# Adaptation and Self-adaptation of Developmental Multi-Robot Systems

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***Abstract*—In this work we explore several adaptive and self-adaptive processes in systems with a high degree of developmental plasticity. It is indicated that such systems are driven by two different forces: design goals and self-concept, which define what the system "should be" and "may be". The paper discusses mechanisms, leading to adaptive and self-adaptive behavior, as well as possible conflicts between them. Bound and unbound self-concepts are introduced. The discussed mechanisms are exemplified by a collective locomotion of reconfigurable multi-robot system, where several self-organizing and evolutionary approaches are exploited.**

***Keywords*-Collective robotics, artificial multi-robot organisms, adaptation, self-adaptation, self-development, long-term artificial evolution.**

## I. Introduction

Adaptability and self-adaptability represents an important characteristic of systems working in real environments [1][2]. Different uncertainties, variation of parameters or even an appearance of unknown situations require such mechanisms, which allow the system to find a compromise between achieving the main goal, set by a designer, flexible behavior to fit the environment and self-developmental features, expressed by a self-concept. Finding this compromise requires three important mechanisms: plasticity of the system itself [3]; regulative mechanisms, which uses system's plasticity to perform adaptation [4][5]; and, finally, a goal and self-concept, which drive the system along adaptive and self-developmental changes.

Plasticity of the system can be achieved by exploiting the principle of heterogeneous multicellularity [6]: each module is compatible with other modules and they can assemble and disassemble themselves into structures with different functionality [7], see Figure 1. Not only structural functionality, but also regulative and homeostatic mechanisms can be self-developed; they are addressed by developmental robotics. Multi-robot systems with high-developmental plasticity are explored in several research projects, e.g., [8][9], in common they are referred to as artificial organisms [10].

Structures and functionality of artificial organisms are closely related to each other, by changing macroscopic structure, the system also changes its own functionality and correspondingly behavior [11]. Relation between structures, functions and behavior can be represented as shown in Figure 2. We denote this relationship as "generating" because the upper level generates the lower level, i.e., structures generate functions and functions generate behavior. Controllers in functions and structures – they represent *the regulative level* – allow some degree of flexibility (adaptability) for the system. The targeted behavior on the regulative level is expressed by a "goal", which describes aims of the system itself and the criteria for achieving adaptive behavior. Adaptivity on this level depends on capabilities of a designer to foresee possible environmental changes and to integrate a reaction on these changes into the controllers. To react on unpredictable changes on the design stage, the second *generating level* is required, which can modify controllers. The generating level contains different deriving and evolving mechanisms, which can generate the regulative level and essentially, when not completely, change the system. The targeted behavior on the generating level is expressed by a "self-concept", which is defined in a broader way than a "goal". It describes possible developmental changes and determines what the system "may be". When the behavior on the regulative level is referred to "adaptive", the generating level is associated with "self-adaptive". Such changes on the generating level, which are not directly related to adaptation, but rather to ontogenetic self-modification, can be also associated with "self-development", which originates from the neuroscience community, e.g. [12]. Despite "self-development" is a more general notion, targeting primarily cognitive capabilities, the "self-adaptation" and "self-development" overlap in several points since they are developed in parallel.

Technical systems possess goal-oriented behavior, but should be also adaptive to uncertainties and changes in the environment and have some degrees of freedom for self-development. To some extent, these systems are driven by two different forces: by a goal and by a self-concept. When the degree of adaptation is low, there are no essential conflicts between them. When the plasticity is high, the system can be hindered by self-adaptive processes from reaching the main goal. Here we are facing a new conceptual problem about long-term controllability of self-adaptive and self-developmental processes. Obviously, that either the goal should be formulated in such an invariant way, which allows multiple approaches for its achieving, or self-adaptive processes should basically be limited.

This paper extends and generalizes several ideas expressed in [1][13][14] and introduces a more detailed link between a high-level notion of adaption and practical implementation of adaptive mechanisms. The rest of this work is structured in the following way: firstly, a short introduction into developmental robotics is made in Section II and then different adaptive and self-adaptive mechanisms are overviewed in Sections III and IV. Adaptation and self-adaptation, as well as bound and unbound self-concepts are discussed in Section V. To exemplify the mentioned ideas, the Section VI introduces the problem of macroscopic locomotion for artificial multi-robot organisms. Adaptability of macroscopic locomotion is approached with four main mechanisms: adaptive multi-functional local drivers in Section VI-A, adaptive self-organization on the level of interacting structures in Section VI-B, evolving by using a global fitness evaluation in Section VI-C and a generation by using the bound self-concept in Section VI-D. Finally, this paper is concluded in Section VII.

## II. Developmental Robotics

Artificial developmental systems, in particular developmental (epigenetic) robotics [3], are a new emerging field across several research areas – neuroscience, developmental psychology, biological disciplines such as embryogenetics, evolutionary biology or ecology, and engineering sciences such as mechatronics, on-chip-reconfigurable systems or cognitive robotics [15]. The whole research area (not only of artificial systems) is devoted to an ontogenetic development of an organism, i.e., from one cell to a multi-cellular adult system [16].

A closely related field is evolutionary robotics [17], which uses the methodology of evolutionary computation to evolve regulative structures of organisms over the time. Evolutionary robotics tries to mimic biological processes of evolution [18], but also faces challenges of embodiment [19], reality gap [20], adaptation [21] or running on-line and on-board on a smart microcontroller device [5].

In several points the developmental and evolutionary methodologies differ from each other:

- "*... should try to endow the [developmental] system with an appropriate set of basic mechanisms for the system to develop, learn and behave in a way that appears intelligent to an external observer. As many others before us, we advocate the reliance on the principles of emergent functionality and self-organization ...* " [3];
- "*evolutionary robotics is a new technique for the automatic creation of autonomous robots. Inspired by the Darwinian principle of selective reproduction of the fittest, it views robots as autonomous artificial organisms that develop their own skills in close interaction with the environment and without human intervention*" [17].

Despite differences, evolutionary and developmental approaches share not only common problems, but also some ways to solve them, it seems that both are merging into one large area of self-developmental systems [10].

Both developmental and evolutionary methodologies impose a set of prerequisites on a system; one of the most important from them – it should possess a high degree of *developmental plasticity*. Only then an organism can be developed or evolved. Developmental plasticity requires a specific flexible regulative, homeostatic, functional and structural organization – in this point evolutionary/developmental systems differ from other branches of robotics. Since collective systems, due to their high flexibility and cellular-like organization, can provide such a versatile and re-configurable organization – collective robotics is a suitable object for application of evolving and developmental approaches.

The approach, used in our work, is based on modularity and reconfigurability of the robot platform, as shown in Figure 1. Individual modules possess different functionality


Figure 1. **(a)** Prove-of-concept: individual robots; (b) Prove-of-concept: aggregated robots into an artificial organism; (c), (d) Real prototypes: aggregated robots (images ©SYMBRION, REPLICATOR projects).

and can dock to each other. Changing the way of how they are connected, an aggregated multi-robot system (organism) possesses many degrees of structural and functional freedom. Due to a capability of self-assembling, robots have a control over their own structure and functionality; in this way they can emerge different "self-*" features, such as self-healing, self-monitoring or self-repairing. These self-* features are related in many aspects to adaptability and evolve-ability, to emergence of behavior and to controllability of long-term developmental processes. The self-issues are investigated in manufacturing processes [22], distributed systems [23], control [24], complex information systems [25] or cognitive sensor networks [26].

Flexibility and changeability of structures and functions are one of the most important aspects of artificial multi-robot organisms [11]. In Figure 2 we demonstrate the dependencies between structures and functions, as well as introduce a two-layers control architecture with regulative and generating levels. The first level is related to control,

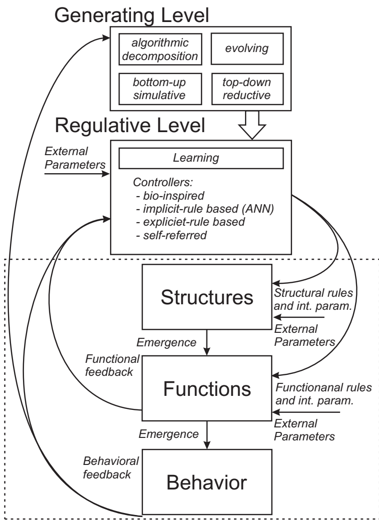



Figure 2. Functional scheme of regulative and generating levels in structural systems (image from [14]).

we denote it as the *regulative level*. It contains different controllers, such as explicit and implicit rule-based (artificial neural networks), different bio-inspired, self-referred or learning systems. These controllers influence structural or functional rules as well as change parameters of the corresponding level. All controllers work based on the scheme: *change of input parameters* $\rightarrow$ *changes of output parameters/rules*. The main goal of the regulative level is to maintain an internal homeostasis of the system, to execute different tasks or, more generally, to demonstrate purposeful behavior depending on external conditions. Controllers at the regulative level allow some degree of adaptability, defined by design goals.

In detail, it depends to which extent a designer of these controllers was able to foresee possible changes of the environment and to integrate a reaction on these changes into the controllers. The controllers allow different degrees of reaction on changes. However, the system at the regulative level is able to react only to changes whose parameter range was predicted in advance during the development of controllers or learning mechanisms. When changes are not predictable at the design stage, we need to introduce the second level, which can modify regulative controllers – we denote this as the *generating level*.

Deriving is primarily related to distributed problem solving and planning approaches, known in the multi-agent community [27], symbolic tasks decomposition [28], structural decomposition [29], self-referred dynamics [30] and others. These approaches are fast, deliver a predictable behavior and can be applied when a new situation is at least structurally known. Evolving is basically related to evolutionary approaches, see e.g. [31], and can be applied when the situation is completely unknown and a large search space of possible solutions should be explored. Recently, evolutionary approaches have been applied to a wide class of robotic problems [32].

Collective systems with such a two-layered control architecture and self-assembling capabilities possess extended developmental plasticity and allow a wide range of adaptation and self-modifications. However, there are several open questions about "driving forces" of adaptation and self-adaptation. Since currently there are several theories towards adaptive systems, we need first to identify classes and mechanisms of adaptation, as it is shown in the next section.

## III. Three Mainstreams in Adaptive Systems

Adaptability is often considered in biological terms of natural evolution [33] or environmental uncertainty [34] as well as in management and business processes [35]. There have been several attempts to create a common theory of adaptability, such as the approach suggested by Michael Conrad [34]. Overviewing the vast literature on the field of adaptation, we can recognize three main streams driving further development and representing different methodologies and different approaches to adaptation. The first and oldest stream is related to the theory of adaptive control. Several early works in adaptive control date from the late 50s - early 60s [36][37]. In the mid-late 70s several issues related to temporary stabilities [38] appeared, which in turn led to iterative control re-design and identification, and contributed in the mid-80s to robust adaptive control [39][40]. Overviews of adaptive architectures can be found in textbooks [41][42], which can be generalized as a high-level architecture, shown in Figure 3(a) [43].

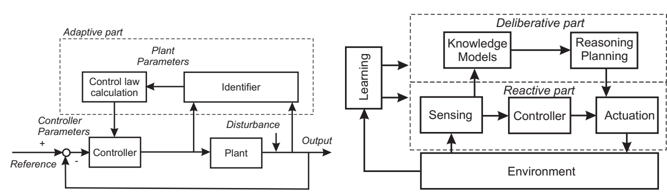



Figure 3. A high-level architecture for **(a)** adaptive control **(b)** adaptive behavioral systems (images from [14]).

Adaptive control consists of two parts, a conventional feedback-based control loop and an adaptive part, depicted by the dashed line in Figure 3(a). The environment is not explicitly integrated into this model, it is implicitly reflected by introducing disturbances and by uncertainties in the plant. The goal of the adaptive part is to estimate the behavior of a plant (by the identifier) and to calculate dynamically the control law (by the control law calculator). When in optimal control, a control law is designed off-line by a designer, an adaptive controller does it on-line. Most challenges in adaptive control theory are concentrated around adaptation of control to parameters of a plant when these parameters are unknown or changing.

The second mainstream of adaptation is located around adaptive behavior, which first arises within the AI community, e.g. [44], and involves cognitive aspects of adaption [45]. There appear a few new components in the scheme from Figure 3(a): explicit environment, sensing and actuation, as well as the deliberative cycle, shown in Figure 3(b). When the reactive part of this scheme is in fact the optimal controller from Figure 3(a), the deliberative part represents a new AI component. The adaptive system is now embedded into the unpredictable/dynamically changing environment; these systems are often referred to as situated systems [46]. Sensing and actuation represent a "body" of the system, intelligence (and so adaptation) is treated in terms of embodiment [47]. Achieving adaptivity in this context is spread into several approaches: different learning techniques in reactive and deliberative parts [48][49][50], behavior-based approaches [51], adaptive planning and reasoning [52], biological inspiration in cognition [53], evolutionary approaches [54] and many others. The goal of adaption can be formulated as achieving desired environmental responses according to some selected fitness/reward criteria.

The third mainstream towards adaptation is related to the community around distributed and software-intensive systems, computational, communication and sensor networks. With some degree of generalization, the business applications can be also related to this mainstream [55]. The environment involves explicit users; the system itself is separated into different levels (applications), which run in parallel [56]. The goal of adaptation here is related to scalability, self-optimization and self-protection, recognition of context, as well as to the software-engineering issues addressing reliability [57].

## IV. Mechanisms of Adaptation in Collective Systems

Three mainstreams in the theory of adaptive systems, considered in the previous section, allow making several conclusions towards their underlying adaptive mechanisms. These mechanisms are closely related to three following issues: *developmental plasticity*, *capabilities to determine desired modifications* and, finally, *mechanisms, allowing reaction on changes by utilizing plasticity*. Since adaptive systems are approached from several independent directions (see the first bio-inspired work on adaptation by Ashby [58]), understanding of these underlying mechanisms differs from community to community.

Generalizing experience from the adaptive control theory [42], AI domains [44] and the latest developments in bio-inspired [32] and software intensive systems [59], there are four classes of developmental plasticity:

**Plasticity level 1. Fixed interactions.** For several applications, mostly in industrial environment, collective agents are expected to work in well-defined environment, where all possible environmental fluctuations can be absorbed by external mechanisms (e.g. by human personal). In this way, it is much cheaper to make agents with fully or partially predefined behavior. Cooperative behavior of collectively working robots includes some number of adaptive mechanisms, however is mostly preprogrammed [60].

**Plasticity level 2. Tunable and reconfigurable cases.** These collective systems have several degrees of freedom related to developmental plasticity. Adaptivity here is achieved in different ways: from parameter changing, feedback-based mechanisms [61], adaptive self-organization [62] until fully reconfigurable systems. Here also a multitude of learning mechanisms can be applied [63].

**Plasticity level 3. Bounded development.** Adaptivity is designed to be in some range of possible variations. Normally, it is defined by some structural mechanisms, for example by a nature of reward. The limit of adaptive systems is reached when a new structural change happens or the system is not able to identify the required reward (for reward-based mechanisms). In this case the system needs to modify its own structure to absorb environmental changes. We refer the systems, capable of structural changes with flexible reward/feedback mechanisms, to developmental collective systems (see more in Section V).

**Plasticity level 4. Unbounded development.** "Unbounded" means a very high degree of developmental plasticity, similar to biological cellular systems. Such systems are potentially capable of unbound increasing of their complexity, diversity or information capacity (see more in Section V).

Considering capabilities to detect changes and to determine desired modifications, we basically refer to three following schemes:

**1. Model-reference based detection.** This is a widely used scheme in e.g. adaptive control [64], machine learning [63], artificial evolutionary systems [17] and many other areas, where the detection of changes represent an error between a model and a system ("plant" in control theory). Multiplicity of *Feedback-*, *Reward-*, *and Fitness- based* mechanisms [61][65] originate from this model-reference based approach. This is the main detection mechanism for adaptive systems.

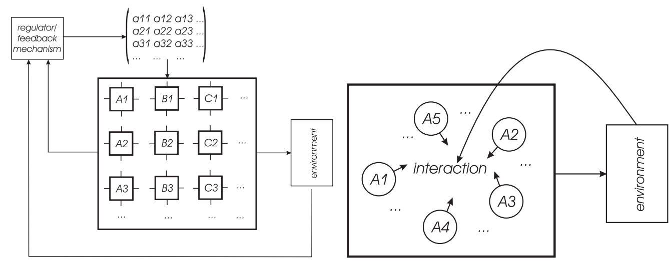
**2. Self-tuning based detection.** This is also very popular approach, see e.g.[66], the first ideas are referred to [67]. It consists of a parameter estimator, a design calculation and a regulator with adjustable parameters, the idea is to select "a design for known plant parameter and to apply it to unknown plant parameter, using recursively estimated values of these parameters" [64, p.189]. Self-tuning mechanisms are often used in terms of self-adaptive control, especially in the 60x and 70x [68].

**3. Concept-based detection.** Self-developmental systems with a high degree of plasticity cannot use model- or tuning-based detection mechanisms – mechanisms of detection are not plastic enough to follow these systems. Instead so-called self-concept-based approach has been proposed (first in human psychology [69][70], see more in Section V). This mechanism determines desired modifications based on internal stimuli, containing in the self-concept; in many cases each self-modification creates a new generation of adaptive changes, which are absorbed by the model-reference based detection. This mechanism is mostly utilized in self-adaptive systems.

The mentioned developmental degrees of freedom, together with the detection mechanisms, can create different combinations, which result in several adaptive and self-adaptive mechanisms. Focusing now on adaptation, we indicate three main classes of such mechanisms:

**1. Parameter-based adaptive mechanisms.** This kind of adaptive mechanisms has a long tradition in the control theory, see e.g. [41]. Here the system is controlled through control parameters, see Figure 3(a). By modifying the values, the controlled system responses by changing its behavior (in the terminology of control theory – the transfer function). There exists a multitude of possible variations: when the system is known, its analytical model can be used for control purposes; when the environment is simple – it is incorporated into the analytical model; when the system is unknown (the black box approach) – different feedback mechanisms can be utilized for control purposes. Different ways of how to adapt the system are the focus of unsupervised reward-based learning approaches. The parameter-based adaptive mechanisms are very efficient, however possess several drawbacks. First of all, the system is adaptive only within such variations of a transfer function, which are allowed by changes of control parameters. The second point is related to the feedback mechanisms/analytical regulator – this element represents a general bottleneck. For example, a feedback mechanism expects only a temperature as a feedback parameter. In a situation where not only a temperature but also a light becomes a feedback parameter, the predefined regulator will not provide an adequate regulation.

**2. Modularity-based adaptive mechanisms.** To increase flexibility of the systems to react to environmental changes, another principle has been suggested. This principle is based on the so-called "atomic structure", where the system consists of modules, which can be dynamically linked to each other. The linkage can be of binary as well as fuzzy character, see Figure 4. Examples of such systems are artificial neuronal networks (ANN) [71], Genetic Programming (GP) [31], reconfigurable robotics [72] and others. Modular structure has several dedicated issues, i.e., granularity of modules – how large are changes of the transfer function by re-linking only one elementary module. Developers are trying to design the modules so that to make this change as small as only possible – i.e., to provide possibly smaller granularity. Not only the system itself, but also the regulator can be based on a modular structure; this eliminates drawbacks of parameter-based mechanisms related to a fixed structure of regulator.




(a) (b)

Figure 4. Simplified structure of **(a)** modularity-based adaptive mechanisms ; **(b)** self-organized adaptive mechanisms.

**3. Self-organized adaptive mechanisms.** In contrast to the two previous adaptive mechanisms, the self-organization represents another approach for adaptation. Self-organizing systems consist of many interacting elements with a high degree of autonomy [73], see Figure 4. The transfer function of such systems is "generated" dynamically through interactions. Usually, when these interactions are not synchronized, the transfer function is irregular or even chaotic. However, when these interactions become synchronized in some way, we observe an appearance of "ordered transfer function". Self-organized adaptive mechanisms introduce a feedback directly into the interactions among elements. In this way, any changes in a local feedback modify the whole collective behavior [74][75]. In many cases it happens without any regulators at all; all interacting elements modify their own interactions [76].

Since environmental changes require an adaptive reaction from a system, which in turn requires specific control mechanisms, we can divide changes and reactions into those forecast in advance and correspondingly those not forecast in advance. This division is relative, because in practical situations each change has forecasted and not forecasted components.

Now, based on the introduced concepts, we can define adaptability [14]. **Adaptability** is closely related to environmental changes and the ability of a system to react to these changes and the capability of the designer to forecast reaction of the environment to the system's response. Therefore adaptability is defined in term of the triple-relation: *environmental changes* $\rightarrow$ *system's response* $\rightarrow$ *environmental reaction*. In general, adaptability is the ability of a collective system to achieve desired environmental reactions in accordance with a priori defined criteria by changing its own structure, functionality or behavior initiated by changed

Table I
FOUR TYPES OF ENVIRONMENTAL CHANGES IN ROBOTIC APPLICATIONS AND EXAMPLES OF CASES BOTH FORECAST AND NOT FORECAST IN ADVANCE, FROM FROM [14].

| Environmental changes leading to: | Examples: Forecast in Advance | Examples: Not Forecast in Advance |
|---|---|---|
| Appearance of new situations | Installation of industrial robots in a new workshop | Work in previously unexplored environment (e.g. landing on Mars) |
| Changed functionality | Changing a type of locomotion (e.g. from wheeled to legged), when changing a terrain type | Search and rescue scenario when robots encounter unknown obstacles |
| Modified behavioral response | Gravitational perturbance of flying object in space and finding new control laws for engines | Distributed control of legged locomotion for obstacles of random geometry |
| Optimization of parameters | Changing of day/night light and adapting intensity of additional light | Adapting locomotive parameters for randomly moving obstacles |

environment. In Table I we roughly specify four different categories of environmental changes.

According to environmental changes from this table, we can identify five different classes of adaptability in collective systems, capable of structural phenomena: optimization mechanisms; behavioral control; functional control; derivation of new regulatory functionality and, finally, evolving of new regulatory functionality. These mechanisms are graphically represented in Figure 5. Since we involve in this figure

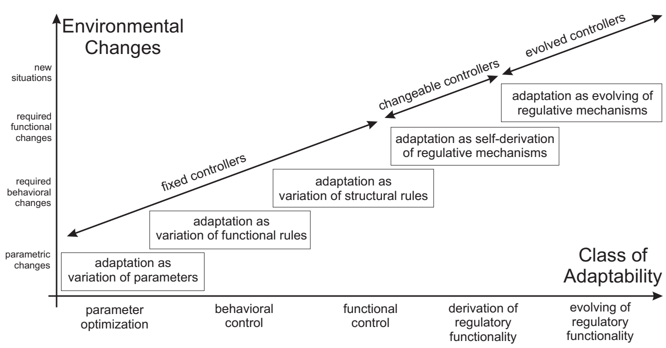



Figure 5. Different adaptivity mechanisms in collective systems, from [14].

several evolutionary mechanism, we closely touch the issues of self-adaptivity, considered in the next section.

## V. ADAPTATION VS. SELF-ADAPTATION

The ideas, expressed in the previous sections are related to adaptation. There are several differences between adaptation and self-adaption. For example, Bäck in [77] distinguishes between *dynamic parameter control*, *adaptive parameter control* and *self-adaptive parameter control*. Here "self-adaptive" includes (evolutionary) mechanisms for changing regulative structures, whereas "adaptive" means merely feedback-based regulative mechanisms. This and similar definitions of self-adaptivity is widely used in evolutionary [78] and in autonomic [79] communities.

The theory of adaptive control also uses the term of self-adaptation, however in another context. It is primarily related to different variations of well-known self-tuning mechanisms [67][66], where the detector and regulator uses iterative approach for identification of control laws. On the early stage of 60x and 70x the term of self-adaptation was widely used, e.g. [68], whereas modern literature refers self-tuning approaches to adaptive systems [64].

Taking into account regulative and generating levels from the Figure 2, the difference between adaptive and self-adaptive seems to be more complex. We start from the commonly accepted fact, that "adaptive" and "self-adaptive" are placed on different levels of hierarchy. In Figure 6 we draw these two levels (as two dashed boxes).

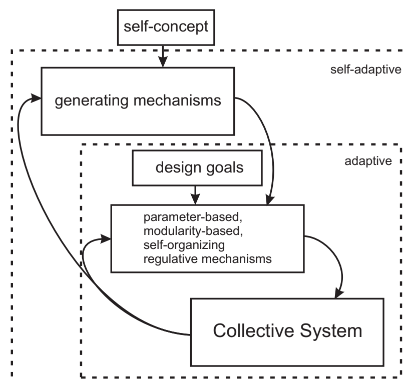



Figure 6. Adaptive and self-adaptive mechanisms.

The mechanisms in the first box allow adaptive behavior, related to the design goals of a system. These "goals" are implicitly formulated as a transfer function, model-reference and other mechanisms related to behavior in environment. In the same manner, the self-adaptation needs also a "goal", however the self-adaptive goal should be expressed in a more broad and flexible way and should be related to the system itself. It describes developmental goals as "what a system may be", instead of "what a system should be". To explain the difference between both, we can consider the case of macroscopic locomotion for such an organism, as shown in Figure 1(b).

This organism can have a series of specifications: legged or wheeling principles of motion, specific limitations imposed on energy consumption or on a structural stability. They can be formulated even broader, as e.g. "a system capable to move from A to B", and expressed as a fitness function of the traveled distance and constrained by e.g. segmented (such as insects) construction of body, symmetric movement of legs or humanoid-like structure of body. All of them are different examples of design goals, which, when touching with reality, produce some adaptive locomotive structures and behavior. Obviously, that formulating design goals more or less broad, we allow more or less degrees of adaptability.

Now, we can assume, that driven by human developmental history, we have a specific vision of how this organism may be: complexity of regulative and homeostatic functionality, degree of "intelligence", flexibility of structural reconfiguration, scalability. They can be also broader, such as "increasing of information capacity". These visions are not directly related to locomotion, they express some desire of how to see the whole systems. From these visions, it is not always possible to obtain some locomotive structures directly. Each change along the "vision axis", requires follow-up changes along "adaptive axis". In other words, "self-vision axis" and "adaptation axis" are different. Such a "vision of itself" is expressed in terms of a "self-concept". The notion of self-concept originated in human psychological research, e.g. [70], and is basically related to human self-developmental processes, e.g. [69][70][80]. Recently, there appear several works, which apply psychological ideas to robotics, e.g. [81][82].

In self-adaptation we have to point out one principal element, related to the bounded and unbounded character of changes. When in adaptive processes, these driving forces are mostly bounded, expressed e.g. by reward or fitness, the self-concept may include driving forces, which are of unbounded character. **Self-adaptation** can be formulated as a series of changes, undertaken by the system alone, and intended to adapt to its own vision of itself.

When the self-concept has an unbound character, the system is in fact continuously changing itself. In this context, sell-adaptation can be related to another process – self-development. The notion of self-development in robotics is most probably originated from another community – neuroscience, e.g. [12][83], which through artificial neural networks (ANN), e.g. [84] and evolutionary communities find its own way to robotics, e.g. [82]. The development focuses on ontogenetic processes related to cognitive science and the concept of embodiment [3], whereas self-development is understood more broadly as e.g. self-exploration, self-supervision, self-learning and others. To be consistent with the logic of these notions, the **self-development** is a more general ontogenetic mechanism of continues changes, which targets cognitive aspects and may be unlimited in time and complexity, i.e., it possesses unbounded properties. Both self-adaptation and self-development are related to the self-concept.

In evolutionary community unbounded properties are often related to open-ended evolution, which *is characterized by a continued ability to invent new properties – so far only the evolution of life on Earth (data partly from the fossil record) and human technology (data from patents) have been shown to generate adaptive novelty in an open-ended manner* [85]. We find some first ideas about open-ended evolution in [86] and [87]. Open-ended evolution is also related to indefinite growth of complexity [88] and unbounded diversity [89]. Ruiz-Mirazo and co-authors expressed the interesting idea that *"the combination of both self-assembly and self-organization processes within the same dynamic phenomenon can give rise to systems with increasing levels of molecular as well as organizational complexity"*. They also proposed to decouple genotype and phenotype from each other. A similar idea of increase homeostatic autonomy in macroevolution was proposed by [90], which leads us to not-fitness driven self-developmental processes. Several implementations of open-ended evolutionary scenarios, e.g. [91], do not use any explicit behavioral fitness, moreover, there is no complexity growth in such "classical" artificial life simulator as Tierra and Avida [92]. In this work Russell Standish proposed to improve these systems: "*a key step in doing this is to generate a process that adaptively recognises complexity, since it will be impossible to include humans in the loop, even when run on conventional computing platforms*".

These works lead us to an interesting question about the unbounded self-concept: which process can generate complexity? One of the first remarks is from von Neumann: "*synthesis of automata can proceed in such a manner that each automaton will produce other automata, which are more complex and of higher potentialities than itself*" [86]. A similar approach is observed in L-Systems [93] (authors used evolutionary process but human operator in the selective loop) as well as in self-referred dynamics [30]. It seems that structural production can lead to growth of complexity and diversity.

However, considering the Kolmogorov complexity of fractal structures, which is equal to the shortest production set of rules [94], we note the complexity of the whole fractal is independent of its size – the self-similar structural production does not increase complexity. Thus, we require that production systems include parameters, which perturb generating structures. In this way, structural production rules parameterized by a random (environmental) value may lead to infinite growth of complexity and diversity, and are candidates for the unbounded self-concept. In Table II we collected several possible self-developmental processes in structural collective systems with bounded and unbounded self-concepts.

To conclude this section, we argue that adaptation and self-adaptation are two different, hierarchically placed processes, *related to an origin of changes and not to the used mechanisms (both processes can use the same mechanisms)*. Related to the utilized degrees of plasticity and origin of modification, different adaptive and self-adaptive mechanisms can be combined into three groups and represented as shown in Figure 7.

Design goals and self-concept also differs from each

Table II
SEVERAL CHARACTERISTICS OF SELF-DEVELOPMENTAL PROCESSES IN COLLECTIVE SYSTEMS, FROM [10].

| Process | Developmental plasticity | Self-Concept |
|---|---|---|
| Regulatory | Structural and functional plasticity of the system, controllers can change their own transfer functions. | *(bound)* Achieving a targeted goal in changing environment. *(unbound)* Increasing performance characteristics. |
| Homeostatic | Like in the regulative case, but related to maintaining steady internal states in changing environment. | *(bounded)* Endogenous steady state. *(unbounded)* Achieving best possible homeostasis for diverse scalability metrics. |
| Learning | Changeable structure of regulative system. | *(bounded)* e.g. positive or negative rewards. *(unbounded)* Fitting very large (infinite) parameter space, e.g. by exploring structural-functional relations. |
| Planning-driven | Structural, functional and regulative plasticity. | *(bounded)* Minimizing deviations from a plan. *(unbounded)* Self-referred planning. |
| Fitness-driven | Structural, functional and regulative plasticity. | *(bounded)* Explicit fitness. *(unbounded)* Implicit fitness (optimizing energy balance, maximizing off-springs). |
| Open-ended | Capability for unbounded evolutionary activity. | *(unbounded)* Unbounded metrics. |

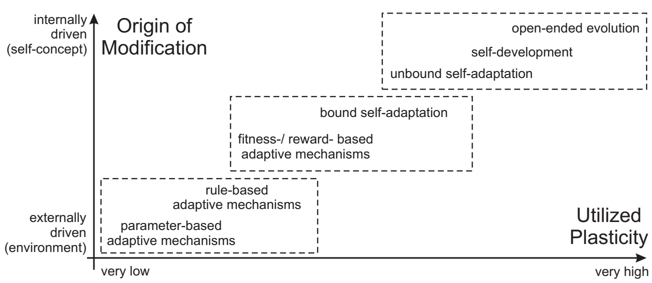



Figure 7. Three groups of adaptive and self-adaptive mechanisms placed along the used degrees of plasticity and origin of modification.

other; self-concept is more "system common" description and has more degrees of freedom. Normally, during adaptation, a system cannot change its own goal. However, during self-adaptation, a system can potentially change the design goals, i.e., self-adaption and goals can potentially be conflicting. When the plasticity is high, and the system can be hindered by adaptive processes from reaching the main goal, we are facing a new conceptual problem of a long-term controllability of adaptive and self-developmental processes.

There are several strategies to avoid conflicts between achieving design goals and self-adaptation. One of them is to formulate the self-concept invariant to possible adaptations. There are several mechanisms expressing such an invariant property of the generating level: symmetries, conservation laws or e.g. "templates". Templates are well-known in cognitive science [95] (also as "schemas" or "prototypes"), in topological research (in knot and braid theory) [96], as well as known as "frames" in the AI community [97]. The self-concept can be also expressed by symmetries, conservation laws, be planning- or fitness-driven or even have a character of unbounded metrics for open-ended evolution.

## VI. APPROACHING ADAPTABILITY OF ARTIFICIAL ORGANISMS FOR COLLECTIVE LOCOMOTION

To exemplify the discussed concepts of adaptation, self-adaptation and self-development, we consider the problem of collective locomotion for multi-robot organisms. Figure 8 shows a top-down view on a hexapod organism. The whole

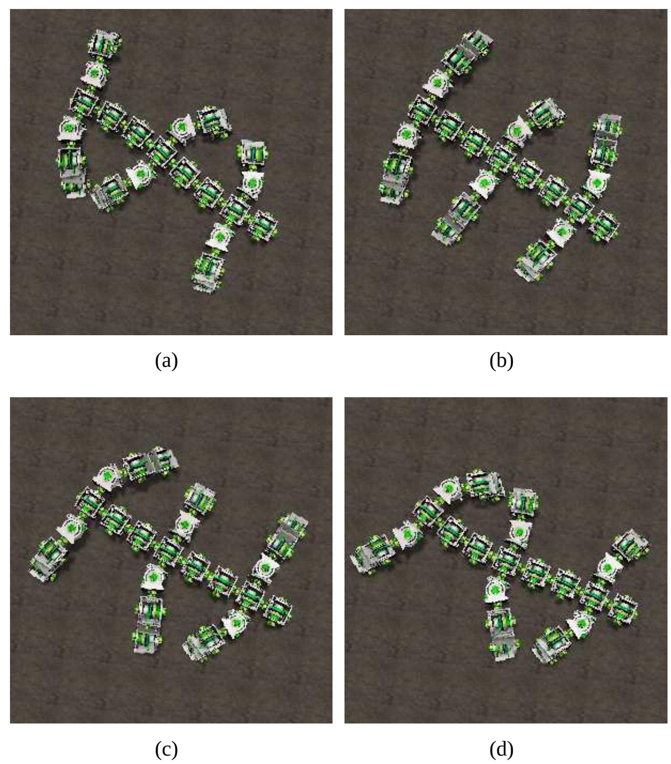



Figure 8. Top-down view on a hexapod multi-robot organism from Figure 9(a). Shown are four different positions of legs to illustrate a complexity of collective locomotion.

organism represents a collection of aggregated modules, which form the central vertebral column and six legs connected to the spine. Since 1DoF modules are connected in vertical and horizontal planes, legs as well as the vertebral column possess multiple angular and dispositional degrees of freedom, required for the legged locomotion. This organism moves on a flat surface without any obstacles; four different frames of this movement are shown.

From these images it is well visible, that the regular motion patterns (when there are no obstacles) can be split onto three different parts:

(a) Periodical (or rhythmic) activation of "active joints" (elements, which connect legs to the vertebral column).

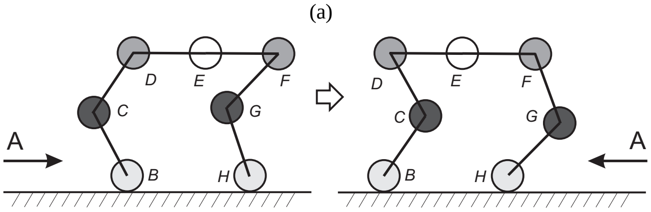
(b) Motion of legs in a vertical plane. This patterns is basically the same in all legs.

(c) "Rippling" of the vertebral column. The amplitude and frequency of this motion should be synchronized with active joints.

Basically, the motion without obstacles represents a classical controlling problem, which can be solved with e.g. kinematic analysis [98], evolved [32] or resolved by using bio-inspired approaches [99]. The problem of adaptation appears first, when an organism should overpass some obstacle, and this requires multiple co-depending changes of patterns (a)-(b). Moreover, the works on CPG, e.g. [100], indicate that any adaptive modification of the macroscopic multi-cellular behavior requires multiple correlations between individual degrees of freedom and, in the worst case, may essentially increase the complexity.

The need of multiple synchronization may be better understood in Figure 9, which shows the 2D section of an aggregated organism with several active joints in the front (two front legs). We assume that this structure is already created


(a)




(b)

Figure 9. **(a)** Artificial organism, front view; **(b)** 2D section of an aggregated organisms (two front legs with a section from vertebral column), circles are active joints. Shown are two kinematic states of this organism.

(or evolved) and represents some optimum of functionality for a locomotion without obstacles. Each of the aggregated modules possesses independent motors (degree of freedom, displayed by a circle) and can actuate independently of each other. In order to move as an organism, all these motors should perform synchronized individual actuations. There are several requirements, such as:

- the center of gravity should not overstep the nodes $B$ and $H$, other case the organism will be unstable;

- even in homogeneous case there are several non-symmetries caused by differences in docking elements, or more generally by different modules. This leads to non-symmetrical positions of several active nodes, like $C$ and $G$;

- we require that some structural nodes are e.g. strongly horizontal (vertical) as e.g. $D$, $E$ and $F$.

- all nodes have different load. This is indicated by different gray level of active nodes.

Each motor is controlled by a non-linear rhythmic driver, whose control parameters depend on internal sensors (e.g. torque of a motor). Without loss of generality, we say this represents a simple adaptive control on the functional level, where motors are first not connected with each other. This scheme is sketched in Figure 10. Now, we insert a

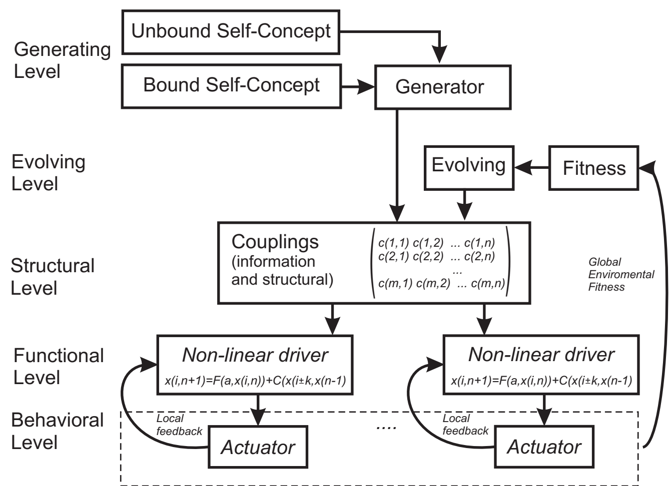



Figure 10. Different levels of adaptive collective locomotion.

structural level, which depends on a morphology of the organism. This level is represented by a coupling element $\underline{\underline{\mathbf{C}}}$, which creates "communication channels" between different nonlinear drivers (there are several different coupling elements $\underline{\underline{\mathbf{C}}}$ on e.g. structural and information levels). Since organisms create generally three dimensional structures, we expect at least a coupling between three elements (as e.g. a tensor of the third order). The coupling element contains values like $c_{ijk} = 1$ (direct coupling between drivers $i, j, k$), $c_{ijk} = 0$ (no coupling between drivers $i, j, k$), $c_{ijk} = -1$ (phase inversion between drivers $i, j, k$) or even any positive (amplification) or negative (decay) coefficients. Collective actuation depends on coefficients in these coupling elements.

As mentioned above, any non-periodical perturbation, e.g. motion with obstacles, requires multiple synchronization between elements, which firstly adapt the collective actuation of all motors; secondly takes into account stability constraints. There are three different mechanisms, which can be used in creating adaptive structure and functionality around $\underline{\underline{\mathbf{C}}}$. Firstly, individual rhythmic drivers use local adaptive mechanisms, know in the theory of adaptive control, as shown in Section VI-A. Secondly, drivers and $\underline{\underline{\mathbf{C}}}$ represent a coupled map lattice (CML) [101]. As we can see from Figure 9, nodes $B$, $C$, $D$, $F$, $G$, $H$ have the most intensive load, which can lead to a more stronger synchronization in $\underline{\underline{\mathbf{C}}}$, where as other nodes do not need any synchronization and their connection will disappear. In this way, synchronization effects in CML represent an emerging adaptability created by self-organizing processes between behavioral, functional and structural levels. This effect is similar to the observation in CPG with environmental coupling [102]. This approach is sketched in Section VI-B. Then, a structure of $\underline{\underline{\mathbf{C}}}$ (and so a collective locomotion) can be evolved, as described in Section VI-C. Here we face the problem of deriving such local and global fitness functions, which adapt a collective actuation within the framework of constrains.

The processes, mentioned above, lead to an adaptive macroscopic locomotion, e.g. when an organism encounters an obstacle. However, changes in collective actuation can be occurred even when an organism does not encounter an obstacle (just to remind this organism already reaches some optimum in fitness, i.e., these changes cannot be driven by an "old fitness"). To initiate such changes, we have to introduce a new "driving force", which is independent of particular obstacles. This will be then a self-adaptation, which takes place on the generating level, as shown in Figure 10. There are several proposals for bound and unbound self-concepts as shown in Section VI-D.

### A. Multi-functional, Locally Adaptive Rhythmic Motor Driver

As described in the previous section, individual motor drivers should demonstrate diverse dynamic behavior. In literature there are known different types of continuous rhythmic generators, e.g. [102], however due to technological reasons of controlling DC motors and running on a small microcontroller, we prefer time-discrete systems. Each time-step can be selected as small as possible, for example a few $\mu sec$ to guarantee a quality of control. Dynamic variables, e.g. $x_n$, represent voltage (current, phase), which are applied directly to DC-DC convertor or H-bridges. To obtain diverse dynamics, we use the idea of changing the determinancy order of normal form (NF) and the following perturbation of nonlinear terms [103]. This can be achieved when to use hierarchical non-homogeneous coupling for any well-know low-dimensional system, for example the logistic map. This approach is very common in the community (e.g. [104][105]). In our case, the map has the following form:

$$\begin{aligned} x_{n+1} &= cy_n + ax_n(1-x_n), \\ y_{n+1} &= cx_n + bx_ny_n(1-y_n), \end{aligned} \tag{1}$$

where $x_n \in \mathbb{R}$, $y_n \in \mathbb{R}$, $c$ is the coefficient of the linear coupling, $b$ is the coefficient of the nonlinear coupling, $a$ is the general bifurcation parameter. As turned out, the dynamics of (1) in fact has little in common with the initial logistic maps. The system (1) is denoted as the ordinary logistic-logistic (OLL) map. Several examples of qualitatively different types of behavior are shown in Figure 11.

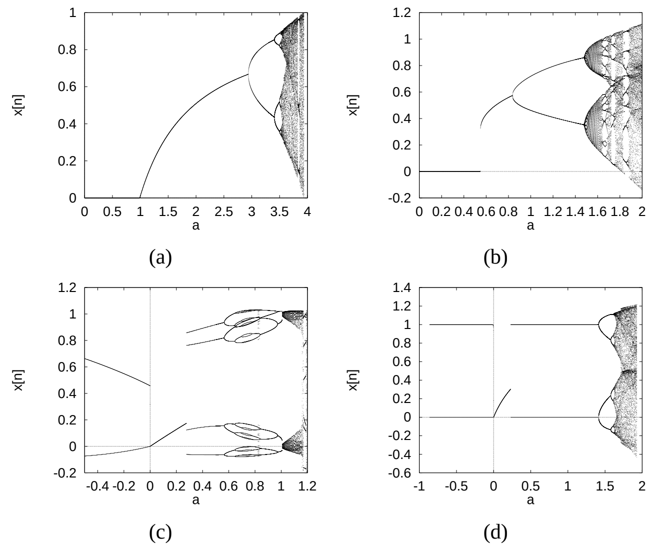



Figure 11. Several examples of qualitatively different types of behavior of the system (1). Bifurcation diagrams of the OLL map (1) at parameters: **(a)** $b = 1$, $c = 0.1$, $x_0 = 0.1$; **(b)** $b = 2$, $c = 0.6$, $x_0 = 0.4$; **(c)** $b = -1.5$, $c = -1$, $x_0 = 0.1$; **(d)** $b = -0.5$, $c = -1$, $x_0 = 0.1$.

As shown in [106], the non-homogeneous coupling in (1) increases determinancy order of initial NF. This can be understood as a perturbation of the original logistic map by couplings. In order to obtain all possible perturbed nonlinear terms, it needs to calculate the universal unfolding that is given e.g. by

$$G(\varphi_n, \lambda_u) = \alpha_1 + \lambda_u\varphi_n + \alpha_2\varphi_n^2 + \alpha_3\varphi_n^3 + \alpha_4\varphi_n^4 + \varphi_n^5 \tag{2}$$

with the codimension 4, where $\alpha_i$ are coefficients. We can see that non-homogeneous coupling method of OLL map changes the codimension of local bifurcation from 1 (transcritical bifurcation contained in the logistic map) to 4.

The approach (2) can be used for designing a programmable series of bifurcations so that to create a desired dynamics of the system (1). This allows us to use this system directly in the mechanisms of local adaptation. Coefficients $a$, $b$ and $c$ can be connected to locomotive sensors (for example a torque sensor). When a load on motor is increased, a local control mechanism (e.g. PID regulator [41]) adapts the coefficient $a$, e.g. to achieve the required torque on the given load. In the next section we will see several adaptive effects, which arise when many of individual motor drives, like (1), are connected into one system.

### B. Adaptive Mechanisms Based on Self-organization

Considering modular robots with the ability to dock to each other and to build multi-robot organisms, the problem occurs how to synchronize the behavior and especially the collective locomotion for different organism's topologies. Traditionally, such problems have been treated by using classical model-based methods. The developed controllers either use such model-based approaches or utilize bio-inspired or evolutionary algorithms. However, most of these approaches are not fully applicable for a large scale modular robotics because of a very high complexity, the huge amount of exchanged data and limited hardware capabilities. Most algorithms fail also due to the lack of scalability and adaptability. The development of new techniques for adaptive treatment of such problems is required.

In the last decades, several approaches from the field of non-linear dynamics have been applied to robotics, especially to solve the problems of locomotion in bipedal [107] or multi-legged robots [108]. The big challenge is still the synchronization between joints or legs so that the generated locomotive pattern become adaptive to environmental changes. Stable attractors provide often the best way to develop a system, which is able to generate several patterns by low-dimensional coupled equations with only a few control parameters. In multi-body systems with many degrees of freedom such methods allow reflecting the real dynamics only in a very limited way. Several attempts have been undertaken to use feedbacks in time-delayed nonlinear oscillators [109][110] or feedbacks based on resonance effects [111][112]. Such feedbacks can address several local and global properties of the dynamics, however currently achieved results target often very specific problems and lack in generalization to other applications. In this section we present an approach based on the Coupled Map Lattices (CML) [101], which focus on synchronization effects achieved in high-dimensional coupled equations.

Each site in the CML is considered as a unit (joint angle, hinge motor, link), which can be coupled with their neighbors through a coupling parameter. We use three different coupling structures: unidirectional or bidirectional coupled rings and four-connections-sites on a 2D lattice. Synchronization between the robots appears through the synchronization effect of spatiotemporal chaotic pattern, modeled by oscillating nonlinear equations. When synchronization appears in a region of the CML, this means that the communication between robots in this region is rapidly decreased and the corresponding part of the organism performs a synchronized movement.

In the first scenario we analyzed the one-dimensional ring-coupled topology (Figure 12). As a "basic" system we use the homogeneously coupled logistic map (Figure 11 (a)). Each site can be additively coupled with their left and/or right neighbor sites either in unidirectional or in bidirectional way. Synchronization appears due to interactions between non-identical systems, which leads to a locking of their phases, whereas their amplitudes remain uncorrelated. As the first test system we take the unidirectional ring map lattices of the length $m$:

$$\begin{aligned} x_{n+1}^i &= (1-\varepsilon)f(x_n^i) + \varepsilon(f(x_n^{i-1})) \\ x_n^{i+m} &= x_n^i \end{aligned} \tag{3}$$

where $x_n \in \mathbb{R}$, $i = 1, 2, ..., m$ and $n$ represent the dimensions of the CML. $f(x_n^i)$ is the logistic map

$$f(x_n^i) = ax_n^i(1-x_n^i). \tag{4}$$

Important parameters are the small coupling parameter $\varepsilon$ that denotes the strength of nearest neighbor coupling and the bifurcation parameter $\alpha$.

Figure 12. Multi-robot organism connected to a ring.

Experimental results show that the synchronization between sites occurs within $0.16 \leq \varepsilon \leq 0.19$, observable as bright areas in Figure 13. During the iteration process, in order to simulate a disturbance, we apply a small fluctuation in the bifurcation parameter $\alpha$, which can be e.g. associated with a disturbance in the communication load. Such a disturbance in turn can be referred to some disturbances in the environment (i.e., obstacles, environmental changes or sensorimotor disturbances). In Figure 13, the bifurcation parameter was slightly disturbed for a short time period and after few time steps when perturbation stopped, the system becomes again synchronized (area in boxes).

Further analysis of the local and global impact has been done by investigating the impact of disturbances in small separated regions (Figure 13 (a)) or if the disturbances appear in local neighborhoods (Figure 13 (b)). As it can be observed in these figures, better synchronization effects occur if a perturbation appears in the sites that are close to each other (local impact). In a multi-robot organism, this means that units in a local range (one leg, arm etc.) perform better synchronization than robots far away from each other.

In the next test scenario we extended the model by coupling the sites with both left and right neighbors (bidirectional coupling). We took again a ring map lattice of the length $m$

$$\begin{aligned} x_{n+1}^i &= (1-\varepsilon)f(x_n^i) + \tfrac{\varepsilon}{2}(f(x_n^{i-1}) + f(x_n^{i+1})) \\ x_n^{i+m} &= x_n^i. \end{aligned} \tag{5}$$

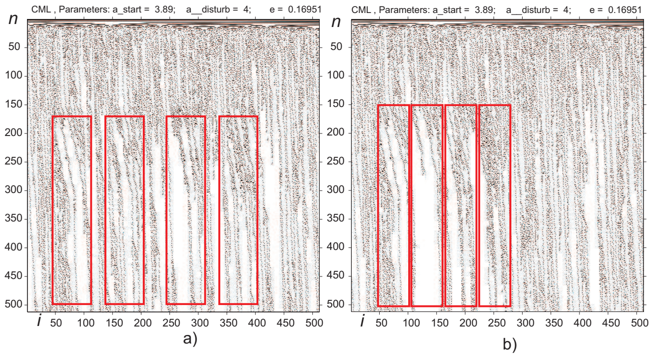



Figure 13. One-way coupled map lattice. Initial conditions: $x_1^i = 0.1 + 0.0000049i$. Boundary conditions: $x_1^i = x_m^i$; **(a)** disturbances (i.e. motor voltage drops) are simulated in a large distance and do not significantly affect each other; **(b)** disturbed sites are in local range and affect more each other than in (a).

In order to get a homogeneous coupling the coupling parameter $\varepsilon$ is divided by two. We observe similar synchronization effects like in the previous experiment in sites that are nearby or far away from each other.

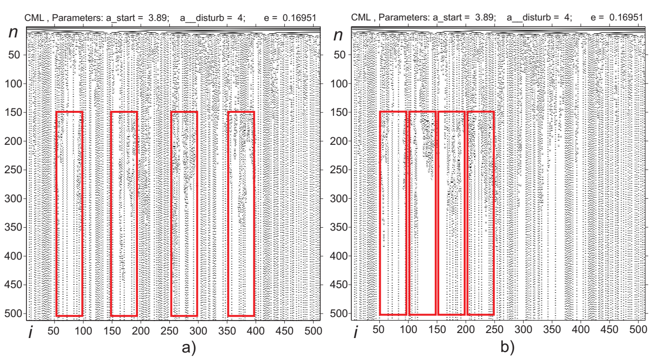



Figure 14. Two-way coupled map. Initial condition: $x_1^i = 0.1 + 0.0000049i$. Boundary condition: $x_1^i = x_m^i$; **(a)** disturbances are simulated in a large distance and do not significantly affect each other; **(b)** disturbed sites are in local range and affect more each other than in (a).

Open or closed chains are the basic structures in many robotic systems since robots often consist of legs and arms. In simulation above we analyzed and developed mechanisms focusing on achieving a synchronized locomotive behavior for multi-robot organisms with only chain-like structures. Now we extend this idea for multi-legged robots with three dimensional topologies. To achieve this, the dimensionality of Equation 5 increased. In this case, the coupling can be performed in all four directions

$$\begin{aligned} x_{n+1}^{i,j} = & \quad (1-\varepsilon) f(x_n^{i,j}) + \tfrac{\varepsilon}{4}(f(x_n^{i-1,j}) \\ & \quad + f(x_n^{i+1,j}) + f(x_n^{i,j-1}) + f(x_n^{i,j+1})) \\ x_n^{i+m,j+m} = & \quad x_n^{i,j}, \end{aligned} \tag{6}$$

where $i, j = 1, 2, ..., m$ represent the system's size. For each time step we generate a separate 2D lattice and perform the time analysis (Figure 15).

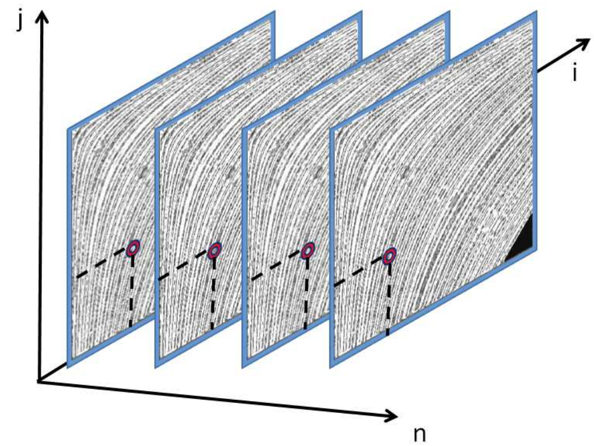



Figure 15. Time evolution through 2D CML sites.

Like in experiments with serial couplings, in order to analyze synchronization properties of 2D spatial lattices, we temporary disturb the bifurcation parameter in a block-shaped regions (Figure 16). It can be considered e.g. as a disturbed part of a multi-robot organism (legs, arms etc.).

The results in Figure 16 show that a small perturbation of $\alpha$ does not cause a chaotic behavior like in the previous experiments for serial coupled sites, but leads instead to a phase synchronization. The reason is the asynchronous updating of the sites [113]. This approach not only synchronizes locomotive behavior but also allow forcing the organism to change the locomotion pattern. In Figure 17 different conceptual layers for the whole framework are introduced: Couplings-, CML-, Actuator-, and the Organism Layer.

In the Couplings Layer (Structural Level), we generate the coupling matrix $\underline{\underline{\mathbf{C}}}$ mentioned in Section VI. This matrix maps the topology of the multi-robot organism by inserting ones and zeros as matrix elements. According to the structure of the coupling matrix the corresponding areas in the CML are activated (one) or not activated (zero). On CML Layer (Functional Layer), we perturb the sites in the activated areas from the Couplings Layer and can observe phase propagation and as well as active phase shifting effects if required (Figure 16). All non-activated sites in the CML can be considered as virtual modules, which do not exist in reality, however are required in order to generate the phase synchronization patterns.

At the Actuator Layer (Behavioral Layer), standard controllers (PI, PID control etc.) can be applied and are often a part of servo motors. Such controllers are well-known from the theory of control and enable motors to follow the generated phase patterns. By learning the phase patterns generated by different perturbations in $\alpha$, we are able to use this knowledge and actively apply it to generate desired locomotion patterns. The bifurcation parameter $\alpha$ is hence

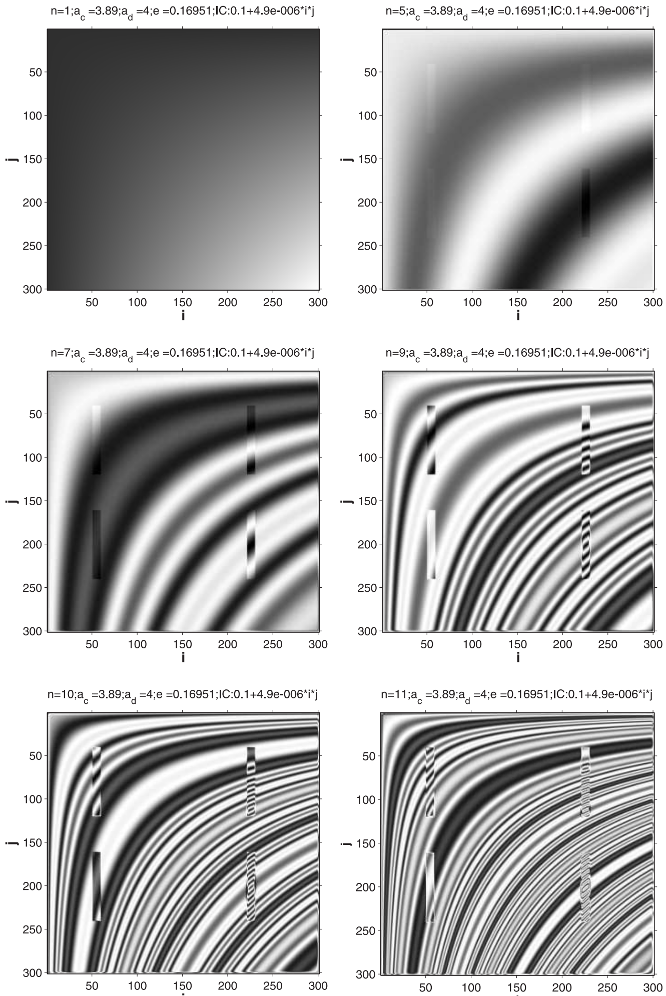



Figure 16. Phase pictures of 2D CML with four disturbed regions.

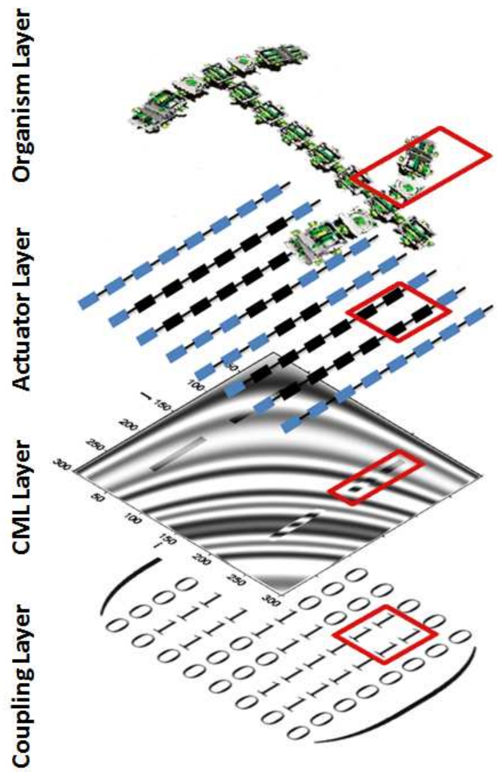



Figure 17. Architecture of Active Phase Perturbation Approach for Locomotion. This figure demonstrates how the CML based approach can directly referred to real robotic applications.

$$
\begin{aligned}
x^{i,j}_{n+1} &= (1-\varepsilon)f(x^{i,j}_n) + \tfrac{\varepsilon}{4}(f(x^{i-1,j}_n) + f(x^{i+1,j}_n) + \\
&\quad f(x^{i,j-1}_n) + f(x^{i,j+1}_n)) + \varepsilon_1 f(x^{i+\Delta i,j}_n) \\
&\quad + \varepsilon_2 f(x^{i+\Delta i,j+\Delta j}_n) \\
x^{i+m,j+m}_n &= x^{i,j}_n,
\end{aligned}
\tag{7}
$$

a control parameter for the phase regulation and can be adapted in runtime.

The activated sites in the Coupling Layer can be additively coupled with other activated areas by additional terms and with different coupling parameters (e.g. $\varepsilon_1, \varepsilon_2$). The coupled sites represent four main links of each leg of the robot organism. The idea behind this approach is to synchronize all four links for achieving desired gaits (walking, trotting, galloping etc.). Depending on the structure of gait, links can be connected in parallel or crosswise, see Figure 18 (top), and can also be adapted dynamically to different situations. Therefore, additional coupling terms have been added to the equation 6, here exemplary a weak coupling $\varepsilon_1$ between links one (upper left) and two (lower left) and between links three (upper right) and four (lower right). The coupling parameter between links one and four and between two and three is $\varepsilon_2$ and is in this example much stronger than the $\varepsilon_1$

where $\Delta i$ and $\Delta j$ are distances between CML sites that represent the links. In order to analyze temporal effects of the phase propagation we need to pick the areas of interest and go through the time steps of the 2D map (Figure 15).

By choosing different values of coupling parameters we are able to synchronize the links for different locomotion patterns. As it can be exemplary observed in the Figure 18, legs can be synchronized for instance pairwise and in a cross-wise manner. It is of course not trivial to find always the suitable coupling parameter set, therefore evolutionary and learning approaches can run in parallel and learn it for achieving a good fitness.

As a conclusion to this section, we summarize our results. Using methods from non-linear dynamics and self-organization, we applied a CML-based approach for achieving synchronization between different limbs of a multi-robot organism. We analyzed serial as well as 2D coupled maps and also analyzed local and global impact of occurred disturbances.

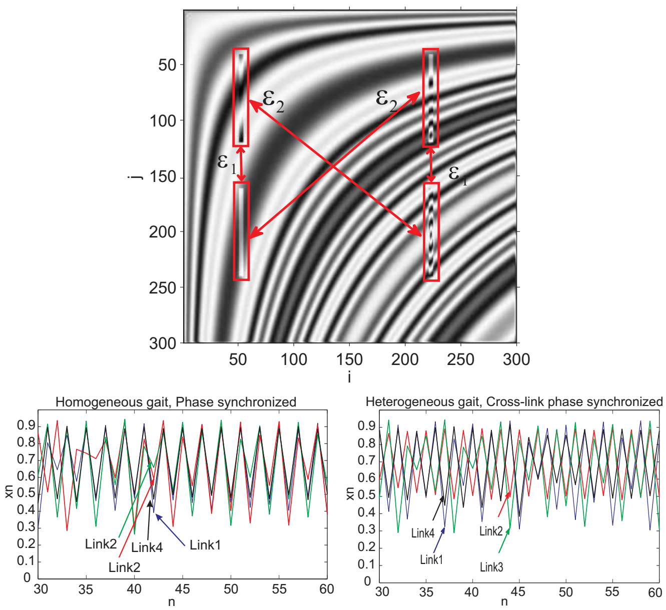



Figure 18. Time evolution of non-coupled (left image) and coupled (right image) sites in the activated areas for the four main links of the robot organisms. Coupling parameter are: $\varepsilon_1 = -0.01$ and $\varepsilon_2 = -0.001$. When system gets synchronized it can be observed that links one and four (blue and black lines) as well as the links two and three (red and green lines) get synchronized crosswise.

### C. Fitness Driven Adaptability

Because it is very hard, to break down a desired behavior into the individual behavior of each robot in a swarm or in a multi-robot organism [17], we support the adaptation process with bio-inspired evolution. Especially, in unpredictable environments, when robots are able to (dis-)aggregate or modules may fail, pure classical approaches can perform suboptimal. Therefore, in addition to the adaptive mechanism based on self-organization from the previous section and artificial evolution of controller design, we adapt the robots by use of evolutionary concepts.

Figure 19 depicts the idea of the evolutionary concept. The key element is the genome, which contains the codified coupling matrix $C_{ijk}$ and control parameters. This genome maps to the coupling of motors within the organism and thus to the behavior of the organism. Based on the previous section, the coupling strength can flow into the equations and extend the existing couplings. Detached from structural coupling, even functional coupling of not physically linked robots can evolve. For example the front left leg of a hexapod-like robot is not physically linked with the left back leg, but has to be synchronized in order to move. Even so, the strength of the coupling of two individuals can vary. Thereby, different strengths of the coupling lead to different behaviors. In order to adapt to a certain structure, which requires a non-trivial coupling, the strength of the couplings evolves.

A crucial point for evolution is the feedback from the

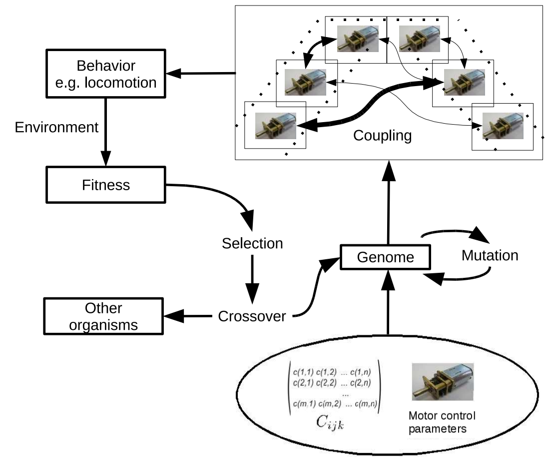



Figure 19. Evolutionary Concept: The genome contains the coupling matrix and parameter of the robot organism. This genome can be evolved over time and thus affects the behavior, respectively adapts the behavior. Through environmental and local feedback, the current fitness can be measured and optional crossover operators with other organisms can be applied.

environment. By evaluation of the current coupling structure in respect to a desired task (e.g. locomotion), a fitness value measures the performance of an organism in the current environment. In case of locomotion the fitness function could be influenced by multiple factors like power consumption, number of couplings (high number of coupling may lead to higher communication traffic) or velocity of an organism.

To cover each point potentially in the search space, mutational operators are used. This mutations can range from a single random change of a coupling entry to complete swapping of areas within the coupling matrix. In an environment with multiple organisms, we can use the evolutionary principle of cross-over. Two or more organisms can exchange their coupling matrices to each other. Depending on the fitness value of both parents, a total or a partial exchange of the genome can be done. The new structure can be either placed in one individual or in both.

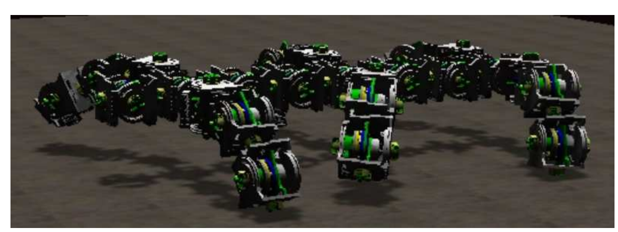


Figure 20. Exemplary hexapod organism in simulation.

For the design of controllers and the evaluation we use the Symbricator simulation [114]. Beside rings and caterpillar-like organisms we are interessted in legged organisms (like quadrupped or hexapod organisms, see Figure 20). The comparison of multiple (symmetrical and asymmetrical) shapes and the corresponding coupling matrices with the reached fitness values (in simulation) can lead to very efficient organisms and locomotion patterns. In the final stage, we want to pre-evolve the controllers in the simulation and deploy them afterwards to the real hardware. This will speed up the time for development and prevent hardware of critical damages. In a downstream step, the mechanism can adapt the robot online and onboard to unpredictable environments and changes during actual operating time.

### D. Bound Self-concept and Structural Generation

Previous sections demonstrate examples of different adaptive processes on functional, structural and evolving levels. In this section we briefly introduce the generating level and self-concepts. As mentioned, adaptive and self-adaptive structures differ in two important points: adaptation uses environment for generating changes, whereas self-adaptation uses the self-concept for this purpose. Moreover, the self-adaptation is formulated in a more broad way than adaptation; to implement this, we need to integrate structural and functional generators into the system's architecture.

Thus, to utilize self-adaptive approach, we need to involve bound or unbound self-concepts and a generating mechanism. Several concrete examples of unbound self-concepts based on information theory are introduced in [1][10]. The unbound self-concept initiates unlimited (open-ended) growth of diversity and complexity; the treatment of this issue oversteps the framework of this paper. To explain the idea of self-concept for the structural generator, we focus on the bound case. The bound self-concept is invariant to adaptive processes. There are several mechanisms expressing such an invariant character of self-adaptation on the generating level: symmetries, templates and conservation laws, production, decomposition rules as well as self-reference. In this work we can briefly demonstrate the use of symmetries and symmetry breaking [115] for structural generation as well as ideas of developmental modularity [116] expressed in the form of "templates" for functional generation.

The most obvious way to generate well-scalable structural symmetries is to create a circulant [117] coupling

$$\underline{\underline{\mathbf{C}}} = \begin{pmatrix} T & 0 & c_1 \\ 0 & T & 0 \\ c_{n-1} & 0 & T \end{pmatrix}, \tag{8}$$

where $\underline{\underline{\mathbf{T}}}$ is a Toeplitz band matrix [118]

$$\underline{\underline{\mathbf{T}}} = \begin{pmatrix} c_0 & c_{n-1} & c_{n-2} \\ c_1 & c_0 & c_{n-1} \\ c_2 & c_1 & c_0 \end{pmatrix} \tag{9}$$

(taking into account dimensions $n$ for $\underline{\underline{\mathbf{C}}}$ and for $\underline{\underline{\mathbf{T}}}$). The idea of introducing $\underline{\underline{\mathbf{T}}}$ consists in making topology and kinematics scalable to the size of this body. In this way, the basic building block is defined by circulant coupling $\underline{\underline{\mathbf{C}}} = circ(c_0, c_1, c_2, ..., c_{n-1})$. Well-known property of circulant coupling is a possibility of its diagonalization by the Fourier matrix

$$\underline{\underline{\mathbf{F}}} = \frac{1}{\sqrt{n}} \begin{pmatrix} 1 & 1 & 1 \\ 1 & w & w^2 \\ 1 & w^2 & w^4 \end{pmatrix}, \tag{10}$$

where

$$w = \cos(\frac{2\pi}{n}) + i\sin(\frac{2\pi}{n}). \tag{11}$$

The eigenvalues can be calculated as

$$\lambda_j = \sum_{i=1}^{n} c_i (w^{j-1})^{i-1}. \tag{12}$$

Maximal eigenvalue $\lambda_{max} = \lambda_1 = \sum_{i=1}^{n} c_i$, i.e., when circulant coupling has only a fixed number of $c_i$ for any $n$, the stability and several other properties of $\underline{\underline{\mathbf{C}}}$ are invariant to the dimension of the whole system. Both, circulant and Toeplitz band matrices demonstrate ideas of invariances in the self-concept. From the view point of the group theory, $n \times n$ circulant can be viewed as a cyclic group $Z/nZ$ of order $n$ and can be generated by a generator $g^n$ in $Z/nZ$. The generator $g^n$ can represent a particular example of the bound self-concept, applied to generate scalable topological structures of an artificial organism.

To integrate symmetry breaking constrains into the topological self-concept, we can use the approach [119] in the form of [120]. Kiziltan and Milan in [120] defined four generators: $R_f$, $C_f$, which the flip first two rows/columns of a matrix and $R_s$, $C_s$, which shift the first row/column to the last position. For any generators, the notation $g \circ g = g^2$, (e.g. $R_f \circ R_f = R_f^2$) is used. Any two matrices are equivalent when they are obtained from each other by applying any of $R^n C^n$ generators, e.g. $3 \times 3$ coupling $\underline{\underline{\mathbf{C}}}$ has 36 symmetrical matrices. The idea of breaking a symmetry is to apply constrains, which order all symmetric objects, like the proposed lexicographical order [119].

Another concept behind self-generation are so-called templates. They are well-known in cognitive science [95] (also as "schemas" or "prototypes"), in topological research (in knot and braid theory) [96], as well as known as "frames" in AI community [97]. The idea of a template is to describe most general "stereotypical" properties or features of some common classes of situations/processes/objects. Concrete instance of a template can be reconstructed or generated by parametrization. There are several attempts to find an universal template, however it seems that different classes of solutions need different templates.

Since we are focusing on dynamic properties of collective actuation, we can assume each motor is driven by a periodic control. In this way a collective actuation represents a system of coupled oscillators with adaptive feedback, as e.g. described in [102]. As known, such systems possess self-adapting properties. Specific (desired, required) dynamic motion pattern can be generated when to parameterize the CML-driving-system with a specific set of control parameters as well as to provide a way to change these parameters, see Figure 21. Thus, we can map the problem of finding a dynamic template to the problem of finding such a bifurcation dynamics, which property reflects the needed changes. Speaking more technically, we are looking for universal

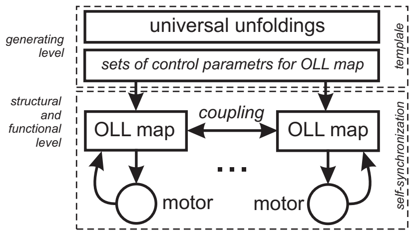



Figure 21. Template for collective locomotion.

unfolding [103]. Obviously, that universal unfolding together with parameter sets can be viewed as templates for collective actuation. Unfolding can be explained in the following way: let the normal forms of a local bifurcations be given by

$$\begin{aligned}\underline{\mathbf{q}}_{n+1} &= \underline{\underline{\Lambda}}_u(\{\alpha\},\{\beta\})\underline{\mathbf{q}}_n + \underline{\mathbf{g}}^{(2)}(\underline{\mathbf{q}}_n,\{\alpha\},\{\beta\}) + \\ &+ \quad ... + O(\underline{\mathbf{g}}^{(r+1)}), \end{aligned} \tag{13}$$

where the term $\underline{\underline{\Lambda}}_u$ presents the diagonal matrix of eigenvalues, $\underline{\mathbf{g}}$ are the resonance terms, dependent on both $\{\alpha\}$ and $\{\beta\}$ and $r$ is the determinancy order. Universal unfolding includes all possible perturbations of this normal form, which are equivalent to original bifurcation problem [103]. In this way, unfolding represents in some sense an invariance to perturbations. Finding universal unfolding allows defining the most general form of the desired dynamics, i.e. template. From the view point of dynamics, the universal unfolding can represent a bound self-concept, applied to rhythmic gait control.

## VII. Conclusion

This paper has two main goals. The first goal was to demonstrate a common picture of adaptive processes and to represent key differences to self-adaptive mechanisms, which include bound and unbound self-concepts. Secondly, it was intended to exemplify these high-level concepts by one concrete example of collective locomotion in reconfigurable robotics.

The self-concept describes a goal of the system in some invariant form, such as symmetries, optimization principles, templates or information-based metrics. It can even generate an unlimited complexity and diversity, as proposed by von Neumann, in L-Systems as well as in self-referred dynamics [30]. It was argued that the origin of changes should be considered as the main difference between adaptation and self-adaption, and not the application of concrete approaches. Since self-adaptive mechanisms provide more degrees of freedom for modifications of behavior, functions or structures, corresponding generators should be integrated into the system's architecture. The self-adaptation and self-development overlap in several points; both concepts are driven in parallel by different communities. To provide consistency in logic of these notions, the self-development is considered to be more general ontogenetic mechanism, related to cognitive structures and their embodiment.

The introduced ideas are exemplified by the problem of collective locomotion in aggregated multi-robot organisms. Self-organizing and evolving adaptive mechanisms for the motion with obstacles have been considered. The synchronization of oscillators for motor drivers can reduce complexity of adaptive mechanisms. It was indicated that for performing further structural and functional changes without obstacles, another driving mechanism on the generating level should be used. Examples are given by symmetries and symmetry-breaking effects in structural matrices, templates or universal unfolding, which can represent a bound self-concept for functional and structural cases.

Several problems remain unsolved. Firstly, the coupling $\underline{\underline{\mathbf{C}}}$ in Figure 10 involves much more diverse structural and functional elements. It seems there is a complex dependency between structural and information couplings, which finally emerges a collective functionality. The whole framework around $\underline{\underline{\mathbf{C}}}$ requires more attention. Secondly, the structural self-concept based on symmetries of $\underline{\underline{\mathbf{C}}}$ can regulate morphodynamics of artificial organisms. However, it is completely unclear, how this concept can work with a more "high-level functionality", e.g. cognitive or hemostatic regulation. Finally, approaches in Sections VI-A – VI-D are only briefly sketched to indicate the used mechanisms. Experimental results for these sections are omitted, since these do not contribute to the main goal of this paper. It needs another work, which concentrates on these approaches and on a multitude of nonlinear effects appearing in them.

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