Major Feedback Loops Supporting Artificial Evolution in Multi-Modular Robotics

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Abstract In multi-modular reconfigurable robotics it is extremely challenging to develop control software that is able to generate robust but still flexible behavior of the 'robotic organism' that is formed by several independent robotic modules. We propose artificial evolution and self-organization as methodologies to develop such control software. In this article, we present our concept to evolve a self-organized multi-modular robot. We decompose the network of feedbacks, that affect the evolutionary pathway and show why and how specific sub-components, which are involved in these feedbacks, should be subject of evolutionary adaptation. Self-organization is a major component of our framework and is implemented by a hormone-inspired controller governing the behavior of singular autonomous modules. We show first results, which were obtained by artificial evolution with our framework, and give an outlook of how the framework will be applied in future research.

1 Introduction

Evolutionary multi-modular robotics (EMMR) is a rather novel approach in the fields of biology, computer science and engineering. It outnumbers 'classical' evolutionary robotics concerning technical challenges: Evolving a functional controller for a predefined fixed robotic morphology is already a challenging goal to reach [1, 2, 3]. Additionally in multi-modular robotics, a huge variety of robot morphologies are built from a set of joined robot modules. See Fig. 1 for an example of such

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a robotic organism. Each of these robots is controlled by a control program, which – in the joined organism – fuses into one meta-controller that moves the whole body. It is not just the set of these controllers that determines the final behavior of the organism, but also the set of physical constraints that are posed by the way of how the modules are coupled (joints, forces, ...).

In our EMMR approach, the robotic controllers should evolve along with the body shape. In addition, controllers of single modules should evolve in a way that enables them to build the joined organism shape from a former unconnected (swarm) mode of operation. We suggest a bio-inspired self-organized process [4, 5] that governs the organism formation in a decentralized way. As it is possible for robotic modules to fail or to end up in an unfavorable place in the organism, the organism's control should be extremely robust but still flexible enough to allow dynamic replacement or displacement of single robotic modules during runtime. Thus, the desired controllers, that we plan to evolve, are described by the following characteristics: decentralized control, self-organization, robust behavior, flexibility and scalability. These characteristics are typical for 'swarm-intelligent' systems and therefore we attribute our organism formation process and organism movement process to be a variant of evolutionary swarm robotics [6, 7].

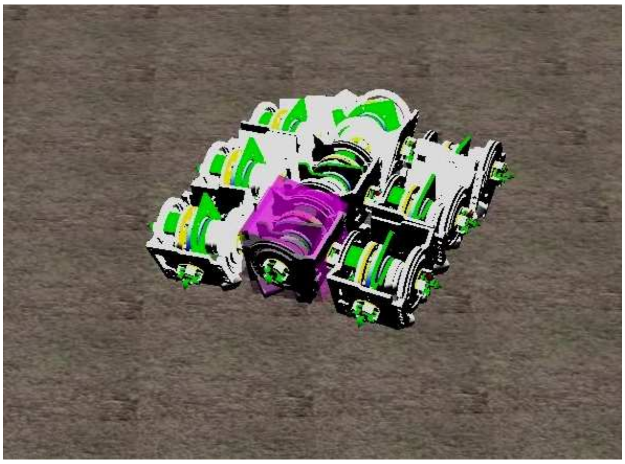

Fig. 1 Exemplary configuration of 9 robots arranged and coupled in a 3×3 layout in our proposed EMMR approach. The process that is able to form this body shape from a swarm of autonomously moving single robot modules has to be evolved. Artificial evolution should then also generate controllers that are able to move this robotic organism in a self-organized way. Multiple feedback loops, that allow self-organization to work at specific points of control, is proposed to enhance and support artificial evolution.

Several approaches have been proposed to achieve this goal: The studies of Shen et al. [8] suggest a framework in which artificial hormones that resemble hop-counts and messages exchanged among modules are used, instead of hard-coded IDs and 'gait table' numbers to coordinate a multi-modular robotic system. In [9], a robotic swarm mimics pheromone excretion of biological organisms and achieves swarm control in doing so. Also in [10] a hop-count-based system is used to control a robot swarm. Similar methods of hop-counts, which form linear gradients in the organism, were also used in [11] to construct dense objects from autonomously moving sub-units. A continuous gradient approach for navigation of modules based on non-linear gradients was investigated in [12] and in [13] within the I-SWARM project [14]. Based on these swarm techniques, we elaborated a hormone-inspired control paradigm for body formation and body control, aimed for multi-modular robots used in the EU-funded projects SYMBRION [15] and REPLICATOR [16].

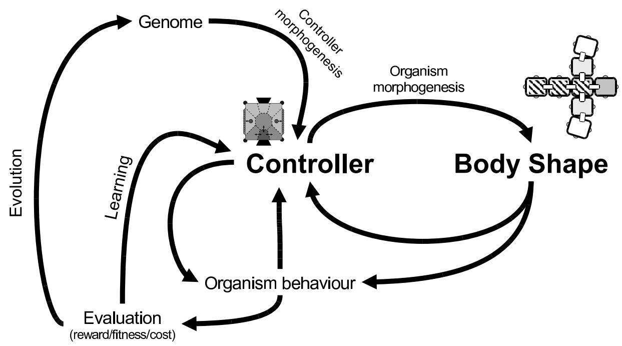

Fig. 2 The feedback loops that affect the evolution of organism shapes in our proposed EMMR system.

In this article, we describe the artificial homeostatic hormone system (AHHS) which we've applied successfully to control a single robot in simulation [17] and in robotic hardware [18]. Using single robots, an AHHS was successfully evolved to move using a 'screw drive', which is non-trivial to control, to avoid obstacles, and to explore the arena [17]. Currently, we develop a system of artificial evolution (AE), that allows an elaboration of this AHHS controller: Our novel controller will be able to control the self-organized body formation process as well as the decentralized control of locomotion of joined robotic organisms. In the following, we describe the concept of our AHHS and discuss the major feedback loops (Fig. 2) that emerge within the system of AE and organism formation. Some of these feedback loops are not existent in 'classical' evolutionary robotics (ER) concerning single robots, others are missing in non-evolutionary multi-modular robotics.

The expected main advantages of this approach compared to others (e.g., classic approaches, artificial neural networks) are an intrinsic spatiality (hormone gradients in connected robots) and a supposed high evolvability (smooth fitness landscapes through mutations that gradually change the behavior). Explicitly defined hormone gradients, that span the whole robot organism, are exploited in the robot organism morphogenesis. The controller of the robot organism is embodied due to the hormone concentrations that are stored in the robot modules. Our hormone controller defines the resulting behavior through hormone production rates, decay rates, and hormone interaction rules that are gradually changed through mutations and therefore only gradually change the behavior. Thus, this approach promises to be successfully applied in EMMR scenarios.

In the following, we identify six feedback loops: classic control, learning, evolution, controller morphogenesis, robot organism morphogenesis, and body motion. In first case studies, we have tested the classic control loop in robotic hardware and in simulation [18, 17] and evolution in simulation [17]. In addition, the controller morphogenesis and the robot organism morphogenesis were tested in preliminary studies.

2 Artificial Homeostatic Hormone System

The basic characteristics and the implementation of our bio-inspired controller are described in [19]. The idea of an AHHS controller is inspired by second-messengers which communicate and ‘compute’ stimuli received through membrane-bound receptors in evolutionary ‘simple’ unicellular organisms (protozoa), bacteria and slime mold. In higher life-forms, such cell messengers act inside of cells and hormones allow to broadcast communication between tissues.

Stimuli received by robot sensors basically trigger the release of virtual hormones in an AHHS controller. The inner body of a single robot module is spatially represented by (virtual) compartments. Each sensor triggers the production of a specific hormone in the compartment with which it is associated. Virtual hormones decay over time, and diffuse to neighboring compartments. This allows information about current and past sensor activation to spread throughout the whole virtual ‘internal body’ of the robot. In an AHHS, hormones interact with each other: One hormone potentially increases or decreases the level of another hormone and is able to alter the sensitivity of sensors and/or actuators. Finally, at least one hormone has to activate one of these available actuators to manifest the robot’s final behavior.

As a result of this actuation, future sensor stimulation is altered. Hence, a sensor–controller–actuator feedback loop emerges. From a cybernetic point of view [20], our AHHS controller actuates the robot such that specific hormone levels are kept at a homeostatic state.

2.1 Artificial genome

Evolution provides an essential feedback loop in our proposed EMMR. As evolution always operates on a genome, which is the ‘substrate’ for adaptation, the specific configuration of an AHHS has to be kept persistent in a data structure that we call ‘genome’. From this data structure, the AHHS controller has to be parametrized. The genome of our AHHS consists of two logical entities: *hormone chromosome* and *rule chromosome*. The hormone chromosome holds only one gene per hormone.

In contrast, the rule chromosome contains an arbitrary number of genes for each hormone. Each hormone excretion, each type of hormone-to-hormone interaction and each actuator activation by a hormone is described in a separate rule gene.

In the following, we give a detailed description of the data structure we developed for holding the needed genetic information of an AHHS (reprinted from [17]):

The hormone chromosome contains the following parameters:

- *hormone ID*
- *fixed decay rate*
- *diffusion coefficient*
- *maximum value of hormone* (value at which a saturation is reached)
- *base production rate* (amount that is produced per time step without sensory stimulation)

The rule chromosome contains the following parameters:

- *rule type*: condition to be met or triggering action
  1. **always:** Action triggered independent from threshold σ
  2. **greater than:** Action triggered if greater than threshold σ
  3. **smaller than:** Action triggered if smaller than threshold σ
- *trigger type*: type of triggered action (hormone concentration θ, actuator value α)
  1. **never triggered:** No action performed.
  2. **sensor influences hormone:** if $(\gamma(t) > \sigma)$ then $\theta(t+1) = \theta(t) + \gamma(t)\delta + \beta$ (sensor value γ)
  3. **hormone influences actuator:** if $(\theta(t) > \sigma)$ then $\alpha(t+1) = \alpha(t)\delta + \beta$
  4. **hormone influences other hormone:** if $(\theta_1(t+1) > \sigma)$ then $\theta_2(t+1) = \theta_2(t) + \theta_1(t)\delta + \beta$
  5. **hormone influences itself:** $\theta(t+1) = \theta(t) + \theta(t)\delta + \beta$

All of these values are integer values allowing fast execution on limited (embedded) hardware.

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3 Feedback 1: Classic Control

The direct feedback loop between the controller and the behavior represents the classic approach of control theory. In control theory this loop is interpreted as a negative feedback because an error value is determined by subtracting the measured system state from the desired state. This error value is used to determine the new input. The controller checks the difference between the desired state and the measured state of the whole system (robot organism and environment) through its sensors. If there is a difference the controller changes the ‘system input’ (e.g., actuator input signals) that is fed into the system.

4 Feedback 2: Learning

The feedback loop controller–behavior–evaluation represents the field of unsupervised machine learning. The robot is interpreted as an agent that has to take actions in an environment in order to maximize a reward. The robot evaluates its behavior online, changes its controller and, hence, its behavior. There is a huge variety of possible approaches. An artificial neural network could be trained online, standard reinforcement learning techniques such as Q-learning could be applied, or even our novel controller approach could be used. The rules of such an AHHS controller can be optimized through learning. This could be done either as a complete learning task from scratch or by optimizing an evolved controller.

5 Feedback 3: Evolution

The loop controller–behavior–evaluation–evolution–genome is of high importance in our standard AE [21]. Hence, we produce a population of robot controllers that are evaluated and selected based on their fitness. A new generation is generated through mutation and recombination of the controllers.

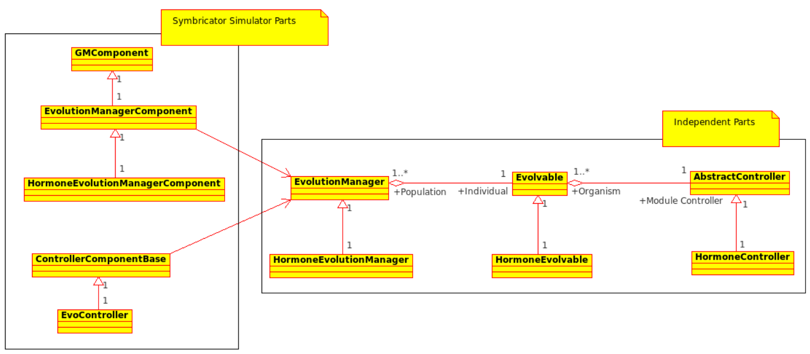

Fig. 3 Software design of our AE framework. It is embedded into the projects’ ‘Symbricator Simulator’ which is based on the Delta3D open-source gaming/simulation engine [22].

Currently we have implemented a naive genetic algorithm to test first evolutionary approaches. In Fig. 3 the class diagram of our software design is shown. It consists basically of three classes: `EvolutionManager` (maintains the whole evolutionary process) which keeps a population of type `Evolvable` (contains evolution specific values such as fitness values) which holds a collection of type `AbstractController` (a container for the actual specific robot controller) for each module in the robot organism. Usually we have homogeneous organisms, that is, we have identical controllers for each robot module in the organism.

The currently evolved controller design is our AHHS controller. However, the software framework is independent from the specific controller design as far as possible – other approaches, such as artificial neural networks, could be used as well with few adjustments. Typically the first evolution run is initiated with a small population (20 to 30 individuals) of randomly generated AHHS controllers. These random controllers generate rather erratic behavior that is evaluated in simulation. The 'Symbricator Simulator', that was developed in both EU-projects REPLICATOR and SYMBRION, is based on the Delta3D open-source gaming/simulation engine [22]. The simulator provides a full simulation of physics, which is indispensable as the locomotion of our multi-robot organisms will usually depend on friction and statics. In addition, it is possible to import the CAD data of the current robot prototype design. For a limited time the behavior of the robot organism is evaluated. For example, in case we evolve simple collision avoidance behavior the evaluation can be based on the covered distance. Following [23] this type of fitness function is called 'aggregate fitness function' because it selects for high-level success (instead of rewarding any kind of motion).

The key challenges in the evolutionary approach to modular robotics are the high computational costs of the controller evaluations and the selection of an appropriate controller design. Due to computational costs only small numbers of generations are feasible within which a valid controller has to be found. Thus, we need a controller that is not only able to represent the desired behavior, but also a controller that shows high evolvability. With 'high evolvability' we refer to a fitness landscape that is as smooth as possible, because it is the preferred shape to avoid local optima. The shape of the fitness landscape is partially influenced by the controller design in connection with the mutation operator but also by the environment. Discrete (stepwise) changes in the controller by the mutation operator should be avoided, because the application of the mutation operator would most likely result in very different behavior and, thus, in very different fitness values. However, typically there is a trade-off between increasing the size of the search space and avoiding discrete changes through mutation.

6 Feedback 4: Controller Morphogenesis

In our AHHS controller, the compartmentalization of the inner body of a single robot module is an important feature. It allows 'embodiment' of the controller, because sensors are allowed to trigger hormone excretion only in those compartments spatially associated with the sensor location on (or in) the robot's body. Only hormones of the same compartment interact, this way the computation being performed in the AHHS, is localized. Therefore, the structure formed by the compartments is important for the behaviors generated by the AHHS. We made the compartmentalization a subject of AE as well and introduced another ‘rule chromosome’ (see section 2.1).

This chromosome contains genes that parametrize a process that forms the compartment structure. One way to achieve internal compartmentalization, is to use a different set of AHHS rules in a ‘constructor’ phase before the robot controller is started. During this phase, hormone values trigger rules in the AHHS from this third chromosome. The only difference compared to the second ‘rule chromosome’ (described in section 2.1) is that hormone values in this phase do not trigger an actuator of the robot. Instead, they trigger a division of one compartment into two compartments, similar to cell divisions in biological organisms: At the beginning, the AHHS starts with just one compartment. This compartment is then successively divided depending on local hormone values. Hence, a self-organized process creates the compartment structure, which is later affecting the robot’s behavior.

AE alters the gene information on this chromosome by altering, deleting, and duplicating rules, by changing the initial starting conditions or by changing the length of the transient period. Fig. 4 shows exemplarily how the compartment structure is altered by a combination of two loci for point-mutations.

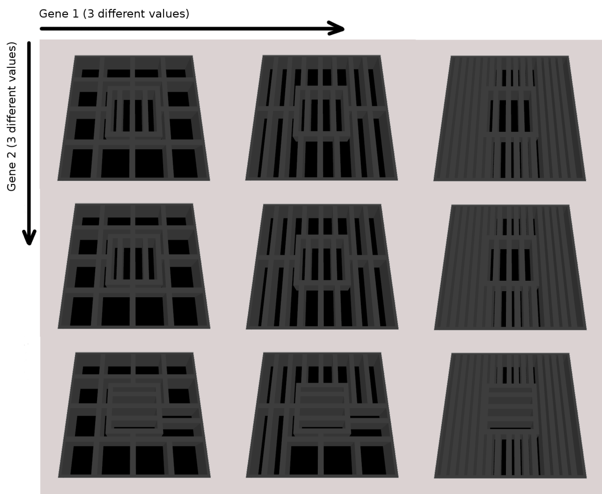

Fig. 4 Internal compartmentalization of the robot. This important structural feature in an AHHS controller is mutated by altering ‘layout rules’. This figure shows 9 configurations that result from a combination of mutations of 2 genes (rules).

7 Feedback 5: Robot Organism Morphogenesis

When it comes to building and reconfiguring robot organisms that consist of autonomous robot modules, we suggest that our AHHS is able to perform this task in a self-organized manner. Thus, the feedback loop ‘controller – body shape’ (Fig. 2) emerges automatically. The main problem concerning the morphology of the robot organism is the trade-off between robustness and flexibility.

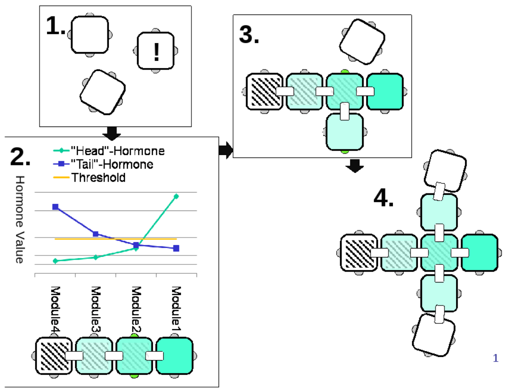

Fig. 5 The development of the body formation in an EMMR. The process of the progress from single module formation in a swarm to robot organism with legs is depicted in four steps. One possible way of achieving this with our AHHS is denoted as a schematic graph of hormone values of two hormones in step 2. For further explanation see text.

We think that there is no conceptional difference between to building a robot organism out of a swarm of single modules, on the one hand, and the reconfiguration process, on the other hand. In most cases for both processes, it is a precondition that an additional number of nearby single robot modules is available. If a join or a change of the morphology of the organism body shape is triggered by the environment, this trigger event has to be perceived by at least one of the modules and it needs to be communicated to other modules.

This kind of body formation process is depicted in Fig. 5. In step one, a module (marked by an exclamation point) detects a situation which is infeasible for a single module which serves as a trigger or a seed for the action of joining together. This perception is communicated to nearby single robots. These modules dock on the opposite of the detected seed. For example, starting from the module that started the joining progress, for example, a simple line is formed.

In such a joined organism (Fig. 5: step two), further environmental stimulation triggers the production of other hormones inside the organism, which consists of connected modules. This process results in the emergence of a gradient of hormone concentrations within the organism. The still existing sensor input, initially triggered the body formation, can now serve as a trigger for a differentiation into a head module and a tail module. Furthermore, a threshold of a 'head-' and a 'tail-hormone' determines, for example, the positions of legs in the middle of the organism (Fig. 5: step three). Despite the fact that this threshold is predefined, the body shape of the robot organism is not determined but influenced by environmental inputs. In this way, different body shapes are established by a self-organized reconfiguration process. The building of legs is based on the same principles as the process of building the main body.

We prefer this approach of exploiting self-organization processes as the main design paradigm in favor of non-adaptive approaches (e.g., predefined shapes) because the latter would lack any flexibility. The approach of self-organization described here in connection with evolutionary methods automatically influences the shape of the robot organism when a new or changed seed is detected by a (joined or free) module. The possibility of self-reconfiguration gives the organism the needed plasticity and adaptability.

8 Feedback 6: Body Motion

In our AHHS control paradigm, there is, in principal, no difference between motion of individual robot modules and of joined robotic organisms. The parallel behavior of single modules sums up to the organisms behavior. Of course, there is a demand of coordination among the modules to achieve a regular motion of the organism. To allow this, hormones diffuse to neighboring robot modules, as soon as modules dock to each other. Hence, the internal body of the organism is structured (compartmentalized) as it is the case for a single robot. Therefore, a robot organism consists of two levels of compartmentalization. There is the logical level inside each single module and the physical level of connected modules.

To demonstrate the diffusion of hormones between robot modules, we performed AE with already joined robot organisms that were allowed to actuate only their 'hinges', which are the main actuators that bend the robot modules with an angle of $\pm 90^\circ$ from the default configuration. No wheels or screw-drives were allowed to be activated. In the following, we shortly describe an exemplary incremental course of AE in our framework:

8.1 Step 1: The first oscillator

In a first period, we coupled two modules. For this organism, the only chance to move was to evolve a set of rules in the AHHS for both modules that actuate both hinges in an 'oscillatory way'. We used the distance the organism moved within 300 time steps as fitness function. The fittest controllers were selected and were subject to point mutation and cross-over producing 20 offspring. The three best individuals were moved to the next generation without any change (elitism) and two new AHHS controllers were generated randomly from scratch in each generation. A behavior that significantly moved the organism evolved within the first 10 generations in a population of 25 AHHS controllers. It increased its performance within the next 20 generations significantly. Fig. 6 shows snapshots of this organism's behavior.

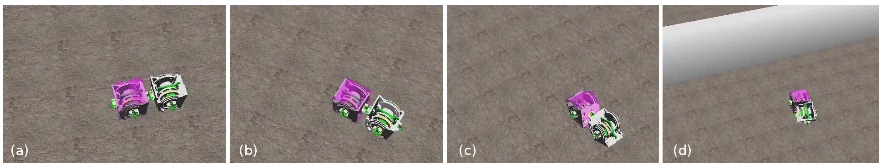

Fig. 6 Evolved motion of two joined robot modules in the projects' 'Symbricator Simulator'. The hinges of the two modules are contracted in an oscillations by the evolved AHHS. This pushes the organism forward.

8.2 Step 2: Motion of bigger organisms

We implanted this oscillating AHHS into robot organisms of increasing size by just adding robot modules at one end of the organism. All of these organisms were able to move slowly. The speed was significantly reduced compared to the former, smaller organisms. After 10-15 generations, the motion speed recovered almost to the prior level again, suggesting that AE successfully adapted the pre-evolved AHHS controller to the new body size. Finally, we ended up with a long line of seven connected robots, which nicely moved across the simulated arena in a caterpillar-like movement pattern. Fig. 7 shows snapshots of this organisms behavior.

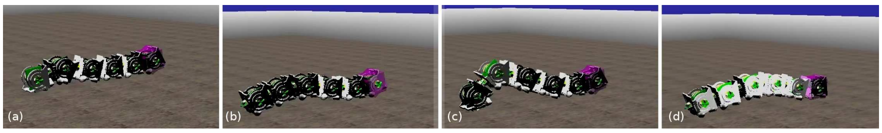

Fig. 7 Evolved motion of several joined robot modules in the projects' 'Symbricator Simulator'. The hinges of joined modules are contracted in delayed oscillations by the evolved AHHS. A caterpillar-like motion pattern was finally evolved.

8.3 Step 3: Motion of more complex organisms

After these successful evolution experiments, we constructed more complex (nested) organism shapes, into which we implanted the pre-evolved AHHS controller described in subsection 8.1. All of these shapes evolved well-adapted AHHS controllers that were able to move the organism in the arena. Here we just want to discuss one example that underlines how the body shape influences the body movement: Fig. 8a and Fig. 8b show two different motion strategies that evolved for the same body shape successively: First, the outer two branches of the T-shaped organism move the organism by oscillatory contraction and release of their hinge while the 'tail' in the back pushes the organism further as well. The whole body is laying almost flat on the floor (Fig. 8a). Then, a different movement pattern emerges in evolution: The central module contracts its hinge which erects the whole organism. This way the three branches of the T-shaped body act like legs and the 'tripod' successfully moves through the arena (Fig. 8b).

9 Discussion

Here, we describe several feedback loops that affect body formation and body movement in an EMMR system. Based on the involved feedbacks, we characterize six levels of adaptation that are exploited by ourselves to generate a bio-inspired adaptive reconfigurable robotic system:

- **Classic control:** The controller–behavior feedback loop is always present in any reactive agent, thus also in any autonomous robot that is able to perform behavior of any kind in its environment. We did not elaborate on this 'classic' feedback loop in the concept presented in this article.
- **Learning:** This feedback adapts the controller during runtime, based on the recent dynamics of the so called 'reward', 'fitness' or 'cost' function. We did not elaborate on this feedback loop in the concept presented in this article.
- **Evolution:** In this feedback loop, the main concern is feasibility due to high computational costs. Self-organizing processes generated by the general controller design, such as homeostatic tendencies in the hormone controller, need to be leveraged as well to obtain smooth fitness landscapes and to decrease the number of generations that are necessary before the desired behavior is evolved.
- **Controller morphogenesis:** In this article we showed in this article that the internal structure of the AHHS controller arises from a dynamic self-organized process, driven by the AHHS itself. Hence, it is subject to AE, together with the other rule set that acts in the AHHS. This compartmental layout is an essential feature to allow 'embodiment' in our approach.
- **Robot morphogenesis:** For the feedback loop of the controller and the body shape we propose a dynamical, self-organized body shaping process which influences the characteristics of the controller. When single modules are docking to or

Fig. 8 Two different motion patterns evolved successively with the same body shape. a: flat body, oscillators move peripheral hinges like fins. b: erected posture of the organisms, peripheral robots moved like legs.

releasing from the robot organism the hormone values are altered and therefore the behavior of the controller itself changes. We think that this approach for a self-organized body formation process in combination with evolutionary learning of the controller could be able to perform the demanding task of flexible body shape.

- **Decentralized body motion:** Body-motion of joined organisms was successfully achieved by AHHS control and by our implementation of AE. Again, it is a self-organized process – consisting of positive and negative localized feedbacks and time delays – that achieves the desired motion patterns.

In our current research projects, we plan to implement all six feedback loops described above in real robotic hardware and in a sophisticated simulation software, that closely depicts the physical abilities and constraints, as well as the computational abilities of our final targeted robots [22]. Using this software, we already successfully implemented our AHHS controllers, evolved them to perform adaptive behavior on single robots and in joined robotic organisms. Morphogenesis of the controller and morphogenesis of the robot organism will be our next focus, as well as enhancing the efficiency, the computational power and the evolvability of our AHHS controllers. Also the necessity of all six feedback loops will be investigated. At the moment, each feedback loop is investigated separately. For example, the body motion was investigated with fixed predefined body shapes. In case of learning and evolution, we note that it is not necessary to have both of them in the system at the same time. In principle, they just differ in their time scales. Learning is achieved during a life time while evolution lasts over generations. For example, there might be scenarios in which learning does not improve the performance significantly because no optimization during runtime is needed.

However, all feedback loops interact in a complex way, which is the key point of this approach. For example, a change of the body shape through robot morphogenesis influences the controller and the body motion. These intertwined feedback loops encourage and challenge evolution to generate adaptive behavior.

We conclude that our AHHS approach allows for self-organization on multiple levels of the organism's formation and movement process. Our evolutionary framework alters the whole genome, which encodes for almost all parameters affecting the feedback networks mentioned above. This genome-based evolution allows us to evolve controller layouts, controller performance rules, virtual physics and virtual chemistry of hormones, organism formation and organism movement all-together in parallel. We think, this multi-level adaptation is essential to create a functioning EMMR approach, as it is desired in the projects SYMBRION and REPLICATOR.

10 ACKNOWLEDGMENTS

We were supported by the following grants: EU-IST FET project 'SYMBRION', no. 216342, EU-ICT project 'REPLICATOR', no. 216240.

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