen, T., 2002. Marine Control Systems: Guidance, Navigation and Control of Ships, Rigs and Underwater Vehicles. Marine Cybernetics AS, Trondheim.
Gallagher, S., 2005. How the Body Shapes the Mind. Oxford University Press, New York.
Gaspar, A., Collard, P., 1999. From GAs to artificial immune systems: improving adaptation in time dependent optimization. pp. 1859–1866..
Harris, C.J., Moore, C.G., Brown, M., 1993. Intelligent Control: Aspects of Fuzzy Logic and Neural Nets. World Scientific.
Harvey, I., 1992. The SAGA cross. The mechanics of recombination for species with variable length genotypes. In: Manner, R., Manderick, B. (Eds.), Parallel Problem Solving from Nature 2. Elsevier, Amsterdam: North-Holland pp. 269–278..
Haykin, S., 1999. Neural Networks: A Comprehensive Foundation, 2nd ed. Prentice Hall.
Haykin, S., Fatemi, M., Setoodeh, P., Xue, Y., 2012. Cognitive control. Proceedings of the IEEE, Vol. 100, No. 12, December 2012 pp. 3156–3169.
Hornby, G., Pollack, J., 2001. Body-brain co-evolution using L-systems as a generative encoding. pp. 868–875.
Hyland, J., Taylor, F., 1993. Mine avoidance techniques for underwater vehicles. IEEE J. Oceanic Eng. 18, 340–350.
Infantino, I., Rizzo, R., 2013. An artificial behavioral immune system for cognitive robotics. pp. 1191–1198.

Ishiguro, A., Kondo, T., Shirai, Y., Uchikawa, Y., 1996. Immunoid: an architecture for behaviour arbitration based on the immune networks. Proceedings of the 1996 IEEE/RSJ International Conference on Intelligent Robots and Systems 3, pp. 1730–1738.
Jacobi, N., 1997. Evolutionary robotics and the radical envelope of noise hypothesis. J. Adapt. Behav. 1997.
Jakobi, N., 1998. Minimal simulations for evolutionary robotics. Ph.D. Thesis. University of Sussex, Brighton, UK.
Kelso, J.A., Dumas, G., Tognoli, E., 2013. Outline of a general theory of behavior and brain coordination. Neural Networks 37, 120–131.
Kelso, J.A., 2012. Multistability and metastability: understanding dynamic coordination in the brain. Philos. Trans. R. Soc. London B 367, 906–918.
Kitano, H., 2004. Biological robustness. Nat. Rev. Genet. 5, 826–837.
Krakauer, D., 2005. Robustness in biological systems: a provisional taxonomy. In: Deisboeck, T.S., Kresh, Y. (Eds.), Complex Systems Science in Biomedicine. Plenum, pp. 185–207.
Krautmacher, M., Dilger, W., 2004. AIS based robot navigation in a rescue scenario. Lect. Notes Comput. Sci. 3239, 106–118.
Lau, H., Bate, I.J., Timmis, J., 2013. Immune-inspired error detection for multiple faulty robots in swarm robotics. Proc. Eur. Conf. Artif. Life 846–853.
Lipson, H., Pollack, J.B., 2000. Automatic design and manufacture of robotic lifeforms. Nature 406, 974–978.
Maaref, H., Barref, C., 2002. Sensor-based navigation of a mobile robot in an indoor environment. Robot. Auton. Syst. 38, 1–18.
Macía, J., Sole, R., 2008. Distributed robustness in cellular networks: insights from evolved digital circuits. J. R. Soc. Interface 442, 259–264.
Macinnes, I., Di Paolo, E., 2006. The advantages of evolving perceptual cues. Adapt. Behav. 14 (2), 147–156.
Maturana, H., Varela, F., 1987. Autopoiesis and Cognition: The Realization of the Living. Reidel, Boston, MA.
Martius, G., Der, R., Ay, N., 2013. Information driven self-organization of complex robotic behaviors. PLoS One 8 (5), e63400.
McClelland, J., 1989. Parallel distributed processing: implications for cognition and development. In: Morris, R. (Ed.), Parallel Distributed Processing: Implications for Psychology and Neurobiology. Oxford University Press, New York, pp. 8–45.
McPhail, S.D., Pebody, M., 1997. AUTOSUB-1. A distributed approach to navigation and control of an autonomous underwater vehicle. Proceedings of the 7th International Conference on Electronic Engineering in Oceanography, 23–25 June 1997, Conference Pub. No 439 IEE.
Meystel, A., 1991. 1991). Autonomous Mobile Robots: Vehicles with Cognitive Control. World Scientific.
Miller, T., Sutton, R., Werbos, P., 1995. Neural Networks for Control. The MIT Press.
Nelson, A.L., Grant, E., Galeotti, J.M., Rhody, S., 2004. Maze exploration behaviours using an integrated evolutionary robotic environment. Robot. Auton. Syst. 46, 159–173.
Nelson, A., Barlow, G., Doitsidis, L., 2009. Fitness functions in evolutionary robotics: a survey and analysis. Robot. Auton. Syst. 57, 345–370.
Nolfi, S., 2005. Behaviour as a complex adaptive system: On the role of self-organization in the development of individual and collective behaviour. In: Bourgine, P., Képès, F., Schoenauer, M. (Eds.), Proceedings of the First European Conference on Complex Systems, Paris: Ecole Polytechnique.
Nolfi, S., Floreano, D., 2000. Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines. MA: MIT Press/Bradford Books. Ref.: Phototaxis: pp. 121–152; Obstacle avoidance/Navigation: pp. 69–92; Learning: pp. 153–188
Nolfi, S., 1997. Using emergent modularity to develop control systems for mobile robots. Adapt. Behav. 5 (3–4), 343–364.
Panait, L., Luke, S., 2005. Cooperative Multi-Agent Learning: The State of the Art. Auton. Agents Multi-Agent Syst. 11 (3), 387–434.
Pfeifer, R., Bongard, J., 2006. How the body shapes the way we think: a new view of intelligence. Bradford Books. MIT Press, Cambridge.
A. Raza, B.R. Fernandez, 2012. Immuno-inspired robotic applications: a review. arXiv preprint arXiv:1202.4261.
Rieffel, J., Pollack, J., 2005. Crossing the fabrication gap: evolving assembly plans to build 3-D objects. IEEE Congr. Evol. Comput.
Roitt, I., 1997. Essential Immunology, 9th ed. Blackwell Science Publishers.
Rozenfeld, A., Ghommam, J., Picos, R., Acosta, G., 2013. Cascade safe formation control for a fleet of underactuated surface vessels using the DCOP approach. Contemp. Challenges Sol. Appl. Artif. Intell. Stud. Comput. Intell. 489, 183–188.
Téllez, R., Angulo, C., 2004. Evolving cooperation of simple agents for the control of an autonomous robot. Proceedings of the 5th IFAC Symposium on Intelligent Autonomous Vehicles (IAV04), Lisbon, Portugal.
Tena Ruiz, I., Petillot, Y., Lane, D., 2003. Improved AUV navigation using side-scan sonar. Proceedings of IEEE OCEANS 2003, Volume 3, 22–26 September 2003 pp. 1261–1268..
Thieme, M., Ziemke, T., 2002. The road sign problem revisited: handling delayed response tasks with neural robot controllers. In: Hallam, B., Floreano, D., Hallam, J., Hayes, G., Meyer, J.-A. (Eds.), From Animals to Animats 7: Proceedings of the Seventh International Conference on Simulation of Adaptive Behavior (pp. 228–229), Cambridge, MA: MIT Press.
Timmis, J., Knight, T., de Castro, L., Hart, E., 2004. An overview of artificial immune systems. In: Paton, et al. (Ed.), Computation in Cells and Tissues: Perspective and Tools for Thought. Natural Computation Series. Springer, pp. 51–86.
Togelius, J., 2003. Evolution of the layers in a subsumption architecture robot controller. Master of Science in Evolutionary and Adaptive Systems. University of Sussex, UK.
Togelius, J., 2004. Evolution of a subsumption architecture neurocontroller. J. Intell. Fuzzy Syst. 15 (1), 15–21.
Tononi, G., Sporns, O., Edelman, G., 1999. Measures of degeneracy and redundancy in biological networks. Proc. Natl. Acad. Sci. U. S. A. 96, 3257–3262.
Trianni, V., Nolfi, S., 2012. Evolving collective control, cooperation and distributed cognition. In: Kernbach, S. (Ed.), Handbook of Collective Robotics – Fundamentals Challenges. Pan Stanford Publishing, Singapore, pp. 168–189.
Tripp, M., Read, M.N., Rose, L.M., Leonov, H., Timmis, J., 2013. Automated calibration of agent-based immunological simulations. Proc. Eur. Conf. Artif. Life 874 MIT Press.
Urzelai, J., Floreano, D., 1991. Incremental evolution with minimal resources. Computation. Nature, Vol. 431, 796–803.
Vargas, P., de Castro, L., Michelan, R., Von Zuben, F., 2003. Implementation of an immuno-genetic network on a real Khepera II robot. 2003 IEEE Congress on Evolutionary Computation, Volume 1, 8–12 December 2003, pp. 420–426.
Vargas, P., Di Paolo, E., Harvey, I., Husbands, P., 2013b. Context and challenges for evolutionary robotics. In: Vargas, P.A., Di Paolo, E., Harvey, I., Husbands, P. (Eds.), The Horizons of Evolutionary Robotics. MIT Press.
Vargas, P., Moioli, R., Husbands, P., Shim, Y.-S., Philippides, A., O'Shea, M., 2013a. Evolutionary robotics and neuroscience. In: Vargas, P.A., Di Paolo, E., Harvey, I., Husbands, P. (Eds.), The Horizons of Evolutionary Robotics. MIT Press.
Villar, S., Acosta, G.G., Sousa, A., Rozenfeld, A., 2013. Pipeline detection system from acoustic images utilizing CA-CFAR. Proceedings of OCEANS 2013, San Diego, CA, September 2013.
Wagner, A., 2005. Distributed robustness versus redundancy as causes of mutational robustness. BioEssays News Rev. Mol. Cell. Dev. Biol. 27, 176–188.
Warren, C., 1999. A technique for autonomous underwater vehicle route planning. IEEE J. Oceanic Eng. 15, 199–204.
Werfel, J., Petersen, K., Nagpal, R., 2014. Designing collective behavior in a termite-inspired robot construction team. Science 343 (6172) .
Whitbrook, A., 2005. An idiotypic immune network for mobile robot control. M.Sc Thesis. University of Nottingham.
Wimsatt, W., 2007. Re-Engineering Philosophy for Limited Beings: Piecewise Approximations to Reality. Harvard University Press, Cambridge.
Yoerger, D., Bradley, A., Walden, B., Singh, H., Bachmayer, R., 1996. Surveying a subsea lava flow using the autonomous bentic explorer (ABE). 1–21.
Ziemke, T., Bergfeldt, N., Buason, G., Susi, T., Svensson, H., 2004. Evolving cognitive scaffolding and environment adaptation: a new research direction for evolutionary robotics. Connection Sci. 16 (4), 339–350.