Abstract

In this paper we show how evolving robots can develop behaviors displaying a modular organization characterized by semi-discrete and semi-dissociable sub-behavioral units playing different functions. In our experiments, the development of differentiated behaviors is not realized through the subdivision of the control system into modules and/or through the utilization of differentiated training processes. Instead, it simply originates as a consequence of the adaptive advantage provided by the possibility to display and use functionally specialized behaviors. These are selected by evolution not only with respect to their capability to perform a given sub-function but also with respect to the capability to support smooth and effective transition with other behaviors. This is achieved by having different co-adapted behaviors and by evaluating the variation affecting the behaviors on the basis of the impact they have on the overall performance of the robots. Moreover this process enables the development of the ability to carry on preparatory actions that are necessary for the effective execution of the following behaviors. We refer to this type of modularity as functional modularity, since unlike structural modularity, it is not based on behavioral modules that are separated by clear boundaries and/or that are programmed or trained independently.

Introduction

The acquisition of new behavioral skills and the ability to progressively expand the behavioral repertoire represents one key aspect of natural intelligence and a fundamental capability of robots that operate in dynamic and uncertain environments. One way to achieve this objective consists in using a structural modular approach in which different layers or modules of the robots controller are responsible for the production of different corresponding behaviors and in which the behavioral repertoire of the robots can be expanded by adding new layers or modules in an incremental fashion. Indeed, the discovery and utilization of control architecture of this type by [Brooks, 1986; Arkin, 1998] enabled the achievement of tremendous progress in robotics.

In structural modular architectures of this type each module has the following characteristics: it is responsible for the production of a specific behavior, it is separated from the other modules by clear boundaries, and it is programmed or trained independently. These characteristics present advantages but also drawbacks that can outnumber the advantages, especially when there is a significant interdependence between the different behaviors. On the one hand, the fact that modules are separated by clear boundaries enables the utilization of a divide and conquer strategy which enables to divide the overall design problem into a set of partially independent simpler problems. Moreover, the separation and independence among modules potentially provide a straightforward solution for the realization of a progressive expansion of the behavior repertoire that can be realized through the progressive addition of new modules. On the other hand, it also inevitably leads to solutions in which the importance of the interdependence between the different behaviors is neglected. Furthermore, the rigid separation between the modules prevents the exploitation of solutions that require the introduction of minor modifications on previous developed modules/behaviors that might be crucial for the possibility to re-use previous capabilities for realization of new additional skills.

In that respect it is important to point out that the behavior of natural organisms typically displays a modular organization characterized by somewhat semi-discrete and semi-dissociable subunits, or sub-behaviors, playing different functions or sub-functions. [West-Eberhard, 2003]. These sub-behaviors are not completely separated, dissociable, and independent. The modular organization of behavior in natural organisms therefore is characterized by both discreteness and the possible presence of boundaries between sub-behaviors and by connectedness and integration among them [West-Eberhard, 2003]. Moreover, it is important to consider that the effective execution of a behavior performing a given function often requires the execution of preparatory actions. For example, the effective execution of a grasping behavior requires the execution of preparatory actions that modify appropriately the posture of the hand already during the execution of the reaching behavior that precedes the grasping activity [von Hofsten and Ronqvist, 1988].

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In the context of structural modular approaches, the possibility to realize smooth transitions between behaviors also depends on the arbitration mechanism utilized. In the case of competitive arbitration mechanisms, in which the transition between behaviors is achieved by suddenly shifting the control of the robot actuators from one module to another, the transitions tend to be abrupt. Instead, in cooperative arbitration mechanisms, in which multiple modules can concurrently control the robot actuator and in which the arbitration is realized by gradually changing the relative weight of the different modules (Arkin [1998]), the transitions between behaviors tend to be smoother. However, the type of behavior produced during the transition phase on the basis of the latter approach, is necessarily constituted by a weighted average of the behaviors that is produced on the basis of the single modules. This type of average behavior is not necessarily effective. Moreover, in a transition between two behaviors, this method does not provide a way to realize preparatory actions, i.e. actions that do not belong neither to the first nor to the second behavior but that represent a pre-requisite for the appropriate execution of the second behavior.

Our work is related to previous evolutionary robotics studies that have addressed the evolution of multiple behaviors (Izquierdo and Bhrmann [2008], Seth [2011], Schrum and Miikkulainen [2012], Petrosino et al. [2013], Williams and Beer [2013]). In these experiments, however, the synthesis and the exhibition of multiple behaviors represented the only possible viable solution since the evolving robots were required to carry on mutually exclusive tasks (e.g. eating or avoid eating a specific food type (Seth [2011], Petrosino et al. [2013]) or moving on the basis of a wheeled or legged actuators (Williams and Beer [2013]). In another related work Rahim et al. [2014] evolved neural network controllers that received as input the output produced by a set of pre-programmed modular controllers. Thus to the best of our knowledge, no previous studies focused on whether behavior differentiation and functional modularity can be observed on robots evolved for the ability to perform a single task.

The Method

To study this issue we decided to consider a cleaning experimental scenario in which a wheeled robot needs to vacuum clean the floor of an unknown indoor environment. We choose this problem since it represents the first (and still the most significant) successful application domain of autonomous robot solutions (Roomba, the first autonomous vacuum-cleaning robot developed by iRobots® under the supervision of Rodney Brooks and commercialized from 2002 has been sold in more than 10 million units to date, see iRobot [2013]). Rather than designing the controller by hand, we studied whether effective controllers can be developed from scratch through an evolutionary method in which the evolving robots are selected on the basis of the percentage of successfully cleaned surface, i.e. on the basis of a scalar value that rates their overall ability to perform the task.

It is important to point out that we chose this domain also because it involves the execution of a task with a single goal (cleaning the environment) that does not necessarily require modular solutions. This enables us to study whether and how functionally modular robots evolve, whether and why behavior differentiation and functional modularity provide an advantage with respect to non-modular solutions, and eventually which are the characteristics and functions of the evolved sub-behaviors. In fact, domains involving multiple conflicting goals, such as those used in the literature addressing the study of action selection cited above, necessarily require the development of solutions characterized by multiple behaviors and implicitly constrain the number and type of required sub-behaviors.

The investigation of the cleaning problem also permits to compare our evolved solutions with those developed by companies that sell cleaning robots. In that respect, the fact that the behavioral policies displayed by different versions of the Roomba and by similar robots produced by other companies significantly differ (Palleja et al. [2010]) demonstrates that finding the optimal solution/s of this problem is far from trivial.

The Task, the Environment and the Robot

To evolve robots that are robust with respect to environmental variations we evaluated each robot for 3 trials/cleaning sessions. At the beginning of each trial, the initial position and orientation of the robot in the environment, and
the specific characteristics of the environment, like wall dimensions, in which it was situated in were randomly varied within limits.

Each trial lasted 6 minutes and 15 seconds. This represents a rather short period of time, although performing a precise comparison with the time required by commercial robots to clean completely or almost completely a surface with similar properties is impossible due to the lack of similar data (for some indications see Palleja et al. (2010)).

To compute the cleaning performance we calculated the percentage of 20x20cm non-overlapping areas visited by the robot at least once during a trial. We used a concave environment (Figure 1) constituted by a large central area and by four peripheral corridors that represent a room-like environment. The average environment had a central area with a size of 6.8m and four corridors with a size of 3.78m in total. The exact size of the environment however was randomly set at the beginning of each trial. This was realized by varying the height and width of the central area and of corridors of ±33% and ±18%, respectively, during different trials. The robot used was a MarXbot (Bonani et al., 2010), a differential drive wheeled robot with a diameter of 17cm. The robot is equipped with 24 infrared sensors evenly distributed along the robot’s body and capable of detecting objects in a range of 10cm. Moreover, it was equipped with a rotating laser sensor capable of detecting obstacles at longer distance. Experiments were run in simulation by using the FARSA open-software tool (Massera et al., 2013) that includes an accurate simulator of the robot and of the environment.

The robots’ neural controller

The robots are provided with a feedforward neural network controller without recurrence. In both experiments the robots are equipped with eight sensory neurons that encode the average activation state of eight groups of three adjacent infrared sensors each and two motor neurons that encode the desired speed of the two robots wheels. The sensory neurons are fully connected with the motor neurons and to hidden neurons (if present), and the hidden neurons are fully connected to the motor neurons. Hidden and motors neurons are provided with biases. The state of the hidden and motor neurons is computed on the basis of the logistic function. The state of the sensory neurons, and the desired speed of the robots wheels are updated every 50ms. Experiments have been replicated in the following two experimental conditions:

(S) Simple: The robots are only provided with the infrared sensors.

(T) Time: The robots are provided with an additional sensory neuron that encodes the time passed since the beginning of the current cleaning session (trial), i.e. whose activation state linearly varies between 1.0 and 0.0 during the course of the trial. This sensor has been added to enable the robot to vary its behavior during the course of a cleaning session. Notice that this sensor enables the robot to access information extracted from the robot’s internal environment (e.g. a robot clock situated inside the robot body) while the other sensors enable the robot to access information extracted from the external environment.

The connection weights and biases, that determine the robots behavior, are initially set randomly and evolved as described in the section below.

The evolutionary algorithm

The initial population consists of 20 randomly generated genotypes, which encode the connection weights and biases of 20 corresponding individual robots (each parameter is encoded by 8 bits and normalized in the range [-5.0, +5.0]). Every generation, each individual is evaluated for three trials in environments that randomly varied in dimension within the limits indicated above. The fitness of each trial is calculated by counting the percentage of 20x20cm portions of the environment that are visited by the robot at least once during the trial. The total fitness is calculated by averaging the fitness obtained during the three trials. All individuals are allowed to generate an offspring that is also evaluated for three trials. The 20 offspring are generated by creating a copy of the parent genotype and by mutating each bit with a 2% probability. The offspring genotype is used to replace the genotype of the worst parents or discarded depending on whether or not offspring outperform some of the parents. The genotypes of the initial population were generated randomly. Each evolutionary experiment was replicated 20 times starting from different randomly generated initial populations.

Results

In this section we first describe the performance achieved in the different experimental conditions. As we will see, the

Figure 1: Example of the concave environment used

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cleaning task in this concave environment requires the exhibition of at least two sub-behaviors that differ in forms and functions: an exploration behavior that enables the robot to explore the large central area and a wall-following behavior that enables the robot to explore the peripheral areas and the borders of the central area. The possibility to discover and to display these two behaviors rather than a single undifferentiated behavior crucially depends on the characteristics of the robots neural controller as demonstrated by the fact that the behavior and the performance significantly vary in the two experimental conditions.

Then we will discuss the mechanisms that support behavioral differentiation and arbitration by analysing the behavioral solutions found in the different experimental conditions. As we will see, the two most important mechanisms that support the evolution of multiple behaviors are the ability to perceive and to generate affordances (i.e. opportunities for behaviors) and the possibility to flexibly and properly handle behavioral transitions.

Performance and efficacy of modular versus non-modular solutions

By post-evaluating the best robot of the last generation of each replication for 500 trials we can see how the evolved robots reach close to optimal performance in the Temporal (T) experimental conditions and relatively low performance in the case of the simple (S) condition (Figure 2, top). The performance of each experimental condition statistically differs from each other (Mann-Whitney U, \(p<0.05\)). The performance obtained in the experiments in which the robots were also provided with the internal neurons (Figure 2, bottom) does not significantly differ from the experiments without internal neurons (Mann-Whitney U, \(p>0.05\)).

The analysis of the behaviors displayed by the best robots of the last generation indicates that the performance level correlates with the ability of the robots to display multiple behaviors. This is clearly illustrated by the behavior displayed by the best (S) and (T) robots that achieved a fitness of 67.4\% and 82.8\%, respectively. While (S) displays a single uniform behavior along the trial (Figure 3, top), (T) is capable of performing two well-differentiated behaviors (Figure 3, bottom).

Indeed, the best robot with a simple architecture (S) always behaves in the same manner during the successive phases of the trial (Figure 3, top-left). In particular it avoids walls and obstacles by sharply turning with an angle of 45-90 degrees (depending on the relative angle with which the robot approaches the obstacle) and moves straight when it is far from obstacles. Through the exhibition of this behavior the robot spends most of the time exploring the large central portion of the environment and only occasionally it explores the peripheral corridors when it happens to approach them with a direction that is almost orthogonal to the entrance of the corridor. The robots of the other replications of the experiments show qualitatively similar behaviors (results not shown). The best robot with the time neuron architecture (T), instead, shows two well differentiated behaviors: (i) an initial exploration behavior that is realized by producing a progressively larger curvilinear trajectory that enables the robot to explore the large central portion of the environment, and (ii) a wall-following behavior that enables it to explore all the peripheral areas of the environment (Figure 3, top-right). Although the way in which the exploration behavior is realized varies in different replications of the experiment, well-differentiated exploration and wall-following behaviors are clearly observable in all cases (results not shown). The high performance of these robots is due to their ability to display different behaviors, which are specialized for the exploration of large open areas and peripheral areas, and to carefully tune the time duration of the two behaviors. Indeed, the relative duration of the two behaviors determines

Figure 2: Boxplots of performance in the cleaning task. The top and bottom figures report the results obtained without internal neurons and with internal neurons, respectively. The boxplots display the performance of the best robot of the last generation in the two experimental conditions, i.e. in the simple (S) and temporal (T) conditions. Each box displays the performance of the best robot of 20 replications of each experiment. The performance is indicated by the percentage of cleaned cells within the walls. The value corresponding to optimal performance is unknown but is reasonably below 1.0 given that the robots have a rather limited cleaning time.

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whether the robot spends enough time exploring the central large area while keeping enough time to explore all the peripheral areas of the environment. A qualitative analysis of the first 10 replications showed that in the best two robots, that clearly outperform the best robots of the other 8 replications, the transition occurs at $3.17 \pm 0.11$ min. This transition time is optimal or nearly optimal as demonstrated by the fact that post-evaluation tests performed by slowing down or speeding up the robots internal clock and consequently the behavior transition led to significantly worse performance (results not shown).

Figure 3: Typical trajectories displayed by the best robots of the two experimental conditions without hidden units. The portions of the trajectory produced during the first, second, and third part of the trial (i.e. from step 1 to 2500, from step 2501 to 5000, and from step 5001 to 7500, respectively) are shown with different colours and line style.

On the mechanisms supporting behavior differentiation and arbitration

We have seen how controllers presenting the ability to display multiple behaviors, can enable the adaptive robots to achieve better performance and that the emergence of this ability depends on the characteristics of robots neural controllers. We will now focus on the mechanisms supporting behavior differentiation and arbitration.

Before entering into this, it is important to point out that the behavior displayed by an embodied and situated agent is a dynamical process unfolding in time that results from the robot/environmental interactions. This implies that the organization of behavior/s vary at different time scales. Moreover, this implies that the sensory states experienced by the robot at a given time step are co-determined by the actions produced by the robot during previous robot/environmental interactions. If we use the term affordance introduced by Gibson [1979] to indicate sensory states that elicit the production of behaviors, this implies that the affordances are not only extracted through sensors from the internal and/or the external environment but are also generated by the robot itself through actions.

The analysis of the behavior exhibited by the robots at a short time scale (i.e. at a time scale of seconds) indicates that in all experimental conditions robots tend to exhibit at least two different low-level behaviors: (i) an obstacle-avoidance behavior that consists in turning while the robot detects an obstacle on its frontal side, and (ii) a move-forward behavior that consists in moving straight or almost straight while the robot does not detect obstacles in its frontal side. This implies that at a short time scale all robots of all experimental conditions displayed a certain kind of functional modularity. The reasons that explain why this type of modularity always evolve are that it plays a fundamental role (i.e. it enables the robot to avoid being stuck and to keep exploring the environment) and that it is supported by the availability of always available and easy to use affordances. Indeed, independently from the way in which the robot behaves, it will always experience a lack of activation on the frontal infrared sensors when the robot/environment context affords a move-forward behavior and an activation on the frontal infrared sensors when the robot/environmental context affords an obstacle-avoidance behavior. The infrared sensors therefore always enable the robot to perceive when the former or the latter behavior should be produced and when the transition between the two behaviors should occur.

This ideal situation, however, in which the robot can rely on robust and ready-to-use affordance states only characterize few lucky cases (incidentally, this probably explains why the combination of obstacle-avoidance and navigation behaviors represents a widely used experimental scenario in robotics). In other cases, the affordance states supporting behavior differentiation and arbitration should be extracted through internal elaboration and/or generated through the exhibition of appropriate behaviors.

As we have seen in the previous section, the studied cleaning task requires behavioral diversification also at a higher time scale, e.g. it requires the exhibition of an exploration and a wall-following behavior lasting for minutes. In this case however, the robot cannot rely on ready-to-use affordances that indicate when the robot should display the first or the second behavior and when the robot should switch from one behavior to the other. To achieve this kind of modularity the evolving robots should find a way to: (i) keep
producing the same behavior for a prolonged period of time, (ii) switch behavior at the right moment, and (iii) realize a suitable transition during behavior switch. We will illustrate in details how the evolved robots manage to master these requirements in the next three sub-sections.

Notice that the evolution of context-dependent behaviors require the concurrent development of two interdependent skills, the ability to produce a new behavior and the ability to regulate appropriately when the new behavior should be exhibited (West-Eberhard, 2003).

Producing behaviors for prolonged periods of time

All evolved robots solve the problem of producing a given behavior for a prolonged period of time by realizing each behavior in a way that ensures that they keep experiencing stimuli of the right type during the execution of that behavior. In cases in which the robots should exhibit two differentiated behaviors, i.e. an exploration and a wall following behavior, this implies that they should realize the former and the latter behaviors in a way that ensures that they keep experiencing stimuli of type 1 and 2 while they exhibit the former or the latter behavior, respectively, and should react to the stimuli of the two types by producing actions that enable them to keep producing the former or the latter behaviors, respectively. The two classes of stimuli thus assume the role of affordance for the first and for the second behaviors, respectively. These affordances are not directly available from the environment, as in the case of the states affording the obstacle avoidance and move-forward behavior discussed above, but are generated by the robots themselves through their actions (i.e. through the ability to realize each behavior in a way that ensure that the robot keeps experiencing the corresponding affordances). This form of dynamical stability presents some similarities with the one that can be obtained in situated agents through homeokinesis (Der and Martius, 2012), a task-independent learning process that can enable situated robot to synthesize temporarily stable behaviors, despite the mechanism and the processes through which this is realized are completely different.

All (S) and (T) robots exploit this affordance generation mechanism. However, in the case of the (T) robots, they also exploit an additional mechanism that contributes to enable the robots to keep producing each behavior for a prolonged period of time.

The problem of producing the same behavior for a prolonged period of time is also solved by exploiting the cue provided by the state of the temporal neuron. Indeed, whether the robot keeps producing the exploration behavior or switches to the wall-following behavior also depends on the state of the temporal neuron (see Figure 4). The state of the time neuron influences the duration of the exploration behavior only during a critical phase, i.e. when the state of the time neuron is smaller than 0.6 and greater than 0.4. During the rest of the trial the ability of the robot to keep producing the exploration behavior or the wall-following behavior rely on the affordance generation mechanism described above. Interestingly, in the case of the best (T) robot, the temporal neuron is also used to progressively vary over time the way in which the exploration behavior is realized so to regulate the probability that the robot keep experiencing sensory state affording the execution of the exploration or wall-following behaviors. Indeed, initially moving forward and turning left of several degrees, the robot eliminates completely the possibility to encounter a wall on its left side (i.e. the possibility to experience stimuli affording the alternative wall-following behavior). Then, by moving forward and progressively reducing the angle of turn over time, the robot becomes progressively less adverse with respect to the possibility to experiencing stimuli affording the wall following behavior. This brings us to the question of how robots manage to switch behavior.

Figure 4: Behavior produced by the best (T) robot during different trials in which it started from the same initial position with systematically varied orientations and systematically varied state of the time neuron. The red and blue lines represent the trajectories produced by the robot during trials in which it switches or does not switch to the wall-following behavior, respectively. The black lines represent the walls. For sake of clarity we only show the local portion of the environment in which the robot is located.

Switching between alternative behaviors

The problem of switching between different behaviors is also solved through affordance generation. To understand how robots can act in a way that enable them to both experience stimuli affording the current behavior and stimuli affording the alternative behavior, we should reformulate the definition of affordance generation in probabilistic terms. Evolved robots solve the problem of producing a given behavior for a prolonged period of time and the problem of switching behavior by realizing each behavior in a way that ensures that they keep experiencing stimuli affording the current behavior with a given high probability and

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stimuli affording the alternative behavior with a given low probability, respectively.

In the case of the robot evolved in the (T) experimental condition, the switch is regulated by both the stimuli experienced by the robot (i.e. by affordance generation) and by the cue provided by the robots internal clock. This double regulation enables the best (T) robot to carefully balance the time allocated to the two types of behavior and to reduce the variability among trials (i.e. the transition occurs 3.17±0.11min). The double regulation process is demonstrated by the analysis of the trajectories produced during a series of trials in which the robot always start from the same position and the orientation of the robot and the state of the time neuron are systematically varied. As shown in the Figure 4, whether the robot switches the wall-following behavior depends both on the state of the internal clock and on the state of the infrared sensor when the robot approaches the wall. Overall this shows that whether the switch between the two behaviors occurs or not depends both on the state of the internal clock and on the way in which the alternative behavior is realized which, in turn, influences the type of stimuli that the robot experiences. As mentioned above, in the case of the best (T) robot, the state of the time neuron is not only used to regulate the probability that the robot switches behavior directly (the probability that the robot initiate a wall following behavior in a given relative position in the environment) but is also used to regulate the way in which the exploration behavior is realized which in turn influences the probability that the robot will later experience stimuli affording the wall-following behavior.

Realize suitable transitions during behavior switch

The connectedness of behaviors, i.e. the fact that alternative behaviors are semi-discrete and semi-dissociable units that are only partially independent, implies that the transitions between behaviors should be handled with care. In the case of our experiments, in particular, the transition between the exploration and the wall-following behavior requires special care since the latter behavior can only be produced when the robot is located near a wall and when the wall to be followed is located on a specific side of the robot. Indeed, the analysis of the evolved robots shows that the way in which the behavior transitions are handled in evolved robots has an important impact on robots performance.

The best solution to the transition problem was discovered by the two best replications of the (T) robot (see Figure 3, bottom). Indeed, as we mentioned above, this robot exploits the cue provided by the internal clock to gradually modifying the exploration behavior so to ensure that the robot will always reach a relative location with respect to the walls from which the wall-following behavior can be effectively triggered during the critical period (i.e. during 3.17±0.11min). Overall this leads to an extremely timely, smooth and effective transition that enables these robots to outperform all others robots.

The importance of realizing smooth transitions and the importance of executing preparatory actions can be appreciated by observing the cases in Figure 4, in which the values of the internal clock are set to 0.35, 0.25 and 0.15. In natural conditions, when the internal clock assumes these values, the robot always produces the wall-following behavior. The robot, however, is only able to initiate a wall-following behavior when it is located near a wall that is situated on its right side. If this prerequisite is not satisfied the wall-following behavior will not be exhibited. In normal conditions this problem never arise since the robots have evolved the ability to perform, during the execution of the exploration behavior, the preparatory actions that enable the successive execution of the wall-following behavior.

Conclusions

In this paper we showed how robots evolved for the ability to perform a cleaning task can develop functional modular solutions that involve the exhibition and the alternation of differentiated behaviors playing specialized functions (i.e. cleaning large open areas and cleaning narrow peripheral areas, respectively).

The development of differentiated behaviors, in our experiments, is not realized through the subdivision of the control system into modules and/or through the utilization of differentiated training processes. Instead, it simply originates as a consequence of the adaptive advantage provided by the possibility to display multiple differentiated behaviors. Indeed, robots displaying multiple differentiated behaviors achieved better performance with respect to robots displaying a single behavior.

This approach provides a series of advantages with respect to structural modular approaches in which the synthesis of robots displaying multiple behaviors is realized by using well-separated control modules that are responsible for the production of different corresponding behaviors and that eventually are designed and or trained independently. In particular it releases the designer from the burden to identify the way in which the overall problem can be decomposed in subproblems to be solved through the exhibition of specialized behaviors. More importantly, it enables the adapting robots to develop behaviors that are not only optimized with respect to the capability to accomplish the corresponding functions but that are also optimized with respect to their ability to operate effectively together. More specifically the adapted behaviors are realized in a way that ensure a smooth transition between alternative sub-behaviors and in a way that ensure that the preparatory actions that are necessary to initiate or to carry on a given behavior are realized before the robot initiates that behavior.

The analysis of the obtained results indicates that the mechanisms that support the evolution of functionally modular solutions are the ability to perceive affordances (i.e. per-
ceptual states encoding opportunities for behaviors) and the ability to realize smooth and effective transitions between different behaviors.

The perception of affordance constitutes a prerequisite for the possibility to develop differentiated behavior and for the possibility to effectively arbitrate them, i.e. selecting the behavior that is appropriate for the current robot/environmental context and regulating the duration of each behavior. Interestingly, the basic mechanism that is used by evolving robots to perceive affordances is affordance generation, i.e. the ability to realize each behavior in a way that ensures that the robot keeps experiencing sensory state affording the current behavior with a given high probability and sensory states affording alternative behaviors with a given low probability.

The limitations of this affordance generation mechanism, e.g. the inability to finely tune the duration of behaviors, are overcome by using additional regulatory processes that rely on internal cues. In particular, in the case of the best evolved robot this is realized by complementing the basic affordance generation mechanism with two additional regulatory processes. One of them consists in using the state of the internal clock to progressively vary the way in which the exploration behavior is realized so to progressively increase the probability that the robot will experience stimuli affording the wall-following behavior. The other additional regulatory process consists in using the state of the internal clock to vary qualitatively the way in which the robot reacts in a specific environmental situation (e.g. to determine whether the robot avoid an obstacle by turning left or right that in turn determine whether the robot will keep producing the exploration behavior or will switch to the wall-following behavior).

Overall this implies that behavior arbitration in the best evolved robots is realized through the combined effects of multiple partially redundant regulatory processes that operate through weak interactions.

Future studies should investigate whether this approach can enable evolving robots to find effective solutions in more complex tasks/scenarios.

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