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Adaptive system design by a simultaneous evolution of morphology and information processing

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Abstract. The continuous need to increase the efficiency of technical systems requires the utilization of complex adaptive systems which operate in environments which are not completely predictable. Reasons include the often random nature of the environment and the fact that not all phenomena can be explained in full detail. As a consequence the developer often gets confronted with the task to design an adaptive system with only little prior knowledge about the problem at hand. The design of adaptive systems, which react autonomously to changes in their environment, require the coordinated generation of sensors, providing information about the environment, actuators which change the current state of the system and signal processing structures thereby generating suitable reactions to changed conditions. In this work we demonstrate the applicability of a concurrent evolutionary design of the optimal morphological configuration, presented as sensory and actuation systems, and the corresponding optimal controller part of a system. We apply the process to the example of an adaptive wing design. Prior experiments for the optimization of the systems, having fixed number of sensor and actuator elements demonstrate the existence of an optimal dimensionality of the systems morphology. We show that the presented growth method is able to detect this morphological configuration and concurrently find the optimal corresponding controller autonomously during a single combined evolutionary process.

1 Introduction

The evolutionary development of higher animals can be seen as a complex process of ongoing body-brain complexification to better adjust to the environment. Since the morphology of the body is tightly coupled to the brain structure, these two functional parts of living creatures are supposed to co-evolve. Admittedly,

an addition of new sensory inputs does not give an individual a performance advantage without the adjustment of a corresponding signal processing structure. Analog to the development of complex living systems, we assume that the design process of technical solutions with high complexity could be improved by starting the system development with an initially simple system organization while performing simultaneous complexification of its functional parts. The majority of the current engineering methods adapt isolated parts of the overall structure, which is in a strong contrast to biological body-brain co-evolution. The design of adaptive systems implies a selection of sensors and actuators, which adjust the system to a changed environment, as well as a generation of a corresponding controller, according to a predefined quality measure. The developers usually design the morphological part, defined as sensors and actuators of the system separately from the development of the corresponding controller unit. This approach has been a usual practice in a field of evolutionary robotics. First, the real mobile robots have been given fixed morphological limitations, such as fixed number and resolution of camera system, fixed joints angles range etc. Than through the following optimization of controller structure a complex behavior, like for example an obstacle avoidance tasks of a robot, can be achieved. Examples of this approach can be found in Brooks [1], Dorigo and Schnepf [2], Cliff, Husband and Harvey [3], Floreano and Mondada [4], Miglino, Nafasi, Taylor [5].

The weakness of the approach is that the controller performance strongly depends on the suitability and the amount of sensory information, as well as on the actuator resources. This causes the problem, that the optimal system performance is difficult to be achieved, if not all detailed phenomena about the system are known during the first phase, in which the hardware configuration is defined. Otherwise it can happen, that some important information about the environment or an actuator at the position in the structure, having a major impact on the system performance, is missing. As an attempt to overcome the problem, we could optimize an initially very rich system, having high number of sensory and actuation elements. This would statistically decrease a chance of missing important environmental factors during the sensors acquisition. However, the optimization progress of the system having a large scale dimensionality might be not possible due to the high number of optimization parameters. To solve the problem we implement a growth method which synchronize the design process of sensing and signal processing system parts during optimization process and additionally frees the system of early structural limitations. Therefore it gives a possibility to develop a system autonomously to optimal morphological configuration.

A variety of approaches for the co-evolutionary design of morphological and controller configurations have been developed in the field of evolutionary robotics. Early work in the field of automatic design of a systems by body-brain co-evolution has been reported by Sims [6]. He demonstrated the evolutionary development of the morphology of virtual creatures in a physical simulation fulfilling simple locomotion tasks starting from simple building blocks without any prior knowledge. Parker and Nathan [7] researched the design of sensor

morphology and controller for a simulated hexapod robot. For this purpose the type of sensors, the heading angle and the range of the sensors as well as the rules for the controller are co-evolved. This method enables the system to extract information from the environment which is relevant to complete a given task by configuring a minimal controller and minimal number of sensors and actuators to increase the system's overall efficiency. Bugajska and Schutz [8] co-evolved the shape and strategies in the design of Micro Air Vehicles (MAV). The target, similar to Parker and Nathan, was to find a minimal sensor suite and reactive strategies for navigation and collision avoidance tasks. Sugiura et al. [9] also proposed a system that automatically designs the sensor morphology of an autonomous robot with two kinds of adaptation: ontogenetic and phylogenetic adaptation. Gomez, Lungarella, Eggenberger, et al. [10] extended the principle of sensor-control balance to developmental enlargement of the system by simultaneously increasing the sensor resolution, the precision of motors, as well as the size of a neural structure (controller). They showed with their experiments that a chosen system starting with a low-resolution sensory system, a low precision motor system, and a low complexity of controller, can learn a given task faster than a system with a complex configuration already in the beginning. The coordination of the growth process was realized through internal learning mechanisms where the active neural units controlling the robot were 'rewarded' or 'punished' depending on the improvement or aggravation in task fulfilling. The authors showed the advantages of concurrent optimization of the sensory and control systems as a dynamic developmental process of gradual complexification. Also Auerbach and Bongard [11] have made extensive research in the field of co-evolution of morphology and control in evolutionary robotics. In their work they implement a growth mechanism to create robots using compositional pattern-producing networks and demonstrate that the concurrent development of the morphological and controller structures of the simulated adaptive robots can give an advantage for the final system performance, compared to the approaches with separate design strategies.

The promising results of the co-evolutionary approach in evolutionary robotics motivated us to implement the biologically inspired growth process for the coordination of the fully autonomous development of sensor, actuator and control structures without dimensional limitation of sensory or actuator setup in the early stages of development. Since the final system configuration is not predefined and is the result of the concurrent optimization process, we expect an evolvable system through enlargement of the search domain and potentially increase the chances of global optima detection. Compared with the reviewed research in evolutionary robotics, we utilize the co-evolution of morphology and information processing structure for the optimal control of an adaptive wing shape. Although the generation of optimal control for adaptive wings is not in the main focus of our research we argue that this problem is a suitable test bed for the research on evolutionary design of adaptive systems. Aerodynamic problems are characterized by highly complex interactions between flow body and flow field which is in most cases difficult to understand in detail. Due to this, the

manual design is generally challenging although excellent tools are available for their simulation and evaluation. In this work we demonstrate that evolutionary methods are able to generate systems which can optimally adapt to environmental conditions, while at the same time we target shedding some light on the precise synchronization of system parts during the developmental process.

In our previous work [12] we implemented the co-evolutionary growth of a sensory and controller structures given a fixed actuation system on the example of the adaptive wing. The promising results motivated us to expand the research to the combined development of all functional parts of the system. In this case the overall system configuration is fully variable during the optimization and initially minimal. Additionally we implemented cost factors for sensors and actuators, which result in a limited growth of the system dimensionality. In this case a system gets a new sensor or actuator only if it gives a significant benefit to the system performance. The target for the optimization of the adaptive wing is the reduction of the drag the airfoil generates while still creating a minimum of lift. Environmental changes are realized through the changes in the angle of attack of the airflow across a wide range of values. The co-evolutionary system development has been implemented as a structural growth process of all it functional parts, such as the number and position of the sensors and actuators and the complexity of the controller structure, defined by its input (sensors) and output (actuators) dimensionality. We show the results of the sensors-actuators-controller growth method and compare them with the optimization of the system with fixed morphological settings as well as with the results of the growth of sensors-controller systems, having a fixed actuation system.

A description of the framework of the adaptive wing with a detailed explanation of the functional set-up of the sensory, actuation and controlling systems is given in section 2. In section 3 we explain and present the results of the experiments with implemented growth method, and compare them with optimization results for a fixed morphology as well as with the results of the growth of sensory and controller systems. Finally, we conclude the paper with a summary of the main findings of our work.

2 FRAMEWORK FOR MORPHOLOGY-CONTROLLER CO-EVOLUTION

In our work we implemented a system, consisting of virtual sensors, actuators and a signal processing structure. The signal processing structure controls the adaptive system under changing environmental conditions by generating actuator signals based on sensor signals derived from the environment. The target has been to achieve a system behavior which reduces the airfoil's drag, calculated in a CFD (computational fluid dynamics) simulation of the resulting airfoil shape while maintaining specified lift values. The actuator signals correspond to changes of NURBS [13] control points and define the current airfoil shape. The virtual sensors of the system have been defined as pressure sensors, at given positions on the airfoil surface. The measurement results of the virtual sensors

correspond to the surface pressure calculated in the CFD simulation and therefore depend on the blade's surface, the angle of attack and the speed of the air flow etc. Fig. 1 (a) shows the described relations between the single parts of

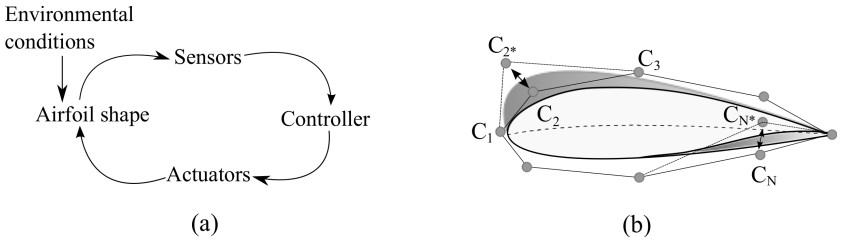


Fig. 1. (a) Adaptive airfoil framework, (b) Example of the airfoil created with NURBS. Airfoil in white, defined by the initial positions of the spline control points. The airfoil shape change (in gray) results from the movements of C_2 and C_N

the test-framework. The described setup allows us to simulate the interactions between control structure and morphology during the operation of the control structure as well as during their evolutionary development.

The two dimensional airfoil is represented by a non-uniform rational B-splines (NURBS) as shown in Fig. 1 (b). The shape of the NURBS curve is determined by the set of spline control points C_n. For the simulation of the aerodynamic airfoil characteristics and pressure distribution the computational fluid dynamic solver Xfoil[1] is used. In the simulation we change the angle of attack in order to generate variations of the airfoil environment. The Reynolds number has been fixed during the optimization ($Re = 10^7$). The pressure coefficient over the airfoil surface represent the virtual sensor data. We used Xfoil to calculate the profile of the pressure coefficients at 160 points on the airfoil surface. The more detailed description of the implemented framework can be found in [12], [14].

The presented adaptive system of a virtual wing requires a suitable controller for processing of sensor data and generating actuator signals. The actuators morph the surface of the airfoil and therefore can reduce the drag and generate the required lift. A wide variety of possible controller designs for similar purposes can be found in the literature. Parker and Nathan [7] as well as Bugajska and Schutz [8] implemented a controller as a reactive system which uses "if...then" rules to control a simulated robot. Haller, Ijspeert and Floreano [15] implemented a controller inspired by the central pattern generators underlying locomotion in animals. In this work we implemented a linear recurrent model to control the presented adaptive system. The controller input signals are the pressure coefficients s_i. The outputs of the controller are the actuator signals C_o and describe the position of the virtual actuators in the two dimensional space. The actuator adjustments ΔC_o are calculated as the sum of the signals of all sensors

[1] http://web.mit.edu/drela/Public/web/xfoil/

of the system multiplied with the corresponding linear coefficients K_{io}. The current state of the actuators C_o determines the pressure coefficients s_i by the nonlinear air flow function f, simulated with Xfoil solver.

3 SENSOR-ACTUATOR-CONTROLLER CO-EVOLUTION

The co-evolutionary approach has been realized by the concurrent development and gradual complexification of the sensory, actuation and corresponding controller systems. Although these different functional parts of the system are coded in a single genome, the described optimization process reflects the main aspect of the co-evolutionary process, since all units are mutually co-adjusted during the entire evolutionary process. In this work we combine the co-evolutionary method with a growth process and implement it as a single dynamic optimization task. We use standard evolution strategy optimization, ES(15,100) developed by Bienert, Rechenberg and Schwefel [16] to optimize the overall system configuration. Although more sophisticated algorithms are available like CMA-ES [17], we stick to the comparable simple strategy which can also be applied in the growth process. A single genome of the individual includes four chromosomes which code the position of the sensors and actuators as well as the controller parameters and additionally the strategy parameters (mutation step sizes). Offspring are the result of the gene intermediate recombination and mutation of the parent individuals with the current mutation step size. The optimization has been implemented, using SHARK[2], open-source C++ machine learning library. One of the important advantages of the growth process is a minimal requirement on the prior knowledge about the system. The growth process shows fast convergence in small search spaces, since it starts with an initially elementary system. Thereby we free the system from the early limitations and allow it to develop autonomously into a final system, having as simple morphology as possible, optimally positioned in the structure and in the same time having an optimal signal processing structure for the given morphology.

The results of our previous work in [12] demonstrate the expected difficulties of the standard optimization strategies on large scale problems. The experiments on the optimization of the systems with different number of sensors showed the infeasibility of the standard ES for detection of the optimal solution for a systems, having more than 5 sensors. We found out, that concurrent growth method, based on the standard ES, could overcome these problems. Additionally, such a system development method resulted a structured system organization, with a strong hierarchical arrangement of the elements of sensor and controller structures. In this way the arranged system organization provides information about the importance of the present sensor elements of the system. However, the overall system configuration in [12] has been pre-defined to the system using 6 actuators at fixed positions. In this work we fully free the system of any

[2] http://image.diku.dk/shark/

morphological or controller system limitations on the early developmental stages and evolve all functional parts of the system simultaneously.

The system is evaluated according to its ability to reduce the drag while changes in the inflow angle of the air occur during the optimization process. The ratio of the drag coefficients before change of the inflow angle happened C_d^t and after C_d^{t+1} a change is evaluated. The fitness of an individual is defined as a sum of drag value ratios over a cascade of 16 different angles of attack. Additionally the cost functions of the sensor and actuator elements multiplied with a number of sensors and actuators respectively has been added to the fitness function.

$$Fitness(Individual) = \frac{\sum_{i=1}^{N} \frac{C_d^{t+1}(\alpha_i)}{C_d^t(\alpha_i)}}{N} + w \cdot S + v \cdot A \quad , \tag{1}$$

where α is the angle of attack, N is the total number of angles of attack applied and on which the individual has been evaluated, C_d^t is the drag coefficient before and C_d^{t+1} - after actuator adjustments, S and A are the number of sensors and actuators, w and v are the cost factors for sensors and actuators. To get a fair comparison we use two constraint parameter derived from the parameters of the NACA 2410 [18] airfoil. NACA airfoils are the aircraft wing shapes, developed by the National Advisory Committee for Aeronautics in 1948 [18] and define since that time a set of standard airfoil shapes. The maximal thickness of the adaptive airfoil was set to the maximal thickness of the NACA 2410 airfoil which is equal to 10% of the chord length. Additionally, we put the constraint on the lift coefficient to be equal or higher than a lift of a NACA 2410 airfoil at corresponding angle of attack.

3.1 Definition of growth process

We defined a system growth process as an optimization through gradual enlargement of the initially minimal system by concurrent addition and adaptation of the sensors, actuators and corresponding connection weights of the controller during entire optimization process. There exists a variety of approaches for the topology optimization of the processing structures in the neuro-evolutionary domain proposed for example by Moriarty and Miikulainen [19] (SANE), Stanley and Miikulainen [20],[21] (NEAT).

In this work we realize the topology optimization of the controller, consisting of a linear recurrent model, as an optimization of the input as well as output dimensionality of the control structure, while adding necessary connections to keep a fully connected network. We use a direct genotype to phenotype encoding as shown in Fig. 2. We use a neutral system mutation by initializing the weighting coefficients of a new sensor or new actuator elements with zero. The new morphological elements as well as the corresponding controller connections get individual mutation step sizes. Through this important method of system enlargement, triggered by the probability based method, we give a mutated system a possibility to evolve new elements individually while keeping the previously

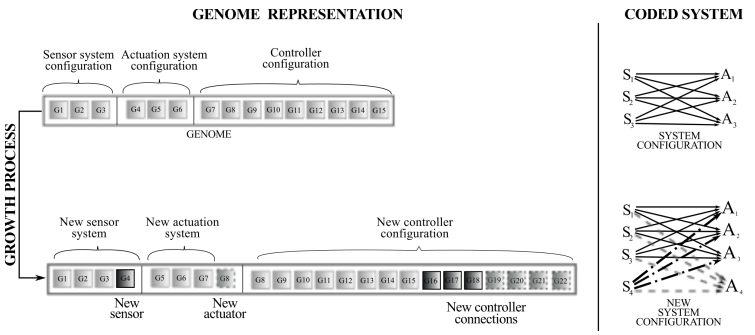


Fig. 2. Demonstration of growth process. Probability based triggering of enlargement of morphology and controller dimensionality

optimized system setup intact. Each individual in a population has a fixed probability $p = 0.2$ to get a new sensor or actuator by mutation. Compared to our previous research we implemented cost factors for the new sensory and actuation elements. The values of the cost factor has been experimentally set to $w = 0.04$ and $v = 0.04$. The cost factors allow the generation of the systems with minimal complexity of morphological and controller configurations required for fulfilling a given task.

3.2 Experimental results of growth process

In this section we demonstrate the experimental results of the presented sensor-actuator-controller growth method of the adaptive wing and compare them with the results of our previous work in [14] and [12].

Fig. 3 (a) present a comparison of the optimization results for different systems. On the one hand we have results of the systems, having different fixed number of sensory elements and equally positioned fixed 6 actuators. On the other hand we get the optimization results for the sensors-controller and sensors-actuators- controller growth method. In following we compare the results and give an explanation to the difference in the final performance. Basically as the performance of the final system is expected to get better, the more sensory information about the environment is available. Indeed Fig. 3 (a) shows a significant improvement of the final optimized system performance with an enlargement of sensory system dimensionality up to 3 sensors. However the high number of sensors and actuators leads to a high number of optimization parameters. The problems of the standard ES on the large scale problem can be seen for a higher number of sensory elements. For experiments with fixed morphological dimensionality we observe a decline of the performance for the systems, having more than 3 sensors. In this case of a morphologically rich system, an optimization has a high chance to get stuck in local optima and not reach the globally optimal solution.

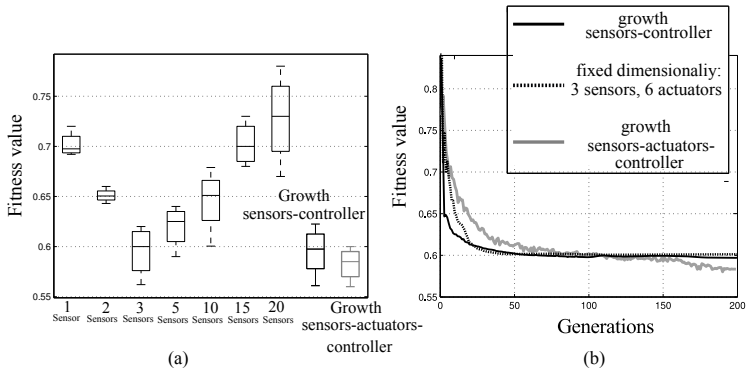


Fig. 3. (a) Final quality of sensors-controller and sensors-actuators-controller optimization runs, compared with a results of the runs with a different fixed morphological configurations. 10 optimization runs with different starting parameters, (b) Comparison of the averaged fitness curves

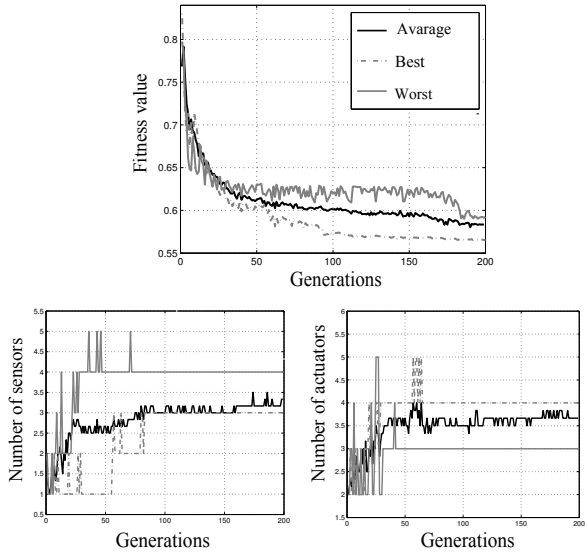


Fig. 4. (a) Average (10 runs), worst and the best fitness progress of the sensors-actuators-controller optimization, (b) Development of the number of sensors over 200 generations, (c) Development of the number of actuators

According to the optimization results, systems with 3 pressure sensors represent an optimal sufficient solution for morphological setting for given optimization strategy, since it reached the best final quality in average. The results demonstrate, that the systems developed with sensors-controller growth method show similar good performance as the systems optimized for 3 sensors, both

having 6 fixed actuators. According to the average achieved quality of the fully variable system design, presented as sensor-actuators-controller growth method, we obtain a significant benefit starting the optimization with initially minimal system configuration, which evolves during the optimization through gradual step-wise complexification. The fitness value of the best and worst individual in each population as well as the average sensors-actuators-controller optimization is presented in Fig. 4. The growth method generated a systems, having in average about 3 sensors and between 3 and 4 actuators. To analyze the functional

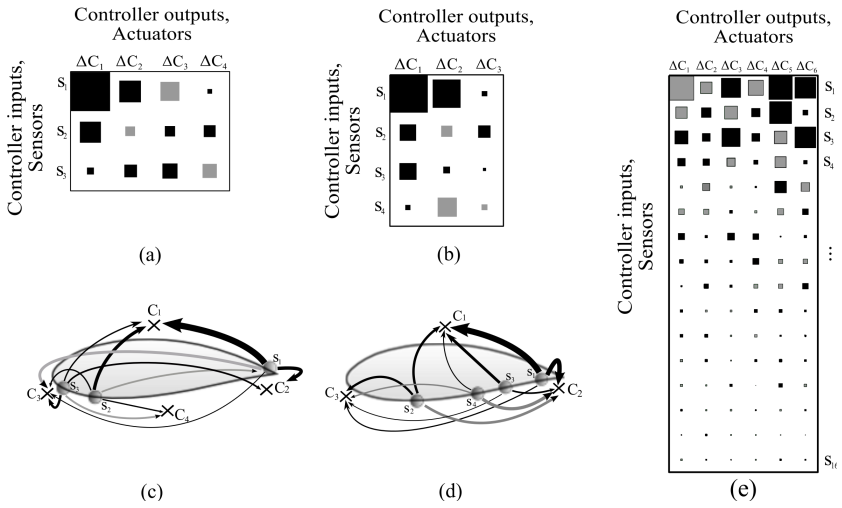


Fig. 5. Hinton diagrams of the system controller of the worst (a) and the best (b) system in Fig. 4, developed by the sensors-actuators-controller growth process at 200th generation, (c) and (d) Position of the sensors and actuators of the systems and schematic airfoil controller with the signal connections between sensors and actuators (thicker lines mean a stronger connection), (e) Example of the system controller developed with sensors-controller method without cost functions

configuration of the controller a Hinton diagrams has been used [22]. The size of the boxes corresponds to the value of the connection strength. The box color (gray and black) represents a positive or negative sign of the connection strength respectively. The values of the connection strengths have been scaled between minimal (no box) and maximal controller connection strength (box of maximum size).

Fig. 5 demonstrates the final controller structures of the worst and the best system, developed with the growth method after 200 generations. Fig. 5 (c), (d) shows the optimized position of the sensors and actuators in both systems. A reason for the performance difference of the two systems seems to be an extra actuator of the first system. The results show in comparison to earlier work, that the actuation resources of the system have a comparable impact

on the system performance than the amount of gathered sensor information about the environment. This means that the pre-definition of the configuration of each morphological structure limits a system's global evolvability gradually. The presented system growth method shows experimentally on a virtual adaptive wing design the potentials and benefits of the fully automatic globally optimal system design.

4 CONCLUSIONS

In the presented work the evolutionary generation of an optimal adaptive system which reacts autonomously to changes in its environment is described. As an example system for the evolutionary development a problem from the field of aerodynamics was utilized. A virtual wing shape had to be adapted to show minimal drag for changing unknown inflow angles based on pressure measurements on its surface. All functional parts of the systems, such as morphological configuration, defined by the sensory and actuation structures, as well as the configuration of the signal processing unit of the virtual adaptive wing are not specied in the early design stage and are the result of the evolutionary optimization process implemented as a dynamic system growth process. We showed that the proposed concurrent growth method could overcome the problems of standard evolutionary strategies on a given large scale optimization task. According to the presented results we obtain a significant benefit in starting the optimization initially as simple as possible while the system undergoes a stepwise complexification during the co-evolution process. Proposed system growth approach, combined with a cost factors for a morphological dimensionality, is able to detect a minimally possible morphological configuration required to fulfill a given task of drag reduction and maintenance of a required lift. Therefore an optimization process supports generation of preferably low dimensionality of morphological and controller units, which is still sufficient to react optimally in a simulated changing environment. Such a system development method results in a structured system organization, with a strong hierarchical arrangement of the elements of sensor and controller structures according to its importance to the system. This system organization provides an important information to the designers about the significance of sensors and actuators for the system performance.

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