Co-evolution of morphology and control in developing structures

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Ich versichere hiermit, dass ich die vorliegende Dissertation allein und nur unter Verwendung der angegebenen Literatur verfasst habe. Die Arbeit hat bisher noch nicht zur Prüfungszweken gedient.

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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 are often random nature of the environment and the fact that not all phenomena which influence the performance of the system can be explained in full detail. As a consequence, the developer often gets confronted with the task to design an adaptive system with the lack of prior knowledge about the problem at hand. The design of adaptive systems, which react autonomously to changes in their environment, requires 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. Within the scope of the thesis, the new system growth method has been introduced. It is based on the evolutionary optimization design technique, which can automatically produce the efficient systems with optimal initially non-defined configuration. The final solutions produced by the novel growth method have low dimensional perception, actuation and signal processing structures optimally adjusted to each other during combined evolutionary optimization process. The co-evolutionary system design approach has been realized by the concurrent development and gradual complexification of the sensory, actuation and corresponding signal processing systems during entire optimization. The evolution of flexible system configuration is performed with the standard evolutionary strategies by means of adaptable representation of variable length and therewith variable complexity of the system which it can represent in the further optimization progress. The co-evolution of morphology and control of complex adaptive systems has been successfully performed for the examples of a complex aerodynamic problem of a morphing wing and a virtual intelligent autonomously driving vehicle. The thesis demonstrates the applicability of the concurrent evolutionary design of the optimal morphological configuration, presented as sensory and actuation systems, and the corresponding optimal system controller. Meanwhile, it underlines the potentials of direct genotype phenotype encodings for the design of complex engineering real-world applications. The thesis argues that often better, cheaper, more robust and adaptive systems can be developed if the entire system is the design target rather than its separate functional parts, like sensors, actuators or controller structure. The simulation results demonstrate that co-evolutionary methods are able to generate systems which can optimally adapt to the unpredicted environmental conditions while at the same time shedding light on the precise synchronization of all functional system parts during its co-developmental process.

Kurzfassung

Stets steigende Anforderungen an neuartige technische Lösungen hängen oft mit der Komplexität deren Aufgaben zusammen. In vielen Bereichen der modernen Technik kommt es zu unvorhersehbaren und erschwerten Umweltbedingungen. Hierbei steht der Entwicklungsingenieur vor der Herausforderung ein adaptives und invariantes Gesammtsystem zu entwickeln, welches auch dann funktionsfähig ist, wenn die Umgebungsbedingungen stark von den Standardwerten abweichen. Die Schwierigkeiten dabei sind häufig sowohl die unbekannten Verhältnisse der Umgebung als auch deren Einfluss auf das Systemvehalten. Für solche Anwendungsgebiete wird die Entwicklung von extrem robusten technischen Applikationen benötigt. Die gehören zu der Klasse der adaptiven Systeme und verfügen über spezielle mechanische und sensorische Vorrichtungen um die Veränderungen der Umgebungsbedingungen wahrnehmen zu können und dementsprechend den Zustand des Systems durch die vorhandenen Aktuatoren optimal anzupassen. Die optimale Konfiguration der Morphologie und die Regelung des adaptiven Systems ist meistens unbekannt und wird anhand des bereits vorhandenen Vorwissen über das Systemverhalten manuel gewählt. Im Rahmen der vorliegeneden Dissertation wurde ein neues Konzept entwickelt zur automatischen Generierung der optimalen Konfiguration der Sensorik, Aktuatorik und Regelung des Systems, basierend auf den Methoden der evolutionären Algorithmen. Die Entwicklung des Gesammtsystems, bestehend aus den sensorischen und aktuatorischen Komponenten sowie dem Regler, findet hierbei parallel mithilfe von einem kombinierten inkrementalen evolutionären Algorithmus statt. Die Optimierung fängt mit einer möglichst einfachen Systemlösung, idealerweiser mit einem einzigen Sensor und Aktuator und einer sehr vereinfachten Reglerstruktur an. Im Laufe des weiteren Optimierungsverlaufs, basierend auf einem im Rahmen der Dissertation entwickeltes Wachstummodels, nimmt das System schrittweise an Komplexität zu mit Hilfe einer graduellen Erweiterung der Morphologie und Signalverarbeitungsstruktur. Der neu vorgestellte co-evolutionäre Algorithmus wurde an den Beispielen eines simulierten adaptiven Tragflügelprofils und dem vereinfachten Model eines autonoum fahrendes Fahrzeug erfolgreich appliziert. Die Simulationsergebnisse der beiden Beispielanwendungen zeigen, dass die co-evolutionären inkrementalen Methoden den Entwicklungsprozes der realen, komplexen, adaptiven Anwendungen wirksam vereinfachen und automatisieren können. Die unterschiedlichen Komponenten der dabei entstehenden Lösungen sind, ähnlich zu biologischen Systemen, evolutionär optimal aufeinander abgestimmt und effektiv hinsichtlich der Hardware- und Softwareressourcen.

Contents

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1 Introduction

The concurrent evolution of morphology and control of adaptive structures also called morphology-control or body-brain co-evolution is a growing area in evolutionary system design and is mainly represented in the field of evolutionary robotics. The idea of the co-evolutionary design of morphology and control of technical systems is motivated by biological systems. The body and the brain of living organisms have been precisely co-evolved during the evolutionary process. Nature possesses an ability to perfectly couple these two dynamics - the one of the body and of the brain. The actions of living systems partially determine the sensory pattern that organisms receive from the environment. By coordinating sensory and motor processes, organisms can select favorable sensory patterns and thus enhance their ability to achieve their adaptive goals. In this manner the precise evolutionary coordination between body and signal processing during evolutionary development takes place. This idea is followed in evolutionary robotics to develop the morphology and the signal processing structures of the robots concurrently and, therefore, ensure their unique suitability. In Fig. 1.1 the main idea of concurrent design has been illustrated.

A big challenge for researchers and developers is to find out which elements of the natural design process are applicable to the technical system and could give a significant improvement of evolutionary design process compared to conventional system development techniques. The reasons for such a high interest in the co-evolutionary design of morphology and control of modern robots are manifold. First reason is the complexity of the tasks for current robots, which have to fulfill a wide range of challenging functions, for example, locomotion in unknown environments with obstacle avoiding, which implies the processing of multidimensional data for environment and target objects recognition. To create the systems able to solve these complicated tasks the designers used to end up with systems having highly complex morphologies, to ensure that all relevant environmental information has been captured and the required actuation is available to perform optimal system reaction to external stimuli. The complex morphologies in return require appropriate control strategies respectively capable of controlling the resulting overall system. The main problem of evolving large controllers is that it gets easily infeasible to

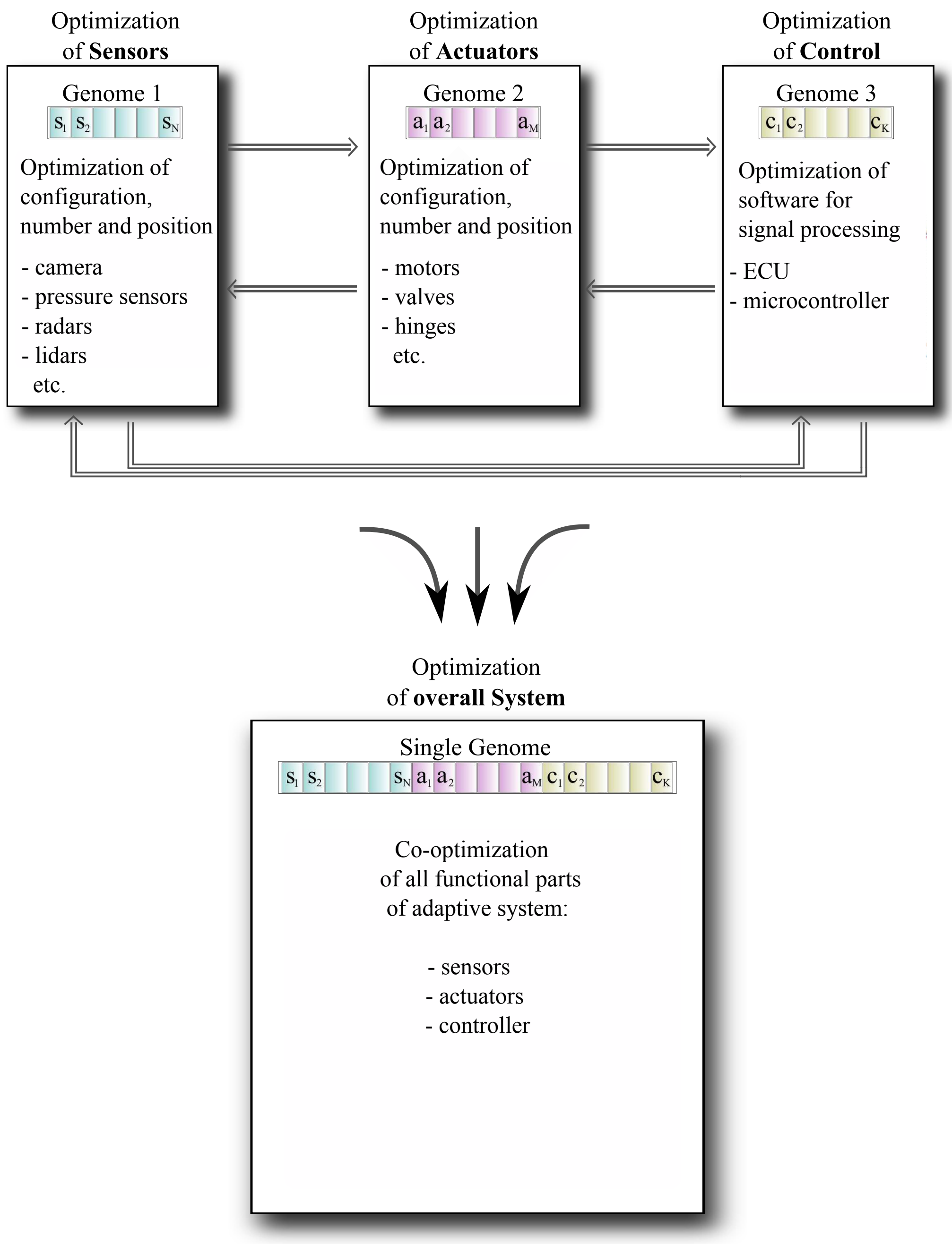


Figure 1.1: Main idea of the co-evolutionary approach for the development of the overall system

evolve. Creating a complex robotic system and only later trying to find a controller capable of operating it has the difficulty of scaling, since it is entirely possible, that the robots morphology is overdesigned and the robot is too complex to be reasonably controlled. Searching for the optimal controller of such a system means the optimization of hundreds and thousands of parameters.

This situation brought the conventional evolutionary optimization algorithms working typically with direct genotypic representations, where the individuals genotype is one-to-one mapped to its phenotype, to its limits. The problems of the evolvability of large-scale controller networks stimulated the researchers to consider alternative genetic representation to improve the learning speed and final quality of complex systems. Development of novel representations gave an origin to the popular research area called generative and developmental systems. The basic idea is to reduce the quantity of coded information in the genome and, therefore, increase the feasibility and the evolvability of the solutions. The compression of the genome could be achieved through two mechanisms. The first is the utilization of ontogenetic growth, which in biology means the development of an organism from the time of eggs fertilization to the organism's mature form. For the evolutionary algorithms, this implies the integration of a developmental step into the genotype to phenotype mapping of individuals in the evolutionary process. The genes, in this case, represent rather the rules how to build the system than describe separately the phenotypic features of all its functional parts in a one-to-one manner. Regarding the fact that the locomotion tasks are usually successful in the case of symmetric limbs and historically the majority of robots has been developed for different kinds of locomotion, an idea of reuse of the same genetic information to build the multiple identical or similar body parts came up. By the means of developmental representations, the significant reduction of the genome length could be achieved, which in return essentially increased the evolvability of robots morphology.

However, the introduction of indirect encodings has not been a panacea. It can be fully agreed to the fact, that dealing with complex modular and symmetric phenotypes for locomotion tasks, the indirect encodings have their benefits due to the fact that individual mutations can produce coordinated changes in multiple elements of the phenotype. However, in many real-world engineering problems the search space is highly irregular and makes it difficult to find the optimal solution using indirect representations. In the recent research [1],[2] the positive properties of direct encodings for the co-evolutionary system development has been rediscovered. Based on new insights, the so-called hybridized representation modifications has been introduced [1],[2] to concurrently optimize the morphology and control of systems. The novelty of the idea has been the combination of indirect and direct encodings, which first discovers the regularity inherent in a problem and then accounts for the exceptions in the structure. Nevertheless, the utilization of indirect representation in the first phase of evolutionary design could not exclude the bias towards symmetrical structures completely and has been tested on rather simple test problems.

In this thesis, the focus lies on the investigation of possibilities and introduction of effective methods to transfer essential aspects of biological design such as previously described body-brain co-evolution to the design of complex engineering real-world applications. The co-evolution of form and function has been successfully performed for the examples of the complex aerodynamic problem of the morphing wing and an intelligent autonomous transportation system. In contrast to the described co-evolutionary approaches in evolutionary robotics, the results have shown that it can be sufficient and highly effective to use direct genotype-phenotype mapping, when applied for example to such a highly irregular problems as an aerodynamical optimization with complex, strong nonlinear relationships between flow body and flow field or situation-based decision making during autonomous driving of intelligent vehicle. The sticking point to makeing such a complex systems evolvable with standard evolutionary optimization algorithms has been the development of such representation, which could be able to describe currently unknown structures with an arbitrary complexity while at the same time it has to allow for an evolutionary adaptation of the currently represented structure. To realize a sufficiently high degree of freedom for the evolutionary process an adaptable representation is required. This can be solved by the integration of genome representation of variable length and therewith variable complexity of a system which it currently represents. The configuration of sensory, actuation and controller of the resulting system has been coded in a single combined genome which develops during the evolutionary process controlled by an internal gradual system complexification mechanism. The initially basic structures with single external stimuli and primitive actuation possibilities growth into structures capable of complex behavior during a progress of a simulated evolutionary process. The low complexity of the initial systems as a starting point of the evolutionary process has a positive effect, known as "benefits of starting small" [3], [4], in shrinking the multi-dimensional search space of complex morphologies and controller strategies and can give an impressive boost to the learning capabilities of finally complex system. The developed representation simplified genotype-phenotype mapping of morphology-control co-evolution compared to developmental models and allowed direct translation of genes to the phenotype of the evolved morphology and signal processing of the resulting system without intermediate ontogenetic developmental steps. This allowed the resulting morphologies be less bias towards symmetry (final solutions has been highly irregular) and the correlations between evolutionary development of single genes and its impact on the phenotypical characteristics be more analyzable and intuitive.

For the investigation of regulation of the differentiation process during system development under the influence of environmental conditions in developing structures, preliminary research on a cell pattern generation problem has been carried out. The research exhibits the applicability of co-evolutionary development of artificial multi-cellular organism under the regulation of simple GRN model and has been an important groundwork for the development of the new proposal of the co-evolutionary growth method presented in this thesis. The first realistic application in this thesis utilized the co-evolution of morphology and information processing structure for the optimal control of an adaptive wing shape of an airplane. The second application is concerned with a developmental approach in the area of intelligent driver assistance systems, where the proposed growth method has been applied to the co-evolution of the morphology and signal processing of simplified automatically driving vehicle. Both applications have been excellent test beds for the research on different aspects of the co-evolutionary design of adaptive systems.

The results presented in this thesis demonstrate that co-evolutionary methods are able to generate systems which can optimally adapt to the unpredicted environmental conditions while at the same time it is shedding light on the precise synchronization of all functional system parts, such as sensory and actuation systems as well as control structure for the given morphology during its co-developmental process. The results of the concurrent evolutionary growth of sensory, actuation and controller systems of the simulated morphing airfoil as well as of the automatically driving vehicle have been compared with the results which could be achieved with the conventional evolutionary optimization techniques. These worked well in the low dimensional search space, struggling with the optimization of systems with higher complexity with multiple sensory inputs, more sophisticated actuation and controlling strategies, already for the systems of the medium dimensionality of sensory and actuation systems. It has been caused presumably by the complex fitness landscapes of given applications. The results of conventional optimization approaches endorsed the existence of earlier discussed evolvability problems of direct encodings on large-scale optimization problems and represent the widespread process in engineering with the long iterative process of search for the optimal number of sensors and actuators, fine-tuning of its position in the structure and fine-tuning of controller model, parameters and architecture. It served as a baseline for the evaluation of the results of a new developmental approach based on growth methods. The morphology-control growth method outperformed the conventional evolutionary techniques with fixed genome in almost all cases. Combined with cost factors for the morphological dimensionality, the growth approach was able to detect a minimal possible morphological configuration required to fulfill a given task, which allows a considerable reduction of dimensionality of sensors and actuators systems and therewith the hardware costs of final solutions. During the evolutionary growth process of the systems, a precise coordination between the development of morphological and signal processing structures has been observed.

One further advantage of the method has been the fact, that the total number of evaluations, which were necessary to find optimal morphology and its perfectly suited controller, could be significantly reduced in the case of the presented growth method in comparison to the conventional evolutionary techniques with the fixed genome where the evolutionary process was restricted to optimization of system parameters with fixed morphological dimensionality. However, the result of the growth process as a global system optimization depended strongly on selected growth triggering techniques and the correct balance between the evolutionary parameter settings of the longer existing and newer structural elements during the developmental process. It has been ascertained that the new sensor and controller elements should get individual mutation strengths, which have to be higher than the rates of longer existent elements. This system enlargement construct gives new elements a possibility to develop individually while maintaining the overall system performance intact.

A detailed analysis of the solutions produced by the new method indicated the special hierarchical controller organization with a clear arrangement of sensors and actuators according to its importance for the system, where the first sensor has the strongest and the last sensor the least impact on the overall performance. This effect has been caused by the fact, that the sensors and actuators have been added to the system gradually during the evolutionary process. Since the initial systems had only a few perception and actuation possibilities, the sensors and actuators have been placed in the structure by the evolution where it had the most impact on the performance. At the same time additionally appearing structural elements could improve the basic behavior of the initially low dimensional systems. A big advantage of such internal controller organization, compared to the controller where each sensor and actuator has a similar influence on the control strategy, was its high functional transparency and understandability.

All these aspects of developmental co-evolutionary system design have been investigated and analyzed supported by meaningful experimental results in this work.

The structure of the work is organized as follows. The first chapter describes the main motivation of the work and the biggest challenges of engineering design process. Chapter 2 describes the high requirements on the new technical applications and the problems of isolated design of such multicomponent adaptive structures. Chapter 3 presents the related research on the co-evolutionary design of form and function of complex adaptive systems, mainly existing in the field of evolutionary robotics. In Chapter 4 the new developmental design approach based on the new adaptable direct representation has been introduced and compared with the co-evolutionary approaches based on widespread indirect encodings. The next Chapters 5 and 6 describe the results of simulations of two real-world applications, evolved with the new proposed co-evolutionary growth approach. The first application is the adaptive airfoil, which can optimize its performance online during the flight according to the current, continuously changing environmental conditions through structural shape morphing. The second application represents virtual autonomously driving vehicle, which can react through the internal neural controller to the current traffic situation detected with its range sensors. The last Chapter concludes the results of the experiments and highlights the efficiency of the combination of a new co-evolutionary method with standard evolutionary algorithms for the development of complex adaptive systems.

1.1 Main contributions and focus of the work

- The proposed system growth method represents an evolutionary based system design technique, which automatically produces highly efficient systems with optimal and minimally morphology and control - possibly low dimensional perception, actuation and signal processing structures optimally adjusted to each other through combined evolutionary optimization process. The method simplifies significantly the engineering process without the need of taking into account uncertainties.

- Despite of the relatively simple morphology of the systems produced by the proposed growth method, it can perform complex adaptive behaviors, which emerges from the interaction between the control system, sensory and actuation and the external environment during the entire evolutionary development process.

- The system growth method produces solutions, which are robust and show high performance in the environmental situations, which have not been learned by the system during the evolutionary development. The system reaction to the unpredicted changes of environmental parameters (for example strong air pressure deviation) is comparable to the optimal performance of the baselines, which has been individually optimized to these specific environmental conditions.

- This work underlines the potentials of direct genotype-phenotype encodings. It is demonstrated that it can be successfully used for optimization of complex real-world problems when combined with variable length genome which is controlled by the internal growth triggering mechanism during the evolutionary process and represent a current system of continuously increasing complexity. Therefore, is can be assumed that the flexible genome is evolvable during the evolutionary process and can produce the solutions of arbitrary complexity.

- The computational costs of the optimal system development by growth method are significantly reduced compared to the conventional optimization of systems with fixed dimensionality of sensory and actuation structures. This could be achieved primary through the reduction of an overall number of evaluations needed to find the optimal configuration of sensory, actuation and controller parts of the entire system.

- Due to the possibly minimal dimensionality of the environment perception and actuation structures of the optimized system, the reduction of hardware costs for sensors and actuators therefore resources efficiency can be achieved. The integration of cost factors for the sensory and actuation elements in the final system enables the distribution and precise balance between the costs of control and morphology.

2 Challenges of complex adaptive applications design

Humans have long been impressed by the ability of nature to build structures which adapt to their environment. The widespread industrial robotic solutions are the examples of partially autonomous but not adaptive systems, designed to fulfill repeatedly the same mostly individually assigned task. The typical examples of high adaptivity are not yet autonomous drones, which are mostly operated by remote control. Compared to manned aircraft, autonomous drones are often preferred for missions that are dangerous for humans. They originated mostly in military applications, but also in commercial, scientific other applications.

The adaptivity of a technical system, explained more in detail in the next chapter, generally spoken represents the ability of the system to undergo structural or/and material changes as a reaction to the changes in its operating environment to achieve better performance, efficiency, and stability. To enable the adaptive behavior of the system it has to be equipped with the sensors, which measure not only the internal parameters of the system but also monitor the change of relevant environmental parameters which affect its performance. In the case of for example mechanical-structural systems its performance is directly related to the geometric shapes of their components, for example in the adaptronic domain. Such systems require different shapes for different operating conditions, rather than historically widespread implementation of fixed shape that constitutes a compromise with respect to all the operating conditions. To respond to varying operating conditions and external disturbances, the component characteristics, like shape or material distribution density in structure to name the few, have to change adaptively to maintain optimal system performance and enhance versatility.

Additionally to the required sensors for online measurement of the current environment of the operating system, it needs actuators - mechanical constructions with several degrees of freedom - to be able to perform the beneficial structural system adjustments to adapt to the changed conditions. The design of fully autonomous adaptive structures can be divided into following important subtasks:

- Definition of target behavior that the adaptive system will have to accomplish

- Design of physical body of the system and its hardware - design on sensors, actuators that will be used. Creating of a specification of signals coming from sensors and to actuators.

- Decision on the controller architecture, modularity, and software platform.

- Analysis and test of overall system performance with selected morphology and controller strategies.

A described design process of such a system represents a big challenge for a system developer due to the fact, that it requires a fully understanding of the problem at hand to make its design process effective. This means understanding and knowing all the phenomena that influence the performance of the system, which can be quite difficult. Especially for the technical applications which are acting in the environments of arbitrary complexity with unknown correlations between the state of the system and its performance, the acquisition of the global optimal overall system configuration is a big engineering problem. Due to the difficulty to determine an optimal set of stimuli and the means of actuation for the control of the overall system, an engineer's decision at the stage of conceptual design is often quite intuitive. The choice of the sensory and actuation systems takes place usually in the early stages of the design process and is mostly guided by the experience of the designer supported by available data which describes the correlations of the system parameters. When the selection of the morphological configuration of the adaptive system is fixed, a further stage in the design process is the choice of signal processing structure, which is able of controlling the selected morphology.

System's control theory offers a large variety of control solutions, depending on the nature of the process, which has to be controlled. Given a fixed actuation and sensory systems, the optimization of the entire adaptive system is scaled down to the search for the optimal controller. This conceptual sequence of the design of adaptive structures is widespread and represents a standard approach. A variety of research on the application of evolutionary robotics to real mobile robots by optimizing of controller structure with given morphological limitations, such as fixed number and resolution of camera system of the robot, joints angles range etc., has been carried out by Brooks [5], Dorigo and Schnepf [6], Cliff, Husband and Harvey [7], Floreano and Mondada [8], Miglino, Nafasi, Taylor [9]. The robot controller consists of a collection of rule-based behaviors, each of which achieves and/or maintains a specific goal. For example, the obstacle avoidance tasks maintain the goal of preventing collisions with objects in the environment, and the return to the start point behavior achieves the goal of reaching some starting region. Each behavior is a processing element or a procedure, also called a control law in the engineering field of control theory. Each law gets the inputs from the robots sensors (for example, cameras and ultrasound, infra-red or tactile sensors) and sends outputs to the robot effectors (such as heels, grippers, arms or speech).

To get the optimal laws or rules for the processing of the measured stimuli from the robot sensors to the actuator's actions is an optimization task. It could happen that the chosen controller is not capable of generating suitable reactions of the adaptive system for given complexity of the current environment. On the other hand, the performance of the adaptive systems depends on the quality and quantity of the information available about the system dynamics and its performance in the environment depending on its state. Supervised learning methods using neural networks could be appropriate if the complete domain knowledge is available. For example, Pomerleau trained autonomous vehicles based on neural networks [10],[11].

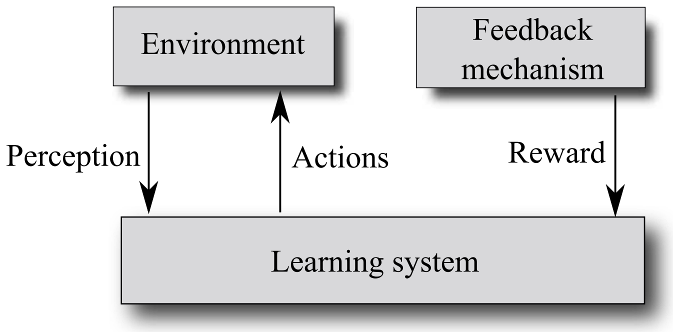


Figure 2.1: Principle of reinforcement learning

Having non-deterministic environment, the robot may need to model not only the state transitions caused by action executions but also the probability distributions of such transitions. In addition, it could be quite difficult to generate a complete knowledge base for the adaptive system due to the intractable complexity of the real world. In this case, reinforcement learning is a popular method for learning in mobile robotics [12],[13]. The principle of reinforcement learning is presented in Fig. 2.1. It refers to a set of problems in which the robot must improve its behavior based on rewards or punishment from the environment. The reinforcement learning model is based on early conditioning work in psychology, and recently an increasing number of robot learning systems have used related concepts from biological reinforcement learning, most notably shaping [14],[15],[16] and operand conditioning [17],[18]. In this case, a robot autonomously acquires a model of the effects of its actions. Equipped with a predictive model it can advance in creating a promising techniques to explore an unknown environment and achieve given goals.

2.1 Definition of adaptivity in technical systems

The term adaptivity is widespread in biology and engineering. Defining adaptation is a trail to study the relationship between the characteristics like anatomic structure, physiological process or behavior of living creatures and their environmental state. On the one hand, the adaptivity of biological systems could be defined as an ability to continuously maintain a sufficient physical health and ability to sufficiently fulfill a set of objectives of the living organisms, by adjusting of morphological settings, depending on the stimuli from sensing organs. On the other hand, the adaptivity is also a global evolutionary process. A biological adaptation is then a physiological process or a behavior trait of an organism that has been selected by the natural evolution under the assumption that such traits increase the probability of reproduction of an organism [19]. The first definition of adaptation reflects more short-term adaptation during the living cycle of the organism. The second definition, on the other hand, describes rather a long-term structural change like an evolutionary growth process of bones in organisms [20], [21]. These evolutionary adaptation processes happen slowly over a large number of generations and change an appearance and functionality of natural systems [22]. The difference between long and short-term adaptation can be analogized to the adaptation of technical systems.

Various definitions for adaptive systems are given in the literature. Beginning in the late 50th, the researchers formalized and described the adaptive systems with possibly few loss of vital content. Formally an adaptive system can be defined as a collection of interdependent and interactive components, which react to a set of stimuli, representing inputs by the means of a set of corresponding outputs - actuators. Analog to the described mechanisms of biological adaptation, an adaptive system is generally a system whose response shows a certain degree of adaptation. In 1959, Bellman and Kalaba introduced a term adaptive in the context of multistage decision process without having full information [23]. When the process which should be controlled is fully known and the controller gets complete information about the behavior of the system with respect to the input parameters, then we have a complete model of the system. In this case, it is a deterministic control problem. When there exist unknown factors in the process, which can be described by known distribution functions, the process is referred to be a stochastic control process. In this case, some input parameters are random processes or when some parameters are unknown with known distribution. Unfortunately, it is very often a case, when neither the whole range of acceptable decisions, nor the impact of this decision on the process characteristics, nor the duration of the process itself is known. In this case, the controller has to learn to improve its performance through the observation of the outputs of the systems for the given inputs. Over a cascade of trials some additional knowledge about the process gets available and an improvement of decisions made by the controller are possible. This case has been defined by Bellman and Kalaba as an adaptive control process and is wide accepted in the area of control theory.

A more general definition of adaptation has been given by Zadeh [24]. He underlined the difficulties to find an appropriate definition of adaptive systems, due to the fact, that there exist a lack of clear differentiation between the objective approach of adaptive behavior and internal mechanisms which lead to this adaptivity. Zadeh proposed a mathematical formulation of adaptivity in system control. Let the performance of a system A be denoted by P and let W denote the set of acceptable performances, $\{S_i\}$ is defined as a family of time functions, indexed by i, to which system is subjected. If the result performance is defined by P_i, then the adaptive behavior of A is defined as following [24].

Definition 1. *The system A is adaptive with respect to $\{S_i\}$ and W if it performs acceptably well with every source in the family $\{S_i\}$, $i \in \Gamma$, that is, $P_i \in W$. In summary A is adaptive with respect to Γ and W if it maps Γ into W.*

The definition proposed by Zadeh implies that all systems are adaptive to some extent if it is an open-loop system if Γ has a single element and a tolerance of accepted performance is large. Hence, a linear time-invariant feedback system seems to be a special case of adaptive system and with that, a Zadeh's definition gets close to the definition of robust control. Due to a large number of different definitions of adaptivity in the literature of system's theory, the topic of adaptive control strongly seems to be strongly affected by a personal view. Generally spoken, adaptive control is needed in two cases. First, if the characteristics of the process and the environmental factors which affect the process dynamics are not completely known. The second case is when the characteristics of the process change unpredictably with respect to time or environmental condition [25]. An adaptive control then is a continuous monitoring of the system performance by a self-adaptation realized by controller actions, which in turn depend on the changes of environmental conditions.

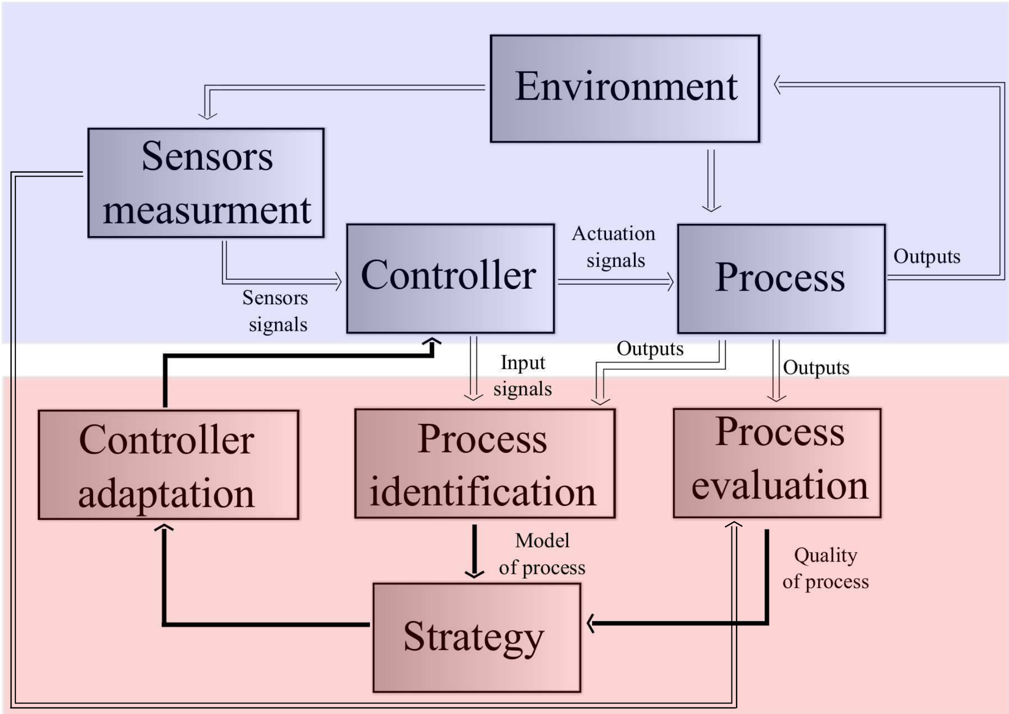


Figure 2.2: Example of structural organization of adaptive control system

Fig. 2.2 shows a schematic rough organization of adaptive systems. One part of the system (in blue) represents rather short-term or instant adaptation of the process to the current changes of environment. The sensory elements of the system detect environmental changes. These measured signals are the inputs of the signal processing structure. The outputs of the controller are the actual reactions of the system to the stimuli from the environment and represent actuation signals. Through the actuators of the system, a process changes its current state, which in turn has an impact on the neighbor environment.

Another part of the system (in red) reflects a long-term or evolutionary adaptation. The evaluation of the process outputs indicates the effectiveness of the process adaptation to the changes of the environmental conditions. Together with the indirect process identification an evolutionary process generates a strategy for the adaptation of the process control parameters.

2.1.1 Sensors, actuators and controller of adaptive systems

In this work, sensors are defined as devices which measure some quantitative value or a variation of the value of some environmental parameter. This could be for example an air pressure value or a temperature, or speed of an ongoing object or air. A sensor detects the event and generates a corresponding output signal in electrical or optical form. A sensory device of a technical application is equivalent to the sensing organs of the living organisms, which they use to sense a neighboring environment.

Besides the sensors, the actuators are the further important means to generate an adaptive behavior of the system. An adaptive system uses its actuators to transfer itself into a new, more beneficial state. The actuators can be formally described as devices or mechanical constructions with several degrees of freedom distributed in the system body. An important feature of the actuator elements is the ability to change the shape of the system's morphology or characteristics of the process by active actions. Through these adaptations of the current state of the system, the performance can be improved for the changed environmental setting, detected by the sensory elements.

The brain of the living creatures represents a global neurological regulation unit. One of its functionality is the processing of external stimuli from the sensing organs to the suitable reactions of the morphological body components, like limbs and organs or activation of specific hormone expressions. Transferred to the technical applications this regulation process can be described as the process, where the measurements of the existing sensors serve as inputs to the controller, which subsequently processes the sensory signals to the corresponding actuation reactions. The realization of a controller can be inspired by the natural neural processing structures and depends strongly on the complexity of the overall system task. While a strong nonlinear time-variant and stochastic processes can be controlled by artificial neural networks or fuzzy control methods, which are capable of process modeling of arbitrary complexity, conventional control methods can be sufficient to fulfill a given regulation task. Figure 2.3 depicts roughly the structural organization and signal flow in adaptive systems. The adaptation of the system through its actuators, for example, shape morphing, can be achieved with conventional controller strategies like PID-controller or nonlinear controllers [26] (4), once the target values of the internal system parameters for the new currently measured conditions are known. But exactly these requirement represents the biggest problem for the design of adaptive structures able of acting in unknown environments - identification of the optimal system parameters for previously unknown conditions. The challenge of adaptive systems design is how to create such a controller, which can estimate what are the optimal parameters of the system to achieve the best performance for the given environmental conditions?

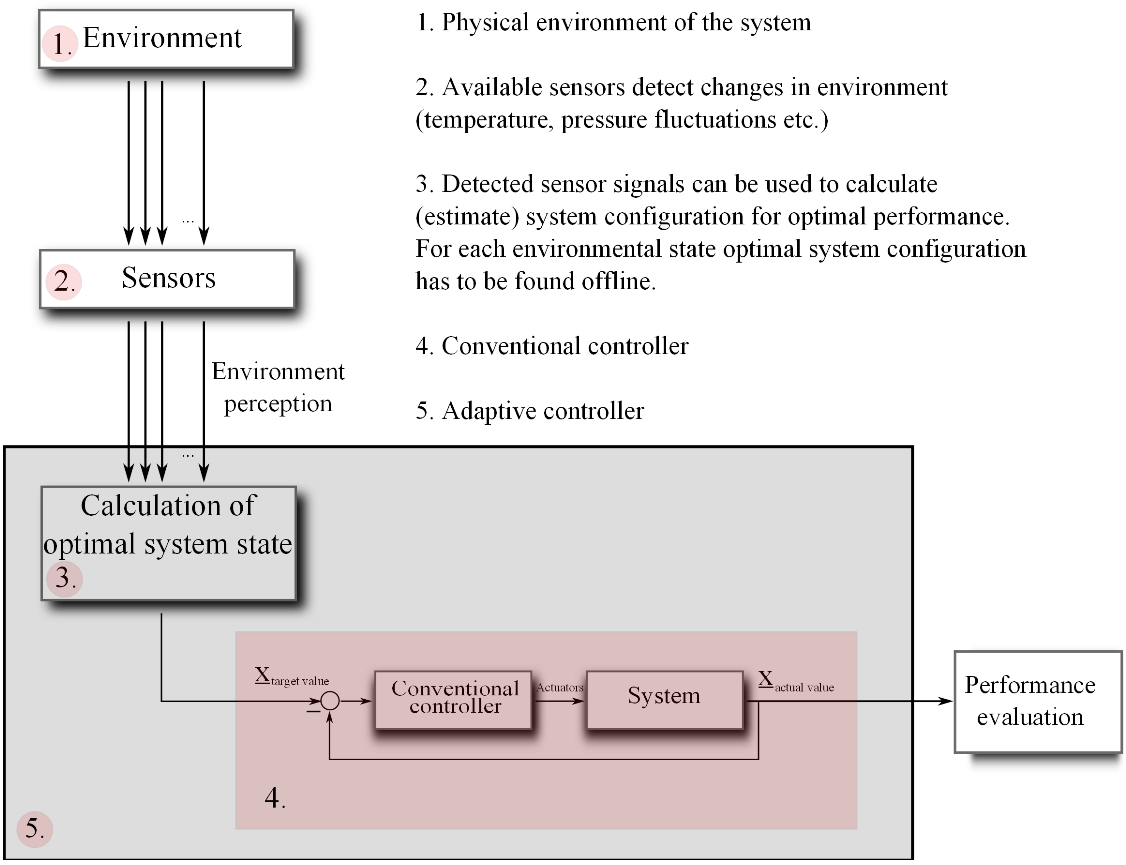


Figure 2.3: Adaptivity versus conventional control strategies

2.2 Problems of manual sequential design of adaptive structures

A large field of robotics serves various examples of implementations of autonomous highly adaptive structures generally denoted as robots. The majority of the approaches to the design of adaptivity in robotics for a quite long period in the past focused rather on the generation of a suitable controller for a given robot, with the target to show on-line adaptive behavior. The shape of the robot, the position, number and the configuration of the sensors and actuators, the locomotion principle etc. are assumed to be fixed and only the controller is evolved. This was often due to the fact, that the mechanics of the actuation and sensing used to have a large number of restrictions. At this points, it is essential to be aware of what is the final target for the designed adaptive system. As described before, mostly regarding the engineering problems domain, the designers target to design systems, which fulfill some specified task and are capable of adaptive behavior in case of environmental changes in their functional area. The investigation of the impact of the environment on the organization of the adaptive systems plays a central role in understanding how we can build efficient adaptive structures, which can deal with processes of arbitrary complexity. Selection of the configuration of sensors and actuators early in the design process means definition and fixing of the amount and quality of the environmental information and actuation possibilities. But how can we exactly know what information about the environment and what actuation is needed at what time to fulfill the given task, especially having variable environmental conditions?

The research of Lichtensteiger and Eggenberger 1999 makes obvious how important a suitable sensory configuration is to fulfill the given task [27]. They made experiments with a small robot, which had an artificial compound eye with 16 light sensors. The task of the controller has been to employ motion parallax to estimate a critical distance to obstacles and was realized with a two-layered artificial neural network. Each of the 16 long tubes contained a light sensor which can detect light within an angle of two degrees. The tubes could rotate about a common vertical axis. The idea has been to optimize the geometrical topology of the eye through the optimization of the relative position of 16 light sensors. The experiments showed a large performance difference between the evolved and the reference configuration of equidistantly distributed sensors. The result configuration of the sensory system was surprising and could not be predicted with the knowledge about the system in advance. This insight is fundamental to the research of adaptive structures since it says that the suitability of cognitive system of the adaptive structure in the unknown environments has a strong influence on its performance. It has been shown in [28],[29], that if the morphology of the sensory and actuation system is not efficient for the particular task in the given environment, the optimal control strategy is not possible, due to the fact that the key information or some particularly needed actuation is missing.

The described situation of unknown optimal sensory, actuation and controller configurations is a big problem in the engineering of adaptive structures. The most widespread technique for building adaptive structures in research and industry used to be a long iterative process of fine tuning of sensors and actuators position, configuration and number and subsequent fine tuning of controller model, parameters or architecture. After often an impressive number of iterations and simulations the developers produce a solution, which fulfills the given requirements to some extent.

The problem of defining the target behavior of the robot and its optimal morphology is caused by the difficulty of foreseeing each problem the robot will have to solve when operating in unpredicted environments. The investigation of the impact of the environment on the organization of the adaptive systems plays a central role in understanding how we can build efficient adaptive structures, which can deal with the processes of arbitrary complexity. Selection of the configuration of sensors and actuators early in the design process means definition and fixing of the amount and quality of the environmental information and actuation possibilities. But how can we exactly know what information about the environment and what actuation is needed at what time to fulfill the given task, especially having variable environmental conditions?

Pfeifer et. al. proposed some principles of adaptive agents design which fit well with the vision of naturally raised adaptivity of agents [30]. One of the principles indicates the need for agent design to exploit the physics and the constraints of the ecological niche it is operating in. An example could be robots with wheels that exploit the fact that the ground is mostly flat, like for example in office environments. Another useful design principle is a redundancy - smart overlap of functionality in the different subsystems. For example just duplicating the components does not lead to useful redundancy. On the other side, combining, for example, visual and the haptic systems both deliver spatial information, but based on different physical processes (electromagnetic waves vs. mechanical touch), would significantly increase the robustness of the final adaptive system in case of the low light level.

However, the most significant and problem-related principle of adaptive agent design is so-called "principle of ecological balance" proposed by Pfeifer in 1996 [31] and extended in 2000 [32], 2002 [33], [34],[35], [36]. The main contribution the authors is that there should be a balance between sensory, motor and controller systems to match optimally the complexity of the task environment. Even more, it seems that in the biology of natural systems, organisms show intelligent distribution between the complexity of morphology, materials and signal processing structure (brain). Ishiguro and his colleagues [37] proved this and showed that if the morphology and the materials are efficient, control will be much less complex. In this case, there are two types of the dynamics: the one of the body and another of the neural structure. The big question is how these two can be coupled in an optimal way.

An exciting example of the described principle of ecological balance and, therefore, use of special morphology to keep the controller simple is a passive walker [38]. Passive walker has been firstly introduced by McGeer in 1990 as shown in Fig. 2.4 and is a simple robot, which is able of walking down an incline. The fascinating fact is, that it does not need any motor to fulfill the locomotion and also does not

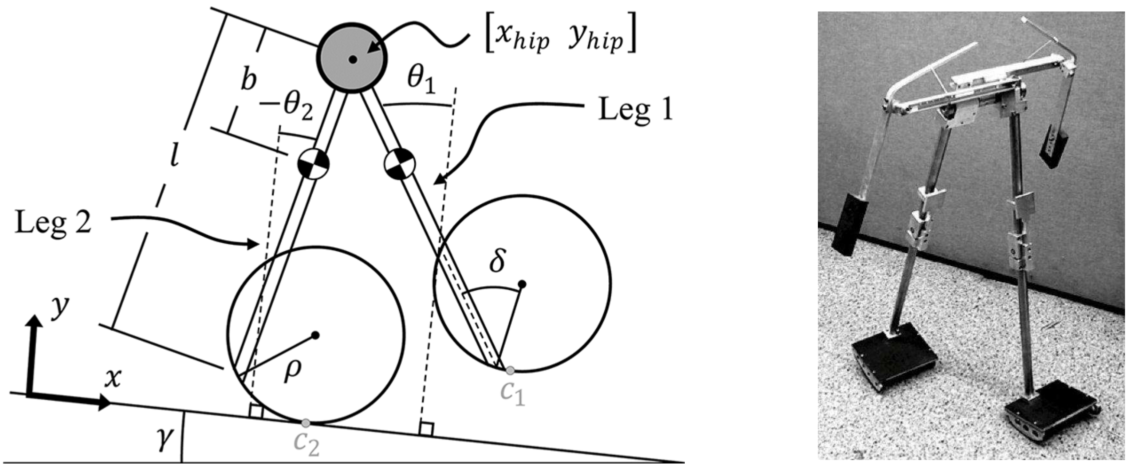


Figure 2.4: The passive walker has such a morphology that no active control is needed [38]

have any active control. In order to be able of locomotion, it has to exploit its body morphology. Taking into account that the passive walker does not have motor or controller, it is extremely energy efficient. Energy efficiency is achieved through the use of passive dynamics of the leg movements, based on the use of gravity in a pendulum-like manner. Surely passive walker is not fully controllable and it needs very special conditions for its operating - inclines of certain angles. Still, the idea of a passive dynamics in the domain of adaptive systems has been novel and highly promising. The fact, that the forward drive of the leg of the human is largely also passive, shows us that nature utilizes the effects of passive dynamics to build a highly complex natural adaptive systems.

The recent research shows that through the high morphological complexity the control could be significantly reduced [39] for a version of evolved virtual creatures in which traditional joint-motor drives are replaced by a simple but powerful evolvable musculature. The authors presented meaningful results [39] which demonstrated that the novel actuation mechanism can support a significant degree of physical intelligence, sufficient to enormously decrease the control intelligence that would normally be used for basic jumping or locomotion tasks. The example shows how the complexity of the controller can be compensated by the new morphological complexity of the body.

The research of Laprin, Pouya et. al. underlined the strong interdependencies between the morphology and control for different locomotion tasks by using the methods for its concurrent evolution [40]. The resulting morphologies and the controller strategies of the quadrupedal robots have been significantly different for straight locomotion and steering since the first needs a bigger, heavier and more actuated body than the second. The fact is, that the stand-alone morphology of the agent does not provide much information about its suitability. Only regarding the specific interaction with the environment, the role of morphology in behavior can be understood. Together with the principle of ecological balance, it can be assumed, that as in biology for the given task environment there exists an optimal task distribution between morphology and signal processing structures. The main question at this point is how this "balance" has emerged? The insights in the area of evolutionary robotics suppose that this balance could be the result of an evolutionary process called body-brain co-evolution - an example of employment of precise "sensory-motor coordination". In the next chapter, the approach of co-evolutionary development of morphology and signal processing structure is broadly explained accomplished with an intensive review of its possible realizations in early and state-of-the-art evolutionary robotics.

3 Related research in co-evolution of morphology and control of adaptive systems

It has been widely accepted that the emergence of the intelligent behavior of adaptive agents is strongly influenced by not only control systems but also their, in the literature often called, "embodiments". The embodiment is termed to be a morphological build, physical property or body of the agent [41].

Nature serves examples for the precise coordination and distribution of the complexity of the architecture between physics and neural signal processing. The wings of insects consist of hard and soft tissue, asymmetrically distributed along the flight direction [42]. The asymmetry in the distribution of hard and soft material in the wing allows an insect to fulfill complex motions like oscillation or twist during each wing flap. Wootton has shown, that having symmetric wings, would significantly increase the complexity of the neural control of the flapping movement. This example reinforces the assumption, that the naturally evolved systems exhibit a precise coupling between nervous and body systems and distribute a given task between these two main functional parts of the entire system.

A further fascinating example of body-brain coupling can be seen in the eyes constitution of the housefly. Even though the fly's brain has four orders of magnitude fewer neurons in their neural processing structure than the brain of the humans, it is capable of very fast and precise flight and landing. Special vision segment distribution of a compound eye of a fly makes it possible. The facets are densely spaced toward the front while wide-stretched on the side. Franceschini et. al. made interesting experiments with real robots which mimicked the vision system of the fly [43]. Artificial robots which had uniformly distributed facets performed worth than the naturally inspired non-uniformly described vision segments in the eye. Obviously, even a simple neural system is capable of complex behavior if combined with a vision system of special organization. Unlike the natural eye system, the standard cameras, which are mostly used for the perception of the environment in robotics and engineering implementations, use the homogeneous distribution of light-sensitive cells. The insects are capable of such a rapid processing of visual information due to decentralized control - the retina pre-processes a high number of the information before transmitting it to a central processing. The given examples show an existing species where the motor and signal processing has been precisely co-evolved during the evolutionary process. It looks like nature possesses an ability to perfectly couple these two dynamics - the one of the body and of the brain. One important aspect, for instance, is the fact that motor actions partially determine the sensory pattern that organisms receive from the environment. By coordinating sensory and motor processes organisms can select favorable sensory patterns and thus enhance their ability to achieve their adaptive goals. The key question here is if the amazing genesis of complex adaptive behavior in natural systems emerged among other aspects due to the fact, that the evolution of cognition, motor and signal processing structures could explore all possible solutions parallel on many scales.

Does it mean that control and body dynamics of an adaptive system cannot be designed separately due to their tight interdependency? This work argues that the inspiration from natural body-brain co-evolution offers a platform for efficient automation and improvement of the design process of adaptive structures in terms of functionality and efficiency. The examples of how the co-evolutionary aspects of the natural developmental process could be transferred to the design process of novel technical applications serve a new domain of evolutionary robotics. In the field of evolutionary robotics, one class of population-based metaheuristics - evolutionary algorithms - are used to optimize some or all aspects of an autonomous robot. The use of metaheuristics sets this subfield of robotics apart from the mainstream of robotics research, in which machine learning algorithms are used to optimize the control policy of robot.

Evolutionary algorithms are population-based, stochastic search methods. The idea of evolutionary algorithm came from Darwins evolution theory. Darwin proposed, that all living organisms continuously evolve to the environment through the means of selection mechanisms, which favor the most adapted species. According to Darwin's theory, the species, which are better adjusted to the current environmental conditions, have a higher probability to survive and pass their genes to the next generation. The canonical evolutionary algorithm is schematically shown in Fig. 3.1

Evolutionary algorithms (EA) use the mechanisms, which have been inspired by Darwin's theory. The evolution produced techniques of global adaptation of individuals using natural selection and variation of genes through cross-over of parent's genetic information and random mutations. EAs inherit the main aspects of the

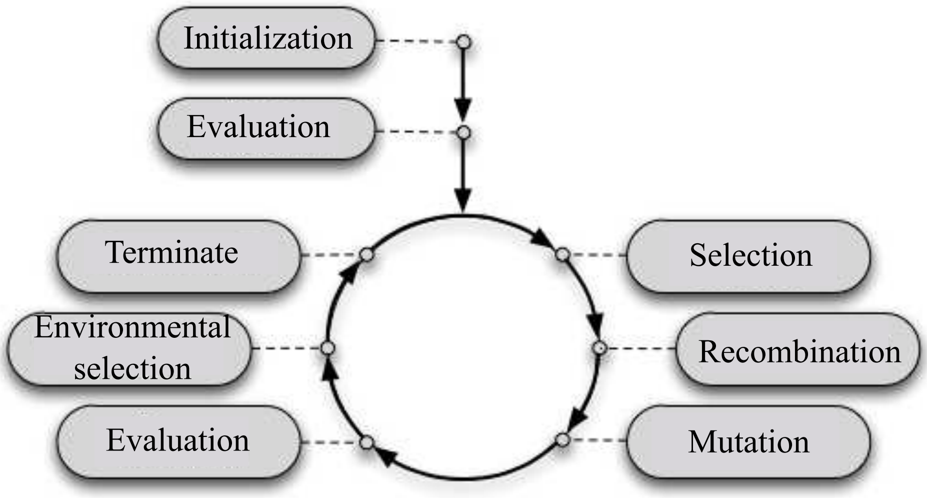


Figure 3.1: Schematic standard evolutionary algorithm

natural evolutionary process and can be successfully used for engineering optimization problems [44],[45]. The main operators of EAs are recombination, mutation, reproduction and selection of individuals, which build a new generation. The reproduction of individuals for the next generation is based on their fitness value. Fitness value has to be defined according to the target of the optimization task. An example of a standard optimization task could be the design of a structural element, which has to have some optimal characteristics. The individual is evaluated according to the defined quality measure, called fitness function. The value of the fitness function depends on how close the characteristics of the element are to the optimal solution. In the case of the fitness minimization task, the individuals with the lower fitness value will be selected.

Applied to the evolution of robot, EA generates populations of virtual robots that behave within the physics-based simulation. Each robot is then assigned a fitness value based on the quality of its behavior. Robots with low fitness are deleted while the robots that have high fitness values are copied into the next generation with slightly modified parameters, simulating the process of the natural mutation. The new robots are evaluated in the simulator and assigned a fitness, and this cycle (generation) is repeated until some predetermined time period exceeds. The most-fit robot then will be manufactured as a physical machine and deployed to perform its evolved behavior.

Figure 3.2 depicts roughly the main directions in robotics and its new branch of evolutionary robotics.

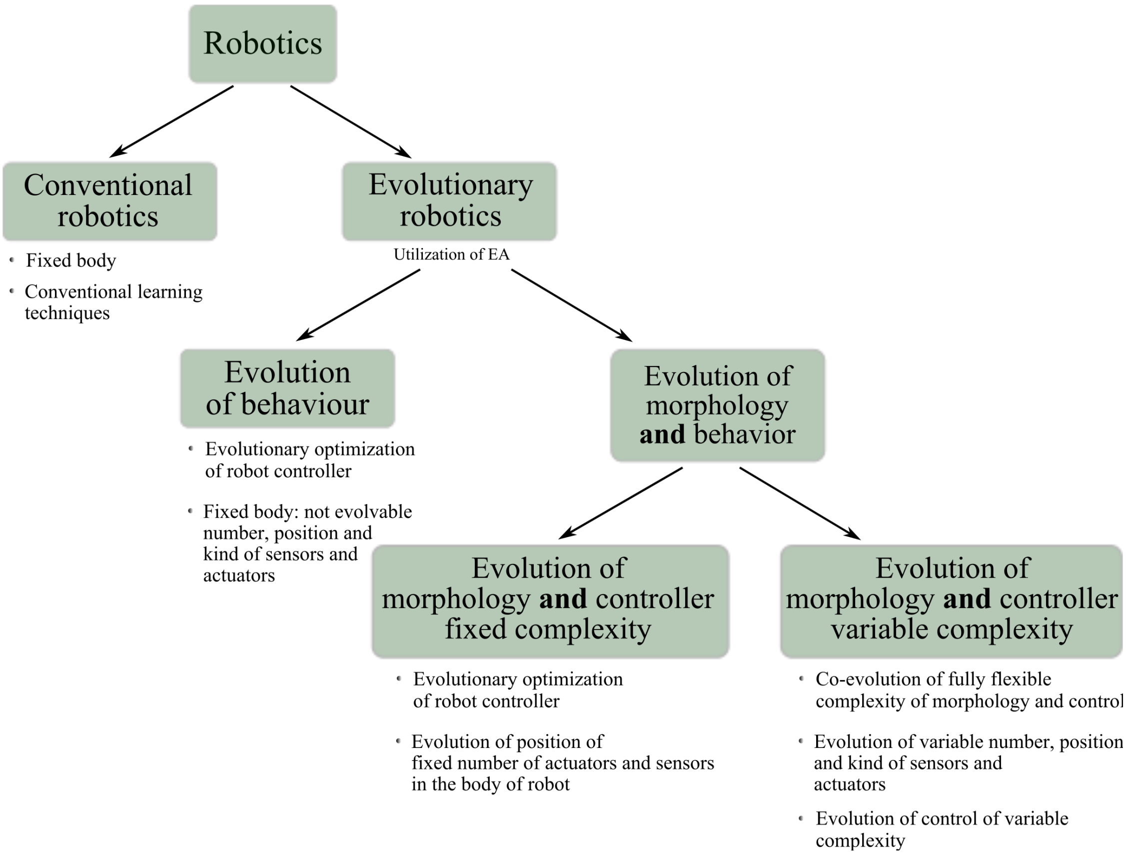


Figure 3.2: Evolutionary robotics

The depicted subdivision of the evolutionary robotics represents the main directions of the research in this domain. As mentioned in the previous chapter, a large number of research has been done to evolutionary optimize the controller strategies of fixed morphology of the robot [5], [6], [7], [8], [9] (evolution of behavior). In this case, the morphology of the robot stayed unchanged during the evolutionary process. The common tasks for the robots imply fulfilling diverse tasks through different kinds of locomotion. Some examples are:

- Wall following, where the robot is placed in a closed environment and has to learn navigation along the walls without collision. Robots sensors: laser, sonar, infrared or vision

- Obstacle avoidance is typically a part of some more complicated task. The goal for the robot is to navigate in the environment without running into obstacles. The environment can be static or contain moving objects.

- Box pushing has several variations. A robot or a group of them are given a task of pushing boxes to the walls, corners or specified positions.
- Legged walking is used with the 2,4,6,8-legged robot. The task is to train controller to synchronize the movement to fulfill the locomotion.
- T-maze navigation is a standard benchmark task. The robot first reads the direction at the entrance to a corridor. When evolved it should follow the corridor to the crossing and turn right or left based on the initial instruction.

All these tasks require environment perception with the existing sensors and the reaction based controller, which calculates the actuators response to the current situation. A robot controller is responsible for selecting an action for the robot to perform, based on the current and eventually past sensory readings and its knowledge. It is usually a combination of specialized hardware and a software running on some embedded microprocessor.

3.0.1 Controller architectures for adaptive systems

Regarding the model of the controller, a variety of different solution can be found in the literature. Parker and Nathan [46] as well as Bugajska and Schutz [47] implemented a controller as a reactive system which uses "if...then" rules to control a simulated robot. Haller, Ijspeert and Floreano [48] implemented a controller inspired by the central pattern generators underlying locomotion in animals.

Nevertheless, the most common controller realizations, which can deal with the behaviors of almost arbitrary complexity, are artificial neural networks (ANN). ANNs can be applied to many real-world problems, like pattern recognition, control of robots and many others. ANNs are computational models implemented as software solutions, which can be used for control of adaptive systems, inspired by biological nervous systems [49]. ANN consists of several interconnected process units, which have inputs and outputs, as shown in Fig. 3.3.

In general ANN is a directed graph with nodes represented by a "neuron". An artificial neural network is an interconnected group of nodes, like neurons in a brain. An artificial neuron is an abstraction of biological neural cell [51] and is described by mathematical models, represented in the Fig. 3.4.

The function f in Fig. 3.4 represents an activation function from the stimuli x_i. The most common biologically inspired activation function is the sigmoid as shown in Fig. 3.5. The neural network is a network of the described neurons, where

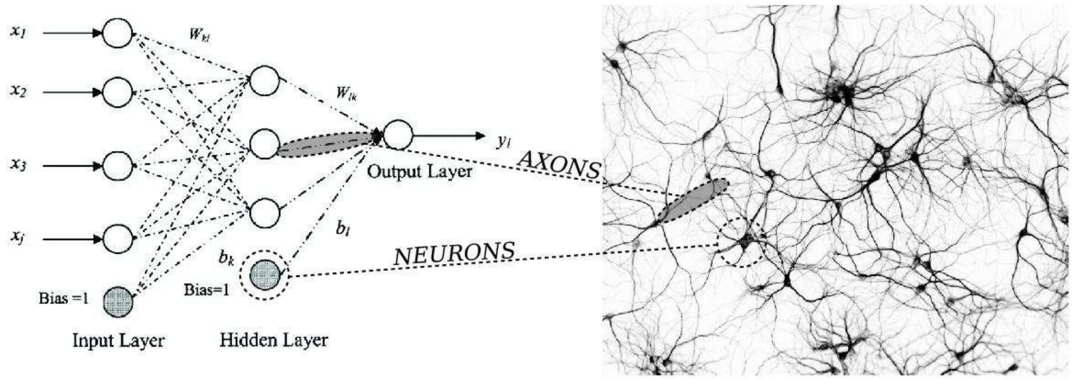


Figure 3.3: Artificial neural network and their biological example [50]

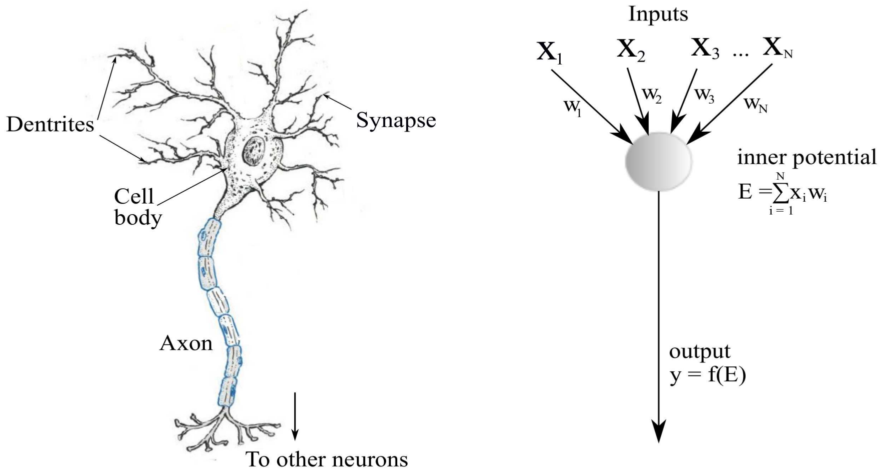


Figure 3.4: Abstraction of artificial axon from neural cell [50]

the output of one neuron is the input of further neuron. The neurons of the ANN can be classified into the input, output and hidden layer neurons, depending on its position and function in the network. The neurons, which sense the environment directly belong to the input layer of the network. The neurons in the inner part have a function to process the information from the input layer to the next or output layer. The output neurons process finally the signals to the effectors (actuators). In this case, ANN is a directed graph, where neuron models involve discrete-time or continuous-time dynamics. Connection strengths representing the edges, which connect neurons with each other are referred to synaptic weights. The input and output neurons represent the means to sense and react to the environment.

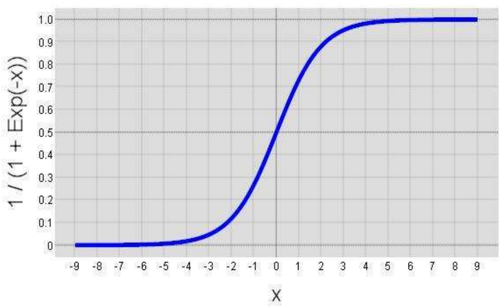


Figure 3.5: Sigmoidal activation function of neuron

The majority of experimental robot controllers are some sort of artificial neural network. The most common controller solutions are artificial feed-forward neural networks. Direct sensory inputs are fed into the layered network, the values propagate through weighted connections, and the sum of inputs in each node is usually transformed by non-linearity before the node outputs the signal to the next layer. The output signals from the last layer are sent to the robot actuators. The example of a standard feed-forward neural network is shown in Fig. 3.6.

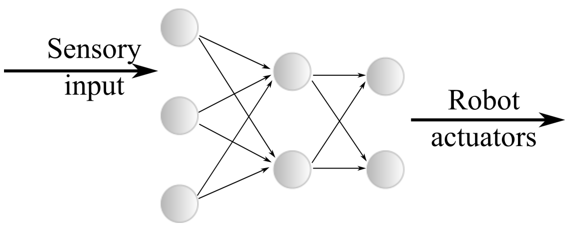


Figure 3.6: Artificial feed forward neural network

A feed-forward neural network can be extended to contain an internal state by adding memory units as extra inputs according to Fig. 3.7. These are the input values of the last measurement cycle. In general, the recurrent neural network can approximate any type of behavior.

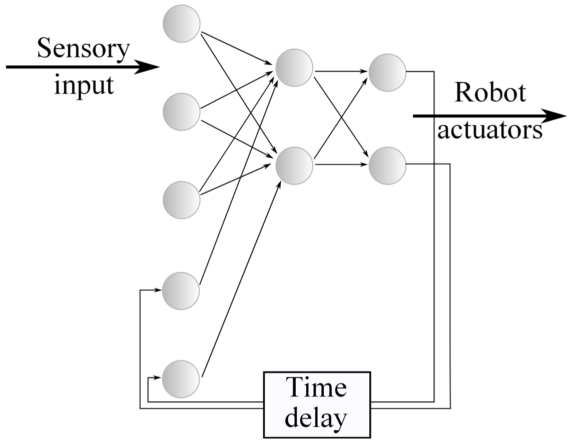


Figure 3.7: Recurrent artificial feed forward neural network

Neural networks were also used in modular architectures. One possibility is to allocate a separate neural network for each module. In another application [52] one neural network deals with all the modules but the outputs consist of two values produced by selector neurons and output neurons. The selector neurons indicate whether the current state of the environment is appropriate for the output neuron value to be taken into account. In this way, the modules compete for control over their assigned actuator.

As described the most wide-spread controller architectures in the domain of adaptive agents are some kind of neural networks with or without additional memory and non-linearities. The input nodes process the external information measured by the sensors and the output nodes trigger the available actuation mechanisms. In the domain of earlier introduced evolutionary robotics, instead of using conventional learning algorithms, some characteristics of the robots, like its limbs, sensory and actuation elements or the controller are coded in artificial genomes and evolved according to a performance criterion during the evolutionary process. The latest, controller of the robot, has been the central objective in evolutionary robotics for decades, where the placement and configuration of the perception and actuation mechanisms of the robot has been rather the tuning parameters in the later stages of the design process, if the optimization of the behavior (controller) of the robot was not successful with the initially selected configuration.

A broadly discussed strong evolutionary coupling between morphology and control of naturally raised adaptivity in biological systems represented the new research domain of evolutionary robotics - co-evolution of morphology and control [53]. The fundamental idea of this sub-domain has been to utilize the coupling of two dynamics of morphology and control through its concurrent evolution, similar to the biological evolution of living organisms. The idea of the co-evolution of form and function for a robot triggered a high number of various studies in the robotics community [47], [46], [54], [55], [7] etc. In this way, an engineer can make fewer assumptions about the morphology and the controller strategies of the robot since the evolutionary process is supposed to find the optimal configuration for the given task automatically. For example, there is often a debate about whether a wheeled or legged robot is more appropriate for moving over a given surface. Although not yet demonstrated, the co-evolutionary robotics algorithm should generate wheels robot if supplied with a simulation of flat terrain and legged robot if supplied with a simulation of rugged terrain since such an actuation is more suitable.

The biggest advantage of the co-evolutionary approach for the concurrent development of morphology and signal processing of adaptive systems assumed in producing arbitrary, unpredicted and optimal solutions leads to the biggest problem of its realization and is described in the next section.

3.0.2 Evolvability problems of complex adaptive structures

The co-evolutionary design in robotics is based on the utilization of strong coupling between the morphology and control and proposes the development of these two functionally different modules of the complete agent concurrently in the same evolutionary scope. This means the configuration of sensors and actuators, its number, calibration and position in the structure of the agents body as well as the corresponding controller, processing the external information to the actuator signals are not fixed and represent the objectives of entire complex optimization task. Regarding the usual tasks in modern robotics, like, for example, autonomous robot navigation in the rough unknown environment, extensive sensing and actuation capabilities of the autonomous agent are required. On the other hand, a large number of sensors and actuators of the autonomous agent result in a complex controller, capable of controlling the resulting morphology. As an example, a network, having 10 inputs, 20 neurons having only single hidden layer and 10 outputs, would already result in a genome size of over 400 genes. The strong coupling between the quality and availability of environment perception and its processing as well as the actuation capabilities makes the fitness landscape extremely complex. Regarding all these factors, the evolution of autonomous agents, completely arbitrary and fully variable during the developmental process gets infeasible, due to the explosion of a number of optimization parameters with the higher complexity of the morphology. The high dimensional search space of completely arbitrary structures leads to its low evolvability. Optimization of a large number of parameters, dealing with the most complex fitness landscapes with multiple local optima, like for example optimization of a robot control in the unknown environment, can cause a rapid decrease of the population diversity [1],[2]. In this case, an evolutionary optimization could easily stick in one of the local optima, not being able to find the globally optimal solution. The genetic coding of the system in the artificial genome represents an

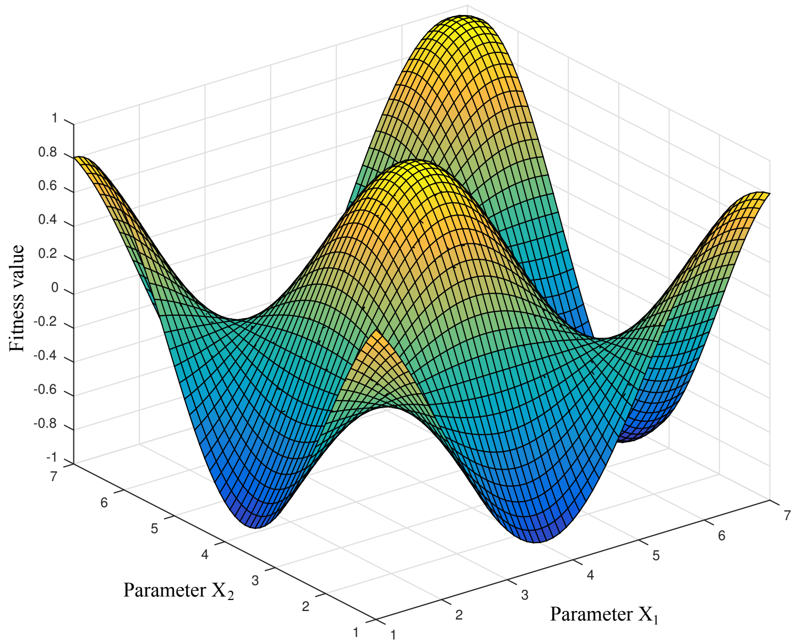


Figure 3.8: Example of fitness landscape for two optimization parameters

important stage of the realization of an evolutionary algorithm for the given optimization task and describes a solution or individual. The choice of representation affects heavily the probability to find a globally optimal solution. The global optimum is defined as the best possible solution in the whole fitness landscape. An example of a hypothetic fitness landscape is shown in Fig. 3.8. The canonical evolutionary techniques utilize direct or implicit representation, where the parameters values map directly one-to-one from the genetic information to the phenotype. In this case, the synaptic weights, neurons and other network parameters, the actuators and sensors parameters are directly encoded in the genome mostly as real values. To name the few, Montana and Davis used a direct representation for the evolution of ANN weights and compared it with the back-propagation algorithm for a benchmark problem of sonar data classification [56]. They showed with fair experiments, that EAs produced better networks and has been less computationally expensive than back-propagation in this case. Direct implicit representations have been used with excellent results for networks of relatively small size. However, the direct encoding when used by the standard evolutionary techniques, like standard ES or CMA-ES had a drawback, that the length of the genome grows rapidly with the size of the neural controller, which in return affected negatively its evolvability.

There have been a large number of problem solution proposals to enable the effective evolution of the agent of arbitrary complexity in the community of evolutionary robotics. However, the basic idea has been similar - the reduction or subdivision of multi-dimensional search space into smaller parts and solve them gradually and independently. The main difference between the studies has been various basic concepts of the incremental subdivision of solution complexity and the complexity of its genetic representation.

A new promising research direction has been the introduction of the indirect and developmental encoding, explained in detail in the next section. The difference of indirect encodings compared to the canonical representations is the complex mapping from the genetic representation to the solution in the phenotypical space. Similar to the protein building mechanisms in the biology, the genome rather contains the information how to build the final solution instead of representing direct the phenotypical features.

3.0.3 Indirect and developmental encodings

A large number of authors research the possibilities of genome representations with indirect genotype-phenotype mapping. Indirect encoding methods use different complex mapping techniques from the genome to the individual and, therefore, there is no direct correlation between the dimensionality of the search space and the size of the chromosome. While one direction of the research of indirect encodings utilizes rule-based grammars for the genome to phenotype transcription, another direction utilizes cell chemistry simulation approaches. One example of the rule based genotype-phenotype mapping is given by Moriarty and Miikulainen [57]. The authors developed an algorithm called symbiotic, adaptive neuro-evolution (SANE).

They encoded the neurons in binary chromosomes, containing a series of connection definitions. Each individual in the population represent only a partial solution to the problem and finally the complete solutions are formed through combining several individuals. Individual neurons are evolved to form the neural network and are connected only to the input and the output layer. Several individuals, representing each a single neuron formed into a neural network have been evaluated. The fitness of an individual partial solution is calculated by summing the fitness values of all possible combinations of other partial solutions and divided by the number of all possible combinations. Due to the fact, that a single neuron can not perform well, compared with a complete network, the diversity in the population is preserved and the EA is able to search for several heterogeneous search space areas simultaneously. Later on, in 1997 Miikkulainen together with Gomez extended SANE approach to the method, called enforced sub-populations [58] (ESP). The difference to the original SANE is that ESP allocates a separate population for each of the units in the neural network and a neuron can be recombined with the members of its own sub-population. ESP has an advantage against SANE due to the fact, that the networks formed by ESP always consist of the representative from each evolving specialization and each neuron is evaluated on the ability to perform its role in the context of all other players. With that the evolution of recurrent neural networks gets possible. The sub-populations architecture of the ESP makes the evaluation of the neuron more consistent. It has been shown, that ESP could be successfully applied to various standard evolutionary computation benchmark problems, like for example the pole balancing problem [59].

However, some later developed methods outperformed ESP on this benchmark. One of such novel methods is an algorithm called Neuro-Evolution of Augmenting Topologies (NEAT) developed by Stanley and Miikkulainen in 2002 [60]. This has been a method for the evolution of both, topology and the weights of the neural networks. Since not only the optimal weights of the neural connections but also the topology of the neural network play an important role in the ability of the neural network to solve the given problem, the concurrent evolution of topology and the connection weights of the network is essential, as shown by Chen et al. in 1993 [61]. The evolutionary development of the neural network's topology means the search for the optimal ANN's architecture to solve the given task. A problem of ANN topology optimization has been identified by Stanley and Miikkulainen and has been the fact, that the structural changes in the network often lead to a fitness decrease [60]. NEAT has been an attempt to solve the problem. The biggest advantage of NEAT is that it allows a crossover between the individuals of different genome size, representing the different topologies of competing ANNs. It is based on tracking genes with history markers to allow crossover among topologies, applying speciation to preserve innovative solutions with initially low fitness, but with the potential to develop into an individual of high quality later in an evolutionary process and developing topologies incrementally from simple initial structures into neural structures of arbitrary complexity [61]. Evolving the neural network's structure requires a flexible genetic encoding. In order to allow structures to develop during the evolutionary process into structures of arbitrary complexity, their genetic representation must be dynamic and expandable. Each genome in NEAT includes a list of connection genes, each of which refers to two node genes being connected. Each connection gene specifies the in-node, the out-node, the weight of the connection, whether or not the connection gene is expressed (an enable bit), and an innovation number, which allows finding corresponding genes during crossover [61]. Another principle NEAT is that the individuals compete primarily within their own niches instead of with the whole population. This evaluation mechanism protects the topological innovations and allows these novel solutions to evolve before they have to compete with other niches in the population. Another problem of the "genome bloating" described previously is also solved by the speciation: species with smaller genomes survive as long as their fitness is competitive, ensuring that small networks are not replaced by larger ones unnecessarily. Protecting innovation through speciation underlines the idea, that novel solutions need its time to develop and mature before the decision about its functionality can be made.

Another novel domain in the alternative genetic encodings has been developmental representations. So-called developmental encodings contain a description of the developmental process of the neural network - rules how to build the network. A pioneer in the area of developmental neural network encoding has been Kitano [62].

In 1995, Gruau proposed a genetic encoding scheme for neural networks called cellular encoding (CE) [63]. The encoding method is based on a biologically inspired cellular duplication and differentiation process. The network developmental process starts with a single cell, which divides and transform to the complete neural network. In CE, the genome consists of the rules, which describes the division process of the mother cell into two daughter cells. Additionally, it describes when the new neural connections appear and also the strength of this connections. A cellular duplication process generates new neural connections. There exist different duplication possibilities in Gruau's model, each using different methods for transmission of connection strength of the mother cell to the daughter cells. Gruau codes the individuals with binary tree structures and evolves the networks using genetic programming. The nodes contain program symbols, which represent instructions for cell developmental processes. During the construction of the network from the genome, the genotype tree is scanned starting from the initial node in the tree base and then following the branches. It can also be a genotype formed by several trees, where the last node of one tree can be a starting point of another one. This specificity of Gruau's encoding model allows the reuse of genetic information and allows to generate symmetric phenotypes, due to the fact that the trees, which are pointed to more than once will be executed more often.

Both CE and Kitano's grammar rules can be used to generate symmetric neural structures, using repeated patterns [64]. The problems of Kitano's approach in comparison to CE is, that the resulting connectivity matrix is often larger than the total number of neural elements in the final network, which has its problems in terms of evolvability. CE methods have an advantage that they can produce networks of arbitrary complexity, still using a genome of comparably small size, through the utilization of the grammar. During the developmental process, some parts of the code can be read by several cells concurrently, which will develop the copies of the same sub-networks. This feature of the network is called modularity. In terms of the genome size, is the CE more advantageous, because all the rewriting rules are used to build the final network, which is not the same for Kitano's rules, where only a part of the rules are actually used. CE have been successfully applied by Guaru in 1995 to the evolutionary optimization of the neural control of a hexapod robot.

Four different encoding models can be classified as geometric grammar [65],[52], [66]. The authors use growing encoding schemes to evolve the network topology together with the neural connection weights. The growth of the neural network takes place during evaluation of the individual and not before. Nolfi used this method to develop the neural controller for the Khepera robot [52]. The genome contains information how the axons growth and the appearance of a new branch are controlled. The environmental impact on the growth of an axon can be modeled as a sensitivity rules, like for example dentries bouncing against obstacles during the growth process. The connection between two neurons appears when the axon of one neuron reached by growth another neuron. The genome contains the information about the minimal value for the neuron activation needed to create the neural connection between the neurons. The final pruning algorithm deletes the neurons, which have no connections to further neurons.

The described method of activity-dependent growth of a neural network is based on the central idea, that the environment has a strong impact on the development of natural neural structures. Zheng and Purves found a practical example of the assumption, that regionally increased metabolic activity induced cortical growth in the developing brain of rats. The cortical growth has been measured to be much higher in regions of increased activity [67]. Obviously, two main factors influence the developmental process: the genetic information coded in the genome and the environment, pushing the neural maturing (growth) to some beneficial structures for the current environmental condition.

Another method for developmental encoding is called Lindenmayer systems (L-systems). L-systems are mathematical models proposed firstly by Lindenmayer in 1968 [68]. Lindenmayer used L-Systems to simulate the plant's cells behavior and their growth process. The L-Systems are grammatical encoding methods for the multi-cellular developmental process.

Another direction of co-evolutionary research is the investigation of developmental models for biological gene regulatory networks. The gradual development of the sensory, actuation and neural capabilities of higher organisms is twofold. The process of system maturing can be divided into ontogenetic and phylogenetic growth process. Ontogenetic growth is defined as the development of an organism from the egg's fertilization to the adult organism. The phylogenetic process describes rather the evolutionary development of the organisms in the history of the evolution. Both ontogenetic and phylogenetic development processes describe a gradual complexification of motion, perception and nervous systems. Besides the evolution of the body and functions complexity of the living creature, the growth process from a single cell to the mature state is highly complex. The researchers found out, that gene regulatory networks control the ontogenetic animal development. Biological gene regulatory networks are the representation of multiple interactions within a cell, a global view intended to help understand how relationships between molecules dictate cellular behavior. Recent advances in molecular and computational biology have made possible the study of intricate transcriptional regulatory networks that describe gene expression as a function of regulatory inputs specified by interactions between proteins and DNA. GRNs have an important role in every process of life, including cell differentiation, metabolism, the cell cycle and signal transduction [69]. The complex control systems underlying development have been evolved for more than a billion years. It regulates the expression of genes in any given developmental process. GRNs describe the regulation of the interactions from the genes to the proteins and their feedback to the activations of the genes. The genes of the organism are concentrated in the cell nucleus and are in each cell identical, controlling the growth, death, cell division, its differentiation, chemical emission etc. The gene regulation emerges through the fact that some genes or its execution get activated or suppressed depending on the current state of the cell and environment presented as a distribution of different transcription factors special chemicals. Therefore the genes can influence their activation or suppression by producing special chemicals, which again influence the production of special chemicals, responsible for the gene regulation. A certain mix of chemicals and its concretely defined minimal concentration is needed to produce the reaction on a particular gene. GRNs are called networks because it describes very complex nonlinear interactions between different genes through the means of gene expressions. Besides the internal gene inter-regulation, the surrounding environment of the organism during the growth period has not less important influence on the direction of the development process of the individual and the final realization as an adult individual. The behavior of embodied and situated organisms is an emergent result of the dynamical interaction between the nervous system, the body, and the external environment. Therefore GRNs ensure high evolvability of the solutions, allowing the organisms having the same genotype to develop differently if their environmental conditions or target task discern.

Several research studies have successfully implemented the co-evolution of morphology and control in developing organisms regulated by gene regulatory networks. Schramm and Sendhoff have made a research in the field of body-brain co-evolution under GRN control [70], described more in detail in the next chapter.

Bongard and Pfeifer used a minimal model of ontogenetic development, which they combined with differential gene expression and evolutionary algorithm, to evolve both the morphology and neural control of the agents [71]. The simple task of the agents has been pushing of the blocks in the virtual environment. The authors utilized indirect genome-phenotype mapping technique and have shown that it results in a dissociation between the information content in the genome and the complexity of the evolved agents. These findings supported the contribution that artificial ontogeny represents a powerful tool for the evolutionary design of complex adaptive systems.

3.1 Incremental evolution of adaptive structures

While the emphasis of a large number of studies has been on the introduction of special genetic representations to solve the evolvability problems of complex adaptive systems, others argued that the problem can be successfully solved through the gradual increase of system complexity during the evolutionary process. Methods followed this idea are called incremental evolutionary techniques. Two main directions of the studies on incremental evolution have been the gradual increase of the complexity of the environment of the agent or the gradual increase of the complexity of agent acting in the environment of constant complexity. The research in the domain of incremental evolution has been triggered by the early work of Turkewitz and Kenny [3]. The positive effect of early morphological limitations on the progress of learning of complex behavior is known in the evolutionary community as so-called "Benefits of starting small", initially introduced by Turkewitz and Kenny in 1982 [3]. Elman in 1993 [4] tried to find the explanation to the fact, that even though the human infant's cognitive and perception abilities are immature in the early stages of their development, they exhibit amazing learning abilities, especially in their first tree life years. Elmans early research describes the possible synergetic interactions between the early maturing process and the ability to learn a complex domain, like for example language on the example of connectionist networks. The networks were trained to process complex sentences. The experiments have shown, that learning of fully formed networks, "adult" networks failed completely. Otherwise, training was successful only in the case of networks with initially limited working memory gradually maturing to the adult state. This results suggested that early developmental restrictions on resources are not crucial limitations in achieving the final goal, but rather necessary for the learning capabilities of a complex behavior domain. For analysis involving componential inputs, like for example language, limited cognitive processing seems to be advantageous because it acts similar to a filter, which reduces the problem space, making it more feasible.

Harvey et al. [7] evolved controllers incrementally to let a robot distinguish between white triangular and rectangular objects on a dark background. The goal was to evolve controllers that would move robots towards triangles only. The task was divided into sub-tasks where the robots would first learn to orient themselves to face a large rectangle, easily detectable by their sensors, then to face and approach a smaller, moving rectangle, and finally to distinguish between rectangles and triangles, and only move towards triangles. Thus, controllers were first trained to follow white rectangles and then later trained not to follow them, but instead to follow triangles only. The authors divided the goal-task into subtasks in which recognition and pursuit were learned in the first evolutionary phase, or increment while discrimination between the two geometric shapes was learned during later increments. The controllers obtained with incremental evolution were shown to be more robust than controllers trained on the complete task from an initial random population.

Gomez and Miikkulainen [72] used incremental evolution, combined with enforced sub-population and delta-coding, to evolve obstacle avoidance and predator evasion. Incremental evolution was performed by first evolving populations of neurons capable of avoiding a single enemy moving at low speed on a discrete 10x10 grid. The size of the grid was then increased to a 13x13 grid and another enemy was added. Two increments followed in which the speed of the two enemies was increased. The authors found that evolving controllers for the complete task directly was infeasible while incremental evolution yielded satisfactory results.

Floreano demonstrated that evolution in changing environment can lead to better results than static environment [73]. In his experiments with nest-based foraging strategies, Floreano first evolved feed-forward reactive neural network in the environment with a constant amount of food. Later he compared it to an evolution in environments where the amount of food decreases, thus the task becomes incrementally more complex. The result of the study has been the insight that the environmental changes lead to significant improvement in quality and efficiency of the foraging strategies.

It has been shown by the various researchers, that incremental evolution of the complex adaptive agents can be beneficial since it allows the development of systems gradually increasing its capabilities during the evolutionary progress. The focus of the next chapter is an overview of the co-evolutionary approaches in the early and modern evolutionary robotics.

3.2 Related work on co-evolutionary approach in evolutionary robotics

The pioneer in the research on the concurrent development of morphology and control in evolutionary robotics has been Karl Sims [74]. Sims developed a novel system for creating virtual creatures which acted in a simulated three-dimensional physical world. The novelty of the research has been the fact that the morphologies of creatures and their signal processing systems for controlling their muscle forces have been both, generated concurrently and automatically, by the means of genetic algorithms.

Sims used directed graphs to describe both the morphology and the neural circuitry of the virtual creatures. A genetic language for representing virtual creatures with directed graphs of nodes and connections had the advantage that it gives a possibility of an unlimited hyperspace of possible creatures to be explored. A variety of successful and interesting locomotion techniques of the Sim's virtual creatures emerged. Some of them have been completely novel and could be difficult predicted or build by the design of an engineer.

The research of Sims in co-evolutionary robotics has been followed by a great number of researchers. Among others, Dellaert and Beer [66] presented work, where they used the developmental model to automatically create autonomous agents. The agents have been evolved by the means of the body-nervous system co-evolution. The developmental models presented by Dellaert and Beer addresses the development of emerging patterns of different cell types, represented by square elements of different color, into fully functional agents, complete with sensors, actuators and a nervous system to control them.

Parker and Nathan [46] 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 number of sensors to increase the system's overall efficiency.

Bugajska and Schutz [47] 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. The target of the research was similar to Parker and Nathan [46] to find the optimal minimum sensor suite and reactive strategies(controller) for navigation and collision avoidance tasks. For the optimization, two cooperating genetic algorithm-based systems SAMUEL and GENESIS were used, while GENESIS is used to evolve characteristics of the sensors of the aircraft, for example: sensor range, area coverage, and placement. SAMUEL, in contrast, evolves the stimuli-response rules(controller). The two systems create a loop in which the output from one learning system is the input to the other one: in the external loop the sensor suite set is chosen, then in the internal loop the control rules are evolved for this concrete sensor configuration. In the system available sensors return range and bearing to the target. The number and the sensor coverage are to be evolved. From the effector side, the only action that is considered specifies discrete turning rates for the MAV. The controller is implemented as a stimulus-response rule. Each stimulus-response rule consists of conditions that match against the current sensor of the autonomous vehicle, and an action that is suggested to be performed by it.

Sugiura et al. also proposed a system that automatically designs the sensor morphology of an autonomous robot with two kinds of adaptation: ontogenetic and phylogenetic adaptation [55].

Also, Auerbach and Bongard [54] 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.

Cliff et al. [7] also co-evolved the control system and the sensory morphology of a mobile robot. The genotype consisted of two parts encoding the control system (the connection weights and the architecture of a neural controller) and the visual morphology (number, size and position of visual receptive fields), respectively. The authors have shown that co-evolution of the two systems allowed evolved robots to rely on very simple strategies, such as comparing the correlated activities of only two visual receptors located at strategic positions on the retinal surface.

Lichtensteiger and Eggenberger [27] evolved the morphology of a compound eye of a robot which had to move a straight trajectory, and observed that evolved individuals had a higher density of photoreceptors in the front.

In the research of Lund et al. [75] control system and some characteristics of the body of Khepera-like robots were co-evolved to navigate while avoiding obstacles. The evolved morphology has been body size, the distance between the two wheels, and the wheel radius. The authors analyzed the distribution of evolved robots in the morphological space and observed interesting correlations between evolved morphological characteristics (such as an almost linear relationship between body size and wheel distance) and the environment.

Some studies demonstrated how co-evolutionary algorithms can be utilized to handle the complex interactions among material properties, physical form and control patterns in aquatic environments. Clark and McKinley exploited the complex internal interactions between actuation and material properties through controller-morphology evolution of a robotic fish [76]. Aquatic environment makes robotic fish behavior difficult to predict and subsequently difficult to optimize. For optimization of robotic fish propulsion, the co-evolution of control patterns and caudal flexibility could be successfully performed using a variant of the conventional genetic algorithm (GA) due to intermediate size and fixed dimensionality of the actuation system.

One of the recently popular branches of co-evolutionary robotics are modular robots as it is highly agile and capable of arbitrary movements, which it can perform due to its special morphology. The modular robots are formed of combinations of different rigid modules. Due to this morphological organization, the modular robots can continue locomotion even in the case of damage due to unpredicted environmental conditions. The problem of modeling and design of such a system is a large number of degrees of freedom. This means neither the optimal structure, nor the number of segments, nor segment lengths, nor the perfectly suited signal processing able of controlling the resulting morphology are known. Together with the strong interdependencies between the controller strategy and the system morphology the design of the optimal entire system represents a challenging large-scale optimization problem. The concurrent evolution of morphology and control of such robots turned out to be very effective [2] since it synchronizes the development of optimal configuration of form and function automatically and exploits its interdependencies during the combined evolutionary process. To solve the optimization problem hybridized evolutionary algorithms have been introduced for example by the recent research of Teo and Shun in 2014, which combined genetic programming (GP) and differential evolution (DE). The morphology of the modular robot has been directly represented using the tree-based structure of GP where each structure unit within the tree structure represents a segment of the robot. Besides that, the tree-based structure has been used to depict the artificial neural network structure of the robot controller. This makes the neural network of the controller flexible in design and directly linked to the changes in the body of the robot.

The co-evolution of morphology and control has been applied also to the design of currently booming area of soft robots which have a soft structure are resilient and deformable and able of shape adaptation [77]. The co-evolutionary approach in this research domain has been especially effective due to the additional problems of design which come along with the elasticity and deformability of the body structure. The soft robots inherit a high degree of coupling between the material properties of a soft body, like stiffness or damping coefficients and its controller small changes to the elasticity of a soft robot can cause unexpectedly large changes in performance. The three central challenges morphology, material and control are all interdepended and a solution to any one is predicated upon existing solutions to the other two. The concurrent evolutionary development of all these functional parts of the overall structure could be successfully carried out by Rieffel et. al.[77]. The approach utilized grammatically based development encoding of L-systems, which represents the domain of indirect encodings. The resulting evolved systems were capable of different locomotion task, which could be partially traced back to the symmetry and modularity of the resulting morphologies.

In the last years a new branch in evolutionary domain arose - novelty search. A new direction of evolutionary technique guides the evolution towards behavioral novelty, in contrast with traditional evolutionary approaches where a static objective is pursued. The novelty search became popular in the field of evolutionary robotics since it is hoped to produce completely novel solutions through the completely or partially elimination of fitness measure [78], [79], [80], [81]. In this case, the evolution is forced towards innovation through the specially constructed difference measure to encourage an exploratory search based on a diverse population of solutions. A common criticism of novelty search is that it is effectively random or exhaustive search because it tries solutions in an unordered manner until a correct one is found. This could be partially neglected in [82] and [79] in the case of appropriate novelty measure, which selection is not trivial and presently mostly problem dependent. The novelty search could be successfully applied in the domain of previously mentioned soft robotics. In [82] it has been discovered, that well-defined behavior metrics can lead novelty search under particular conditions to outperform traditional fitness-based search. Novelty search could improve the performance and diversity in the fitness space as well as contributed the larger variety of morphologies.

In the next chapter, the preliminary research on morphology-control co-evolution of artificial multi-cellular organisms under the regulation of simplified GRN model is presented. The evolutionary optimization of gene regulatory networks allows generation of effective developmental models for growth and differentiation of multicellular organisms during its development while at the same time shedding light on the interaction between environmental conditions and the final system realization. Subsequently, a new co-evolutionary approach for the development of real-world adaptive applications, proposed in the scope of this thesis is described. The new approach utilizes the broadly discussed concept of the coupling of the dynamics of morphology and control of the adaptive structures during combined evolutionary development. At the same time, the basic idea of the early described incremental evolutionary techniques has been realized through the gradual complexification of both, the morphology and control of the agent acting in the changing environments. In contrast to the previously described examples of co-evolutionary approaches in evolutionary robotics, the problems of aerodynamical optimization and situation-based decision making during autonomous driving of intelligent vehicle has been utilized. The new co-evolutionary growth method produced evolvable complex systems with standard evolutionary optimization algorithms through the development of such a representation, which could be able to describe currently unknown structures with an arbitrary complexity while at the same time it allows an evolutionary adaptation of the currently represented structure. The high degree of freedom for the evolutionary process has been achieved through the integration of the adaptable representation - the genome of variable length and therewith variable system complexity. The configuration of morphology has been coded in a single combined genome which develops during the evolutionary process controlled by an internal gradual system complexification mechanism. The initially basic structures with primitive perception and actuation possibilities growth into structures capable of complex behavior during a progress of a simulated evolutionary process.

4 Co-evolutionary development of adaptive systems

As described in the previous chapter the evolutionary development of higher animals is a complex process of ongoing body-brain complexification with the target to better adjust to the continuously changing 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, the contribution of the thesis is that the design process of technical solutions with the high complexity of adaptive behavior could be improved by starting the system development with an initially simple system organization while performing simultaneous complexification of all its functional parts - sensors, actuators and the controller. The majority of the current engineering methods adapt isolated parts of the overall structure, which is in a strong contrast to evolution. The design of adaptive systems implies a selection of sensors and actuators, which sense the environment and have a capability to adjust the system to a changed environment, as well as the 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 a camera system, fixed joints angle range etc. Then, through the following optimization of the 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 [5], Dorigo and Schnepf [6], Cliff, Husband and Harvey [7], Floreano and Mondada [8], Miglino, Nafasi, Taylor [9].

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 achieve 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. An attempt to overcome the problem could be optimization of the initially very rich system, having a high number of sensory and actuation elements. This would statistically decrease a risk 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, described above as evolvability problems. To solve the problem of the unknown optimal system configuration a new system growth model has been proposed. Although 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 are not specified in the early design stage and are the result of the evolutionary optimization process implemented as a dynamic system growth process. The concurrent optimization of the entire system synchronizes the design process of sensing and signal processing system parts during the optimization process and additionally frees the system of early structural limitations. Therefore, it gives a possibility to develop a system autonomously to the optimal morphological configuration for an autonomous agent. Since the final system configuration is not pre-defined and is the result of the concurrent optimization process, it remains evolvable and imposes potentially increased chances of global optimum detection. The contribution is that developed co-evolutionary growth method is able to generate systems which can optimally adapt to environmental conditions while at the same time targeting shedding some light on the precise synchronization of system parts during the developmental process. When the number of mechanical degrees of freedom which are needed to be controlled is initially limited, the complexity of motor learning can be reduced. Through gradual freeing the system from morphological limitation during its evolutionary development, the system acquires advanced perception, motion and functional capabilities [83].

As described in the previous chapter, the co-evolutionary approaches for the development of autonomous agents in evolutionary robotics has been successfully applied and are widely accepted in the robotics community. It has been shown, that it is possible to create agents in evolutionary frameworks, where the morphology and control are co-optimized in virtual environments. Co-evolving the body and control strategy of the simulated robot the researchers could create agents uniquely suited for the machine's task environment. The automatic design of the overall system configuration could improve the efficiency and functionality of the agents compared with the man-made machines.

4.1 Developmental approaches for multi-cellular systems

Traditionally the focus of the co-evolution of morphology and control in evolutionary robotic has been on the utilization of indirect encodings described in detail in the previous chapter like for example by Stanley and others [84], [85]. The indirect encoding has been an attempt to overcome the problems of the evolvability of the neuro-evolutionary approaches. Stanley has shown that indirect encodings were able to capture geometric symmetries appropriate to the evolved systems, like a multi-legged robot for the locomotion [85]. The indirect encodings mostly work well for the systems with inherited symmetry, like for the example of multi-legged robots.

Schramm and Sendhoff used a model for co-evolving morphological development and motor control for simulation of artificial swimming animats. The morphological development is based on a cellular growth model regulated by a GRN, where the motor control is represented by the period and phase shifts of the springs [70]. The authors utilized the basic idea of co-evolutionary approach by using combined genome, which contained both morphological configuration and signal processing structure of an artificial cell. The implemented gene regulation unit controlled the development of the organism from a single cell to an adult individual by the means of cell diving, death or differentiation to a different cell type. The body of the virtual organism consisted of multiple cells. Some of the cells differentiated during the development stage to the control cells, which could perform the behavioral actions of the organisms. The nervous system has been integrated in the morphology through the fact, that the neurons have been basic cells able of differentiation during the organism growth process in the parts of the body, where neural control was required. Since the nervous system was integrated in the body, the concurrent evolution of the morphology and control could be performed. An "adult" individuals were the results of growth process controlled by the evolved GRN. The cellular control has realized through central pattern generators, similar to the coupled rhythmic muscle activation for locomotion. GRN model proposed by Schramm and Sendhoff [70] was defined as a set of genes, each consisting of a number of regulatory (RU) and structural (SU) units. SUs defined cellular behavior, such as cell division, death or production of chemicals for inter-cell communications. The activity level of the

RUs in gene determined if the SUs of the gene were expressed or not. RUs, in turn, regulate the expressions of SUs, where RUs can be activating or repressive. The activation level of RUs is influenced by particular chemical, called transcription factors, which can ignore the RU. In the case the affinity level of transcription factor and the regulatory unit is smaller than defined threshold, the transcription factor is blind to the RUs to regulate the gene activation. The evolutionary optimization of the GRN produced a simple organism, which could produce swimming locomotion.

4.2 Pattern generation under simplified GRN model as example of cell differentiation

The results of the experiments in [70] have shown that the evolutionary optimization of gene regulatory networks allows generation of effective developmental models for structure differentiation of multi-cellular organisms during the growth process. Predefined distributions of chemicals in the experiments simulated the external environment and had strong a impact on the final solution found by the evolution. For the investigation of the regulation of the differentiation process during system development under the influence of environmental conditions in developing structures, preliminary research on a cell pattern generation problem has been carried out.

Fleischer and Barr investigated cell pattern generation using realistic models chemical diffusion, cell collision, adhesion and recognition [86]. They showed with the results that design of the artificial genome that develops into a specific pattern is not trivial and serves an appropriate test-bed for the research on developmental models for structures with different types of functional units. Well-established french flag problem as a special case of pattern generation represents difficult but interesting optimization problem, that of the growth and regulation of a differentiated multi-cellular organism, which looks like a french flag. The cells should differentiate to different types (which are represented in discrete colors or continuous grayscale) at different positions in the computation area. Pattern generation problems represent an abstraction of adaptive structure, since it has different cell types, which in turn can be defined as virtual sensors, actuators or control structure elements. The internal gene regulatory mechanism regulates the development of the two-dimensional structure through the cell differentiation into the target pattern. The resulting cellular pattern is evaluated by comparing it to a French or another flag.

A general problem of optimization and also developmental evolution is to gain stability and the ability of regeneration. Miller developed the French flag and showed that some flags are stable [87]. They do not change if development continues. Some also have the ability of repairing themselves if only small parts of the pattern are destroyed. In the gene regulatory network model of Knabe et al. cells consist of several pixels and it is also used to solve the French flag problem [88].

For solving the French Flag Problem a simple GRN model was utilized. The Macro cellular model is based on the Macro Cell program, which contains the global DNA information. The cell posseses the ability to measure a chemical concentration through its receptors and can also emit chemicals into the neighborhood through its emitters. The control structure of the cell has been realized through artificial feed forward neural network with 10 neurons in a single hidden layer. The neurons of the hidden layer have sigmoid activation function. Receptor signals are the inputs and emitter signals the outputs of the neural network. The genome contains the information about the structure of the cellular system as well as the full description of the input-output relationship. Inter-cell communication, analog to transcription factors, is available from the receptors. In the simulation, two predefined chemical signal concentrations (receptor activators) presented in Fig.4.1 has been used and are the abstraction of the external environment.

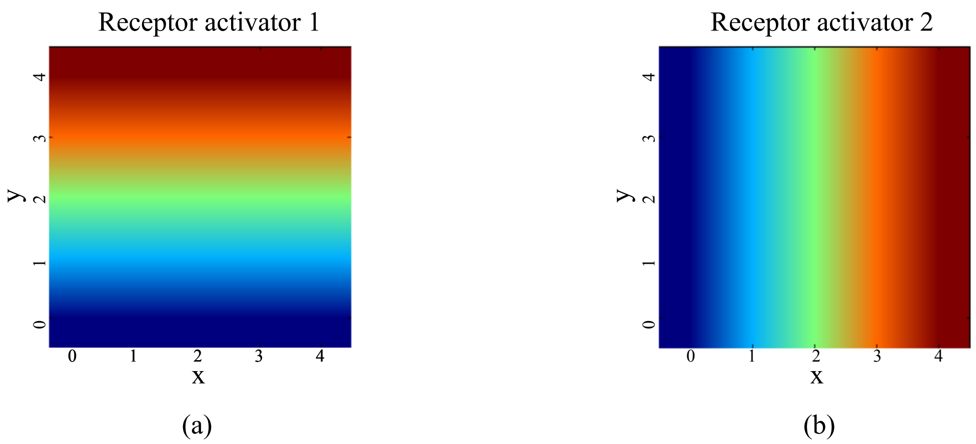


Figure 4.1: Two predefined chemical signal concentrations of TF_1 (a) and TF_2 (b)

These channels are connected to a diffusion process which is realized in every simulation time step. The diffusion process is simulated by a Gaussian distribution of signals along the Euclidean cell space and the signal space. The difference between cell and signal space is depicted in Fig.4.2. The cell activation is the sum of all signals weighted by distance in cell space and signal space.

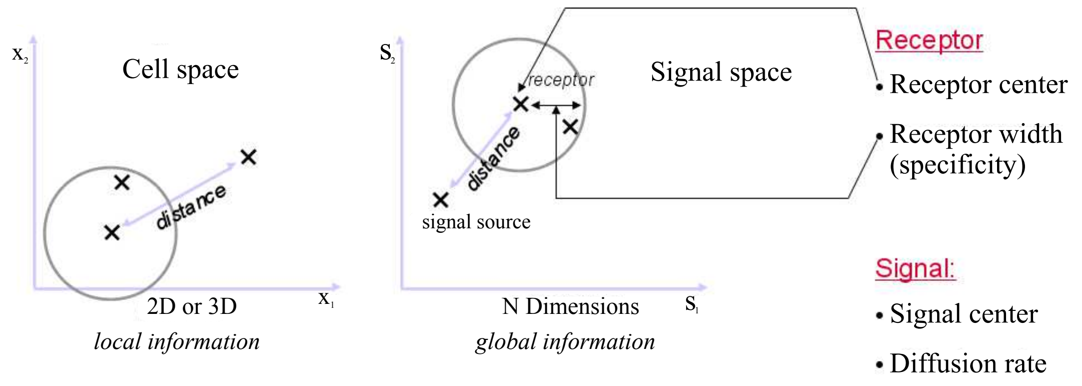


Figure 4.2: Euclidean cell space and signal space

Meta class *Organism* was used to simulate artificial organism, consisting of the cells, all containing identical DNA information. During the simulation of the artificial french flag organism, cells are put into the two-dimensional world space. For each cell, the input signals are processed to the output signals (emitter). At the first time step, two given receptor activators are processed into one emitter signal. Beginning with a second time step both fixed receptor activators and gained emitter signal have been processed by the neural cell controller of Macro Cell.

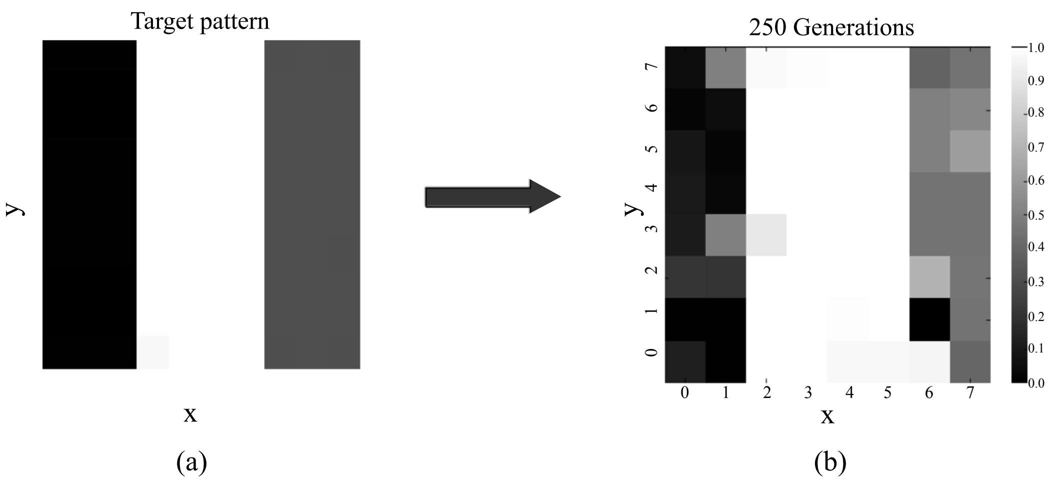


Figure 4.3: (a) Target pattern, (b) Artificial multi-cellular french flag organism

The standard evolutionary algorithm ES(15,100) [89], [90] has been used to optimize both parameter of GRN, described by the weights of the neural network, and the specificity of receptors to contrast different patterns with evolutionary algorithms. The target pattern is presented in Fig.4.3 (a). The model simulated for a single time step contrasted pattern close to the target after 250 iterations as shown in Fig.4.3 (b).

Similar to the differentiation of the cells to the control cells in a multi-cellular organism in [70], differentiation of genetically identical *Macrocells* to black, gray or white cell type during the simulation has been investigated. The results of the experiments have shown that the evolutionary optimization of even very basic gene regulation allows generation of effective developmental models for structure differentiation. Predefined distributions of two chemicals in the experiments simulated the external environment and had a strong impact on the final solution found by the evolution.

The research on morphology-control co-evolution [70], supported by own simulation results, exhibits the applicability of co-evolutionary development of artificial multi-cellular organisms under the regulation of GRN models. However, while the field of computational biology continuously progresses and provides useful and established models for theoretical biology, applications in real-world systems like electronic systems, embedded systems, developmental software etc. still remain at very basic level. The majority of the real-world engineering applications need arbitrary morphological configurations optimally suited to the environmental conditions. For example, the aerodynamic problems are characterized by highly complex interactions between flow body and flow field, which is, in most cases, difficult to understand in detail. When the goal is to create accurate models for biology in order to make predictions for biological systems, the trade-off between computational resource demands and complexity and accuracy can usually be made in favor of the latter. When researching biological processes the questions asked arise solely from the subject itself, which does not make modeling less complex but does not require to implement and interface such systems in non-natural embodiments of which it is not clear how to interface them and whether they are designed in a way that compliments the principles of biological development. While it seems to be obvious which properties of biological organisms are desired in designed systems, it is still poorly understood what the crucial mechanisms are to achieve these behaviors and how to model those mechanisms effectively and in ways that are feasible for artificial systems. Some of the important questions which have to be clarified when designing realistic developmental systems using multi-cellular models are:

- Which available technical structure of the designed system should be represented by one cell?
- What should be the complexity of an artificial cell?

- Is it necessary or advantageous at all to create a complex multi-cellular system when, for instance, a control task can be accomplished using a single cell?
- In nature, cells that are faulty or no longer required die and new ones are grown to replace them; in what ways is this ability limited in artificial systems?

Interpreting the biological inspiration in a straightforward manner in order to apply it to systems design, like for example applications in the aerodynamic area would demand building a very large number of highly complex entities (cells). From an engineering point of view, it seems to be desirable to incorporate a large number of cells into a system in order to achieve scalability. However, due to resource constraints being entirely different to biological systems, a high number of trade-offs need to be made when creating an artificial developmental system and many biological mechanisms and entities need to be implemented in different ways. Therefore the evolutionary development of real-world applications requires a distinct mapping of genetic code to realistic morphological structures.

4.3 New proposal for co-evolutionary growth method

Due to this arguments, in this work a special method has been proposed for the development of the entire system architecture, consisting of sensors, actuators and signal processing structure needed to control the developed morphology of the agent, using direct genotype to phenotype mapping. The developed representation simplifies the genotype-phenotype mapping of morphology-control co-evolution compared to developmental models and allows direct translation of genes to the phenotype of the evolved morphology and signal processing of the resulting system without intermediate ontogenetic developmental steps. This allows the analysis of correlations between evolutionary development of single genes and its impact on the phenotypical characteristics.

As discussed in detail, the main contribution is that the inspiration from natural body-brain co-evolution could make the design process of adaptive structures highly efficient in terms of functionality and actuation and sensor resources efficiency. The idea is to transfer biologically inspired growth process to a design process which can give the possibility to coordinate the development of sensor and control structures without dimensional limitation of sensory actuation or controller setup in the early stages of structural development. A novel growth method presented here inherits two main aspects of biological design: the concurrent evolution of morphology and control and ongoing process of complexification - from simple towards complex system's organization. An evolution starts with the system, having possibly minimal configuration, in the extreme case - single sensor and actuator and a single neural connection. Since the final system configuration is not pre-defined and is the result of the concurrent optimization process, the system is evolvable in many scales.

4.3.1 Definition of new evolutionary system growth method

The co-evolutionary approach has been realized by the concurrent development and gradual complexification of the sensory, actuation and corresponding controller systems. All 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, the co-evolutionary optimization method is combined with a growth process and implemented it as a single dynamic optimization task.

Genetic representation and optimization algorithm of developing adaptive structures

The standard evolution strategy optimization, ES(15,100) developed by Bienert, Rechenberg and Schwefel [89] has been chosen to optimize the overall adaptive systems configuration, presented later. Although more sophisticated algorithms are available like CMA-ES [90], the comparable simple evolutionary strategy has been selected. The decision has been motivated by the poor results of the experiments with CMA-ES, not presented in the thesis. CMA-ES struggled with the adaptation of newly appeared morphological elements during the growth process.

The example of selected genetic representation of adaptive structure is given in Fig. 4.4. A single genome of the individual includes four chromosomes which represent the morphology of the sensory and actuation structures, controller parameters as well as the optimization strategy parameters (individual mutation step sizes). The translation of genetic code to the final morphology is direct and takes place in one simulation time cycle. The genetic representation of the sensory and actuation elements describes its position in the one, two or three-dimensional structure of the adaptive system and its characteristics, like for example specificity of a receiver for the measurement of some chemical concentration in the environment or maximal range and width of a radar sensor. An example of characteristics of an actuator in case of mechanical spring construction could be its stiffness. The overall optimization of the currently represented adaptive structure including sensors, actuators

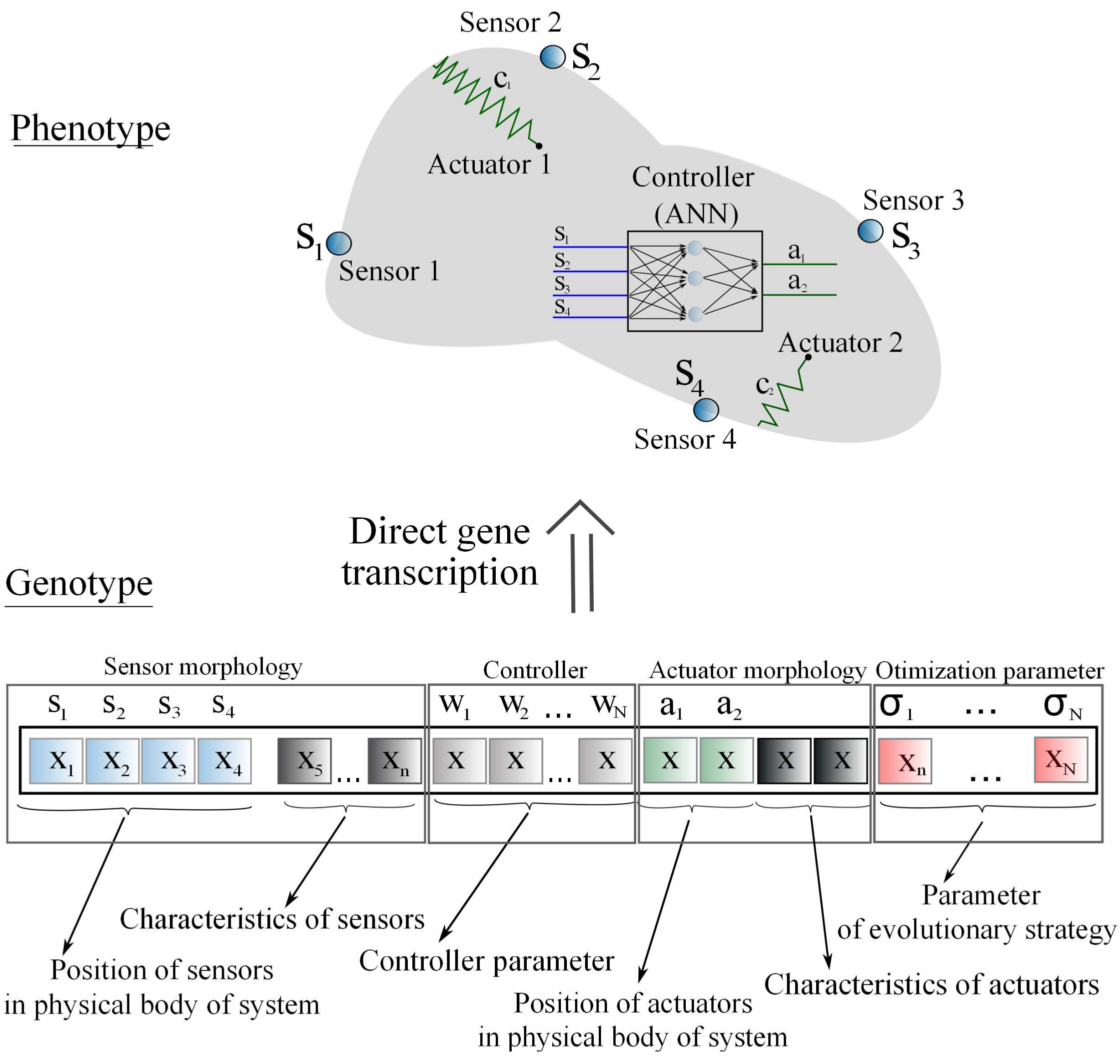


Figure 4.4: Example of adaptive structure and its genetic representation

and controller is scaled down to the optimization of parameter vector $\overrightarrow{x}$. The optimization problem is defined as follows

Minimize $f(x_1, x_2, x_3 ... x_n)$

where each x_i is a real parameter subject to $a_i \leqslant x_i \geqslant b_i$

for some constraints a_i and b_i

Constraints a_i and b_i represent the boundaries of the real mechanical embodiments or perception mechanisms of resulting morphology. An example of the constraints on the position of sensory elements could be the requirement to restrict the placement of the sensors to the surface of the structure. In this case, it is decisive to select appropriate coordination system to minimize the complexity of the genetic representation of final morphology. Fig.4.5 depicts an example of two different genetic representations of sensor position for the same two-dimensional structure. Fig. 4.5 (a) gives an example of the two-dimensional Cartesian coordinate system.

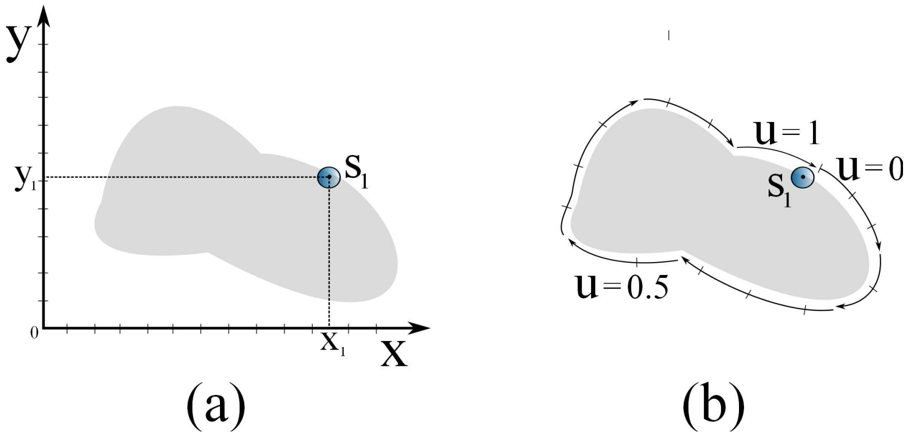


Figure 4.5: (a) Cartesian coordinate system, (b) Peripheral parameter

The position of the sensor s_1 is described by two real values (x_1, y_1) of X and Y axis in the cartesian coordinates. The genetic representation through Cartesian coordinates for the given optimization problem is not beneficial due to the restriction of the sensor position to the surface of the structure. Overall search space includes, in this case, multiple areas of unfeasible solutions - outside of structure surface. Fig. 4.5 (b) depicts more suitable and compact representation through peripheral parameter u. The introduction of a single peripheral parameter is beneficial, since all values of parameter u lead to a valid solution. Fig. 4.6 demonstrates an example of a high number of constraints and therefore a small subset of feasible solutions in the multi-dimensional search space.

The variation parameter in the optimization is realized by Gaussian mutation, which modifies all components of the solution vector $\overrightarrow{x} = (x_1, x_2, x_3...x_n)$ by adding a random noise.

$$\overrightarrow{x}^{t+1} = \overrightarrow{x}^{t+1} + N(0, \overrightarrow{\sigma}) \tag{4.1}$$

The target of the optimization is to generate the optimal adaptive system configuration able of appropriate reactions to the changing environment. The objective function f is defined on the high-dimensional search space of $\overrightarrow{x}$ and indicates the measure of adaptive behavior, according to Eq. 4.2.

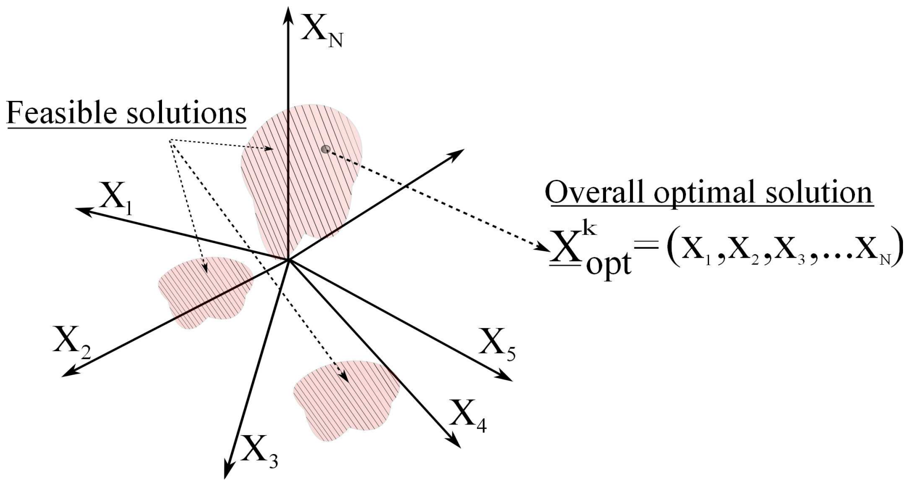


Figure 4.6: Example of multi-dimensional search space and subset of feasible solutions

$$f(\overrightarrow{x}) = \sum_{j=1}^{K} (\frac{P_j^t(\overrightarrow{x})}{P_j^{t+1}(\overrightarrow{x})}), \tag{4.2}$$

where j is the environmental condition, P_j^t is the performance of the system before controller adaptation to the changed environmental condition j, P_j^{t+1} - performance of the system after controller adaptation to the changed environmental condition j. If the adaptation of the system has been successful and leads to the improvement of the overall system performance for the changed environmental condition, then $P_j^{t+1} > P_j^t$. Therefore the minimization of objective function f during the optimization maximizes the adaptation quality according to the definition in Eq. 4.2. The objective function f is characterized by its high dimensionality, nonlinear parameter interaction, and the multimodality.

The evaluation of the overall system adaptivity in the simulation environment requires enormous computational resources. Depending on the application domain the evaluation of the system performance P_j for one condition j can require minutes up to hours on a single core CPU (Central Processing Unit). To evaluate a single individual in the population under 10 different environmental conditions would lead to 20 evaluations, at minimum twice for one condition j - before and after controller actions. During the optimization of for example of 100 generations, this would lead to 200.000 evaluations during the overall optimization process.

4.3.2 Implementation of co-evolutionary growth process

As described before the co-evolutionary design of real-world adaptive applications represents large-scale optimization problems involving a high number of constraints. The difficulties in solving constrained large-scale optimization problems arise from the challenge of finding good feasible solutions for sensory, actuation and controller structures of the adaptive system. The problem is much more challenging when the feasible space is small compared to the overall search space, which is mostly the case for the realistic applications. Solving this type of problem has become a challenging area in computer science due to the presence of high dimensionality, nonlinear parameter interaction, and multimodality of the objective function as well as due to the physical, geometric, and other limitations of sensory and actuation mechanisms. The sticking point to making such a complex systems evolvable with standard evolutionary optimization algorithms in this work has been the development of such representation, which could be able to describe currently unknown structures with an arbitrary complexity while at the same time to allow an evolutionary adaptation of the currently represented structure. To realize a sufficiently high degree of freedom for the evolutionary process an adaptable representation is required. This can be solved by the integration of genome representation of variable length and therewith variable complexity of a system which it currently represents.

Offspring are the result of the gene intermediate recombination with the chromosomes of different size and mutation of the individuals with the current mutation step size. The optimization has been implemented, using SHARK[2], an open-source C++ machine learning library.

The high number of the approaches for the topology optimization of the processing structures in the neuro-evolutionary domain use indirect encodings with a drawback of the increased complexity of the genotype-phenotype mapping algorithms. A big advantage of the proposed growth method is that it utilizes direct genotype-phenotype encoding, avoiding previously described the high complexity of genotype-phenotype mappings and making the evolved system easier to analyze.

The proposed growth method requires controlling of the resulting morphology, through the optimization of input as well as output dimensionality of the control structure, while adding necessary connections to keep a fully connected network. The gradual growth of morphological and controller structures takes place during the evolutionary process and is strongly affected by the changing environmental conditions and the given task of the system acting in this environment. The optimization couples the interactions between control system, morphology and the

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

external environment in a single dynamical system, where all structural elements have a strong impact on each other, resulting the solutions, which can be completely different to the ones produced by isolated approaches. Fig. 4.7 demonstrates the genome organization. Both morphology and control are coded in the same genome. Transcription of the individual genetic information is direct one-to-one and is processed in one time step, omitting the ontogenetic development.

The development of the adaptive system starts with the structure of low complexity, in ideal case with a single sensor, actuator and a simple controller. Even though the most real-world engineering applications require more than one sensor and actuator, such a simple initial configuration of the system as a starting point of its development during the optimization is decisive for the final success of the search of optimal system configuration. During further optimization of the initially simple system, the concurrent complexification of morphological and controller parts of the system takes place. Under some triggering method, described later more in detail, new sensors and actuators and, therefore, new neural connections needed to process and control new sensing and actuation elements occur. This ongoing system complexification is an abstraction of phylogenetic growth of natural systems. The regulation of the growth of natural organisms is executed through the gene regulatory network, detailed described in chapter 3. Unlike GRNs, which regulate the transcription of the fixed genes to an adult organism under different environmental conditions, the proposed growth regulation modifies the genetic information directly and is realized through the probability-based triggering method, where each individual in a population has a fixed probability p to receive a new sensor or actuator by mutation.

The problems of the evolvability of the direct encodings are solved through the gradual step-wise system complexification. Using the described triggering method, the population contains individuals, describing systems of diverse complexity. The diversity of the solutions in the population referenced to its morphological and controller complexity depends on the value of the insertion probability p. Accordingly, the speed of growth of system's complexity correlates with the insertion probability p. The successful realization of the system growth implies understanding which factors impact the progress of the complex concurrent system optimization most. The idea of Elman known as "benefit of starting small" is realized through the set-up of the optimized adaptive system, which is as simple as possible in the first stages of the development. The limitation of the complexity of the initial systems according to Elman [4] allows impressive learning benefits for the further development. Starting with an initially elementary system could have a positive effect on fast

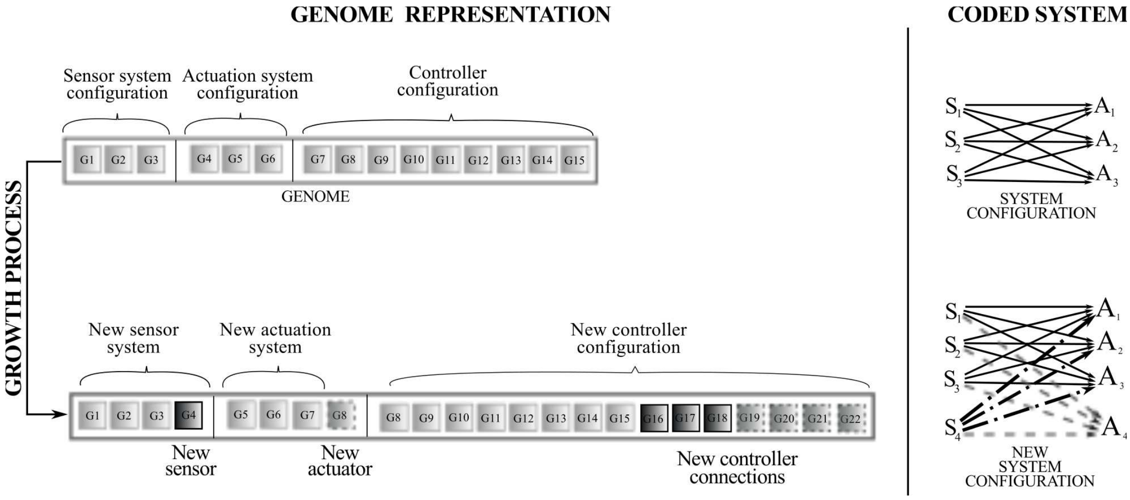


Figure 4.7: Demonstration of the growth process. Probability based triggering of enlargement of morphology and controller dimensionality

convergence in small search spaces. Thereby the system is free from the early limitations and can develop autonomously into a final system of arbitrary complexity, with sensors and actuators optimally positioned in the structure and at the same time having an optimal signal processing structure for the given morphology.

4.3.3 System enlargement techniques and its impact on result of evolutionary optimization process

Besides the important factor of the insertion probability p of sensory and actuation element during the development of the system, the system enlargement techniques play an important role in the final success of the optimization. As described in chapter 3 initially simple structures represent a reduction of the search space, which allows the increase of the convergence and the probability to find the optimal solution in a low dimensional space. By the addition of new morphological elements during the development of the system, extra search dimensions arise step-wise. The assumption is that the solution found previously in the lower dimension space is a good initialization for the search in the higher dimensions. In fact, the accumulation of gained beneficial system configurations during evolution is a central point and has to be ensured for the proposed growth method to be successful.

In the case of enlargement of the recognition system, during the optimization, the structure gets additional sensory elements and therefore a control structure gets extra connections to process the additional information. In this work different procedures for the system enlargement has been investigated. Among the most promising techniques have been the insertion of random morphological elements and a biologically inspired gene duplication [91]. The neutral mutations are important since it ensures the maintenance of the beneficial solutions of the low dimensional structure by transforming it to the more complex system. Depending on the method of system enlargement, the neutrality of mutation is achieved in a different way. During gene duplication, one or several gene segments are copied and inserted in the genome. This means for the adaptive system, that before further development it gets the same information about the environment from two sensors. In this case, the copied element is redundant in the first phase after insertion but is expected to be a good starting point for the differentiation of further structural element. On the other hand, duplicating neural connections of the new element would not result in the neutral mutation of the solution. It can be explained by the fact, that the neural controller is a fully connected ANN, where each input and output is connected to each of the neurons in the hidden layer. An extra input of the ANN with the connection weights of the previously optimized sensor would mean that the inputs of hidden neurons are doubled, which leads directly to the significant decrease of the fitness value. One possible solution to the described problem of neural mutation is the division of the neural weights of the duplicated elements by the number of duplicated elements before its following evolution. The result of such system enlargement is initially identical performance of the system, having a higher dimension of sensory or actuation structures. An example of the described gene duplication applied on the adaptive wing system, presented later in the next chapter, is given in Fig. 4.9 and Fig. 4.8. The duplication of all three optimized sensors of the adaptive airfoil system takes place at the 250. generation. Fig. 4.9 (a) depicts evolutionary development of the sensors position in the adaptive stucture, Fig. 4.9 (b) the corresponding co-evolutionary development of the sensors characteristics. The connection weights were divided by three and duplicated to the final system, having 6 sensors. The gradual progress of the fitness minimization is depicted in Fig. 4.8. The detailed definition of the fitness function is given in Chapter 5. The lower fitness values in Fig. 4.8 indicate higher performance of adaptive airfoil system. A significant fitness improvement can be observed through the described technique for the sensory system enlargement. The progress of the fitness is almost unchanged at the time of duplication, which indicates, that the required neutral mutation could be achieved.

In further experiments presented later in chapter 5 and 6 one more beneficial

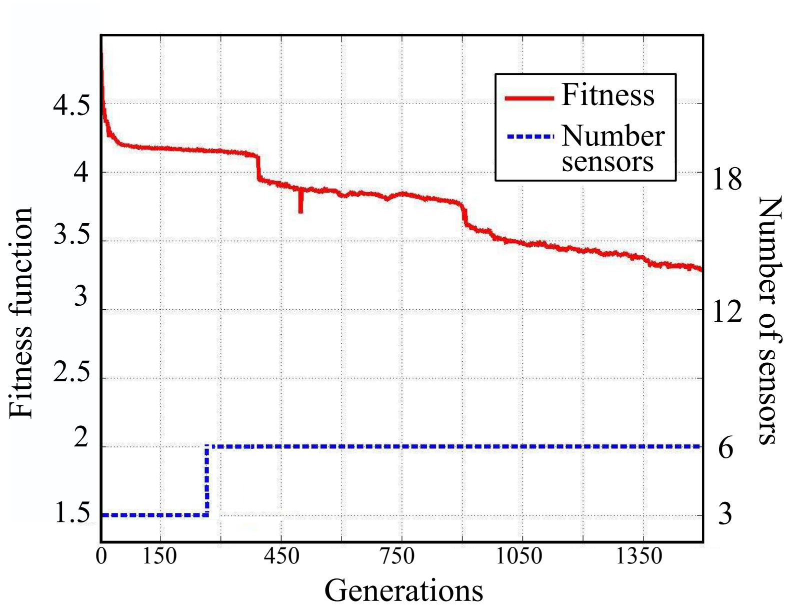
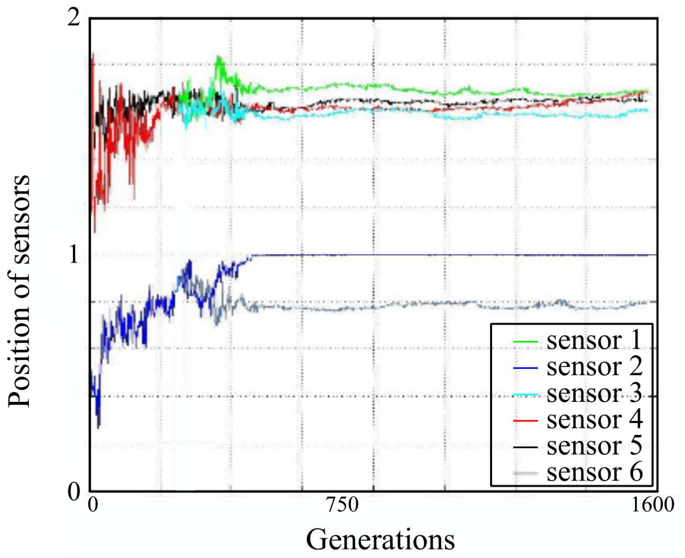
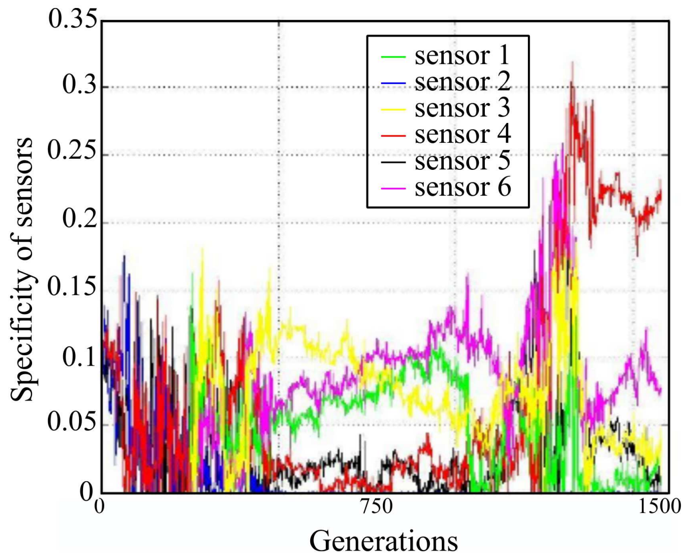


Figure 4.8: Demonstration of growth process by gene duplication of the first application presented in next Chapter . Probability based triggering of enlargement of morphology and controller dimensionality. Progress of fitness function (red) and the development of the number of sensory elements (blue) during evolutionary process

system enlargement method has been established. In this method, the insertion of random structural elements, such as sensor or actuator coupled with initial controller weights of zero has been utilized. An important extension of the growth method here has been the implementation of additional evolutionary strategy parameters for new appearing sensory or actuation elements. An extra mutation rate of the new element has been set higher than the current mutation rates of the longer existent sensors or actuators. Through the extended method of system enlargement, triggered by the probability-based method, a mutated system inherits a possibility to evolve new elements individually while keeping the previously optimized system setup intact. In the next two chapters, the contributed growth method has been applied and verified first on the adaptive wing system and then on the autonomously driving car.



(a)



(b)

Figure 4.9: Demonstration of growth process by gene duplication of the first application presented in next Chapter. Probability based triggering of enlargement of morphology and controller dimensionality.(a) Evolutionary development of the sensors position in the adaptive stucture, (b) Evolutionary development of the sensors characteristics

5 Application of co-evolutionary growth method on adaptive airfoil design

Adaptronic systems offer an interesting application field and can serve as a suitable testbed for the research on proposed co-evolutionary growth approach. These systems integrate sensors as well as actuators and internal controller in order to optimally react to the changing environmental conditions. Suitable examples can be found in the design of aerodynamic active structures which actively adapt their current state based on the measured flow properties. Solutions in this technological area can for example highly increase the aerodynamic performance of vehicles or improve the efficiency of wind turbines to name only a few applications. 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 for the static case.

Conventional aircrafts are designed for a set of required performances. Through its fixed wing geometry, the number of the possible flight conditions and the performance of the aircraft during these particular flight envelopes is limited. While some devices, such as flaps, have been used to augment the bulky wing geometry, new materials are being developed that could allow significant wing morphing capability. New "smart materials" allow shape change of the wing profile during the flight and constitutes a challenging and growing research area of **morphing wings**. These new technologies open new ways of changing the geometry of the wing while in flight, to the optimal state for the current flight condition. For example, a morphing aircraft wing could be capable of changing wing area, aspect ratio, and taper ratio resulting in the plan form change. Variation of camber, thickness or twist could change the cross-section of the wing. There exist various possible mechanisms available to realize geometry changes. For example swing-wing strategy of F-14 changes both sweep and aspect ratio [92].

An adaptive wing needs external sensors to be able to sense the surrounding environment and detect the current flight envelope. It also requires actuators which can morph the shape of the wing profile as well as a central controller, which determines the optimal actions depending on the sensed information. The design of an adaptive wing, capable of optimal aerodynamic behavior through its actuators under changing flow parameters is a challenging optimization task and serves excellent application platform for research on proposed growth method, described in detail in chapter 4.

5.1 Fundamentals of airfoil profiles aerodynamics

An airfoil is a shape of the aircraft wing cross-section [93]. The airfoil deflects the oncoming air, resulting in a force on the airfoil in the direction opposite to the deflection. The two components of the aerodynamic force are lift and drag force. The airflow around the airfoil has the effect of creating an upwards lift force that keeps the plane up in the air, and a backward drag force that has the effect of slowing the plane down. The upward lift force is created in two ways. Faster flowing air moving over the top of the airfoil creates a negative pressure and a force pulling the wing upwards, whilst the slower air moving under the airfoil creates a positive pressure and a pushing force on the wing. Standard airfoil shapes require a positive angle of attack to generate lift. Therefore, the lift force on an airfoil is primarily the result of its angle of attack and shape. Fig.5.1 demonstrates the general schematic design of airfoil.

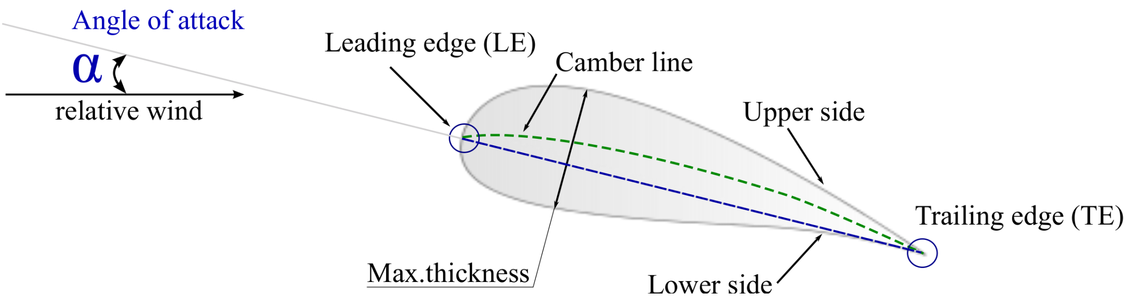


Figure 5.1: Schematic airfoil and terminology of its important characteristics

Whilst the upper surface has a higher velocity and lower static pressure, the lower surface has a comparatively higher static pressure. The pressure gradient between these two surfaces correlates with an amount of the lift force generated by a given airfoil. As depicted in Fig. 5.1, leading edge is the point at the front of the airfoil with minimum radius. The trailing edge is defined at the rear of the airfoil, where the airflow split by the leading edge rejoins [94]. The chord line connects leading and trailing edges. The most important parameter describing the airfoil shape are its camber and maximum thickness. The mean camber line or mean line is the set of midway points between the upper and lower surfaces. The shape of the camber line depends on the thickness distribution along the chord and is usually a few percent of the length of the chord. The thickness of an airfoil varies along the chord and is defined as thickness measured perpendicular to the camber line.

Different airfoil shapes serve different flight regimes and have diverse aerodynamic characteristics such as lift and drag at different angles of attack and air velocity. Lift and drag are then measured perpendicular and parallel to the relative wind, respectively. The angle of attack, α is defined as the angle between the extended chord and the relative airflow direction "relative wind" (usually horizontal) as shown in Fig. 5.1. One useful way to evaluate the aerodynamic forces is to use pressure taps to record the distribution and to integrate the distribution to find the net force. For lift this integration is concerned with the pressure distribution in the vertical direction, while for drag - the horizontal pressure distribution. Airfoils shapes are designed to provide high lift values at low drag for given flight conditions. The wings of conventional aircraft use for example flaps and slats to adapt to different conditions.

There exist two ways to create lift on the airfoil. The first can be an asymmetric profile, which is often the case for subsonic flight applications. The second is to incline the airfoil at an angle relative to horizontal, which is usually the relative wind angle. For low values of the angle of attack the flow remains attached on both surfaces. In this case the lift is directly proportional to the angle of attack for given airfoil shape. For higher angles of attack separation occurs, which increases drag significantly and reduces lift despite high angle of attack.

An aerodynamic force can be calculated by the integration of surface pressure distribution over an airfoil surface as following [94].

$$\vec{F} = \oint -(p \cdot \vec{n})\,\mathrm{d}A \quad , \tag{5.1}$$

where p is the gauge pressure value at the point on the airfoil, $\vec{n}$ - normal vector at current point on the surface.

Taking into account the assumption that wind is traveling in the x direction, the resultant force can be decomposed into horizontal and vertical components to recover the aerodynamic forces of lift and drag [94]:

$$L = F_y = \int -(p \cdot \cos(\alpha))\,\mathrm{d}A \quad , \tag{5.2}$$

$$D = F_x = \int -(p \cdot \sin(\alpha))\,\mathrm{d}A \quad , \tag{5.3}$$

where L and D are the lift and drag forces on the airfoil respectively, α is angle of attack, F_y and F_x vertical and horizontal components of aerodynamic force $\vec{F}$.

To handle different wind conditions, non-dimensional representations are used based on the pressure coefficient. The pressure coefficient, C_p is defined as following [94]:

$$C_p = \frac{p - p_\infty}{\frac{1}{2}\rho_\infty U_\infty} \quad , \tag{5.4}$$

where p is the gauge pressure value at the point on the airfoil at which the pressure coefficient has been calculated, p_∞ - free stream pressure value, ρ_∞ - free stream fluid density, U_∞ - free stream velocity. In comparison to a gauge pressure value at the point on the airfoil, the pressure coefficient is dimensionless and independent from effects of the density and speed of the air.

Equivalent to pressure the coefficient non-dimensional lift and drag coefficients are defined as following.

$$C_L = \frac{L}{\frac{1}{2}\rho \upsilon^2 S} \quad , \tag{5.5}$$

$$C_D = \frac{D}{\frac{1}{2}\rho \upsilon^2 S} \quad , \tag{5.6}$$

where ρ is fluid density, υ is airspeed, S is plan form area.

The optimization of aerodynamic characteristics of the airfoil focuses optimal circulation distribution, defined by the shape of the airfoil for the current angle of attack, which minimizes the produced drag for a given wingspan and total lift. In airfoil design, a developer typically targets to maximize the lift to drag ratio, which is the amount of lift generated by a wing or vehicle, divided by the aerodynamic drag it creates by moving through the air. Since a particular aircraft's required lift is set by its weight, delivering that lift with lower drag leads directly to better fuel economy, climb performance, and glide ratio.

5.1.1 Adaptive virtual wing set-up

In the thesis implemented aerodynamic adaptive system consisted 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 value. The virtual sensors of the system have been defined as pressure sensors at a given position on the airfoil surface. The values 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. 5.2 (a) illustrates the described relations between the

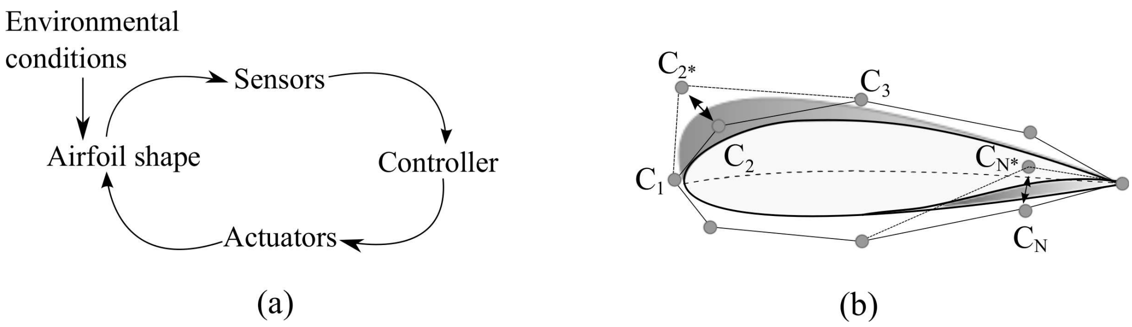


Figure 5.2: (a) Adaptive airfoil framework - schematic view of internal dependencies, (b) Example of the airfoil created with NURBS. The airfoil in white, defined by the initial positions of the spline control points. The airfoil shape change (in gray) results from the movements of C_2 and C_N

single parts of the test-framework. With the described setup an adaptive behavior can be realized by the actuators in reaction to the change of the environmental conditions. Furthermore, a variable number of sensors or actuators can be easily realized. The described setup serves as a test framework for the simulation of 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 was implemented by the utilization of a non-uniform rational B-splines (NURBS) as shown in Fig. 5.2 (b) [95]. The shape of the NURBS curve and with that the shape of the resulting wing profile is determined by the set of spline control points. The splines, defined by its control points C_n, result into a unique two-dimensional airfoil shape. By moving the control points in the two-dimensional space, a shape change of the airfoil can be achieved. The actuator signals correspond to changes of the NURBS control points and define the current airfoil shape.

The computational fluid dynamic solver Xfoil[1] has been used to simulate the aerodynamic airfoil characteristics and pressure distribution. Xfoil has been chosen because its high speed which is decisive for optimization tasks (less than 5 seconds). Xfoil calculates different aerodynamic characteristics for the given airfoil geometry

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

and environmental configurations, e.g. angle of attack, Reynolds number etc. Xfoil is an interactive program for the design and analysis of subsonic isolated airfoils [96]. It consists of a collection of menu-driven routines which perform various useful functions such as viscous or inviscid analysis of an existing airfoil, allowing lift and drag predictions as well as pressure distribution over the surface of an airfoil. The inviscid formulation of Xfoil is a simple linear-vorticity stream function panel method. A finite trailing edge base thickness is modeled with a source panel. The equations are closed with an explicit Kutta condition. A high-resolution inviscid calculation with the default 160 points requires seconds to execute. Subsequent operating points for the same airfoil but different angles of attack are obtained nearly instantly. In Fig. 5.3 example calculation and visualization of given airfoil in Xfoil is presented.

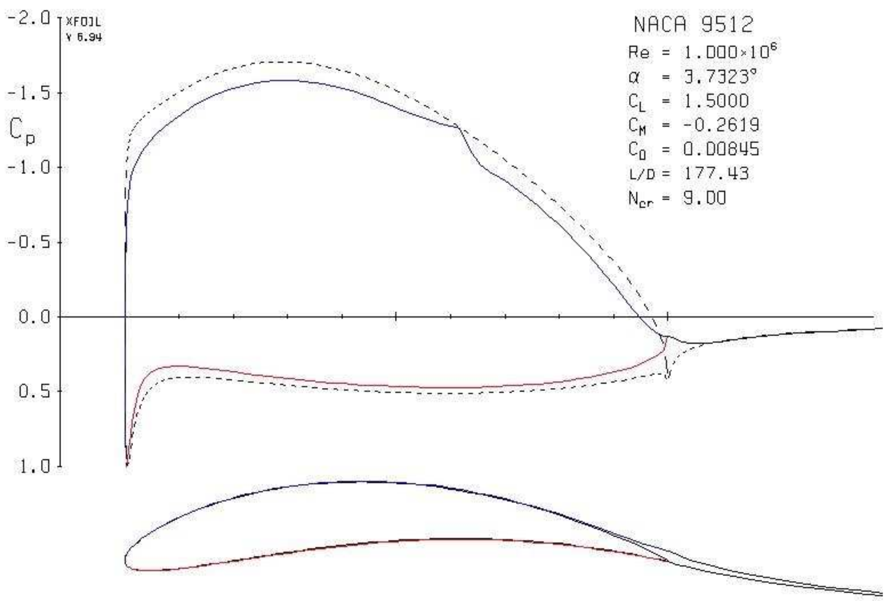


Figure 5.3: Example of Xfoil simulation

The variations of the airfoil environment were simulated through changing of the angle of attack. The Reynolds number has been fixed during the optimization($Re = 10^7$) [94]. As described earlier Xfoil calculates the profile of the pressure coefficients C_p defined according to equation 5.10 at 160 points on the given airfoil surface. A sensor placed at one of these 160 points on the airfoil's surface returns a virtual sensor value corresponding to the pressure coefficient at the airfoil surface.

5.1.2 Controller targets and realization

One of the requirements on the adaptive airfoil application was to achieve adaptive behavior in the variable environment. To simulate the variations of the airfoil environment, the angle of attack has been changed manifold during the simulation time frame of airfoil operation, since it has a major influence on its final aerodynamic characteristics. The task of the adaptive airfoil controller was to generate suitable actuator signals in reaction to the changed conditions in order to minimize the drag of the airfoil and create specified amount of lift by morphing the airfoil surface. A wide variety of controller designs which can be applied for that purpose can be found in the literature. Whilst Parker and Nathan [46] as well as Bugajska and Schutz [47] realized the control structure as a reactive system that uses "if...then" rules to control a simulated robot, Haller, Ijspeert and Floreano [48] implemented controller models inspired from the central pattern generators underlying locomotion in animals. In comparison to these approaches, fully connected feed forward neural networks (first series of experiments) as well as the linear recurrent model (later series of experiments) have been utilized to improve the aerodynamic characteristics of the airfoil during simulated changes of environmental conditions. For the implementation of neural network the SHARK[2], open-source C++ machine learning library is used. The neural network consisted of input and one single hidden layer with sigmoidal activation function and one output layer with a linear activation function. In Fig. 5.4 a schematic overview of the overall system is given.

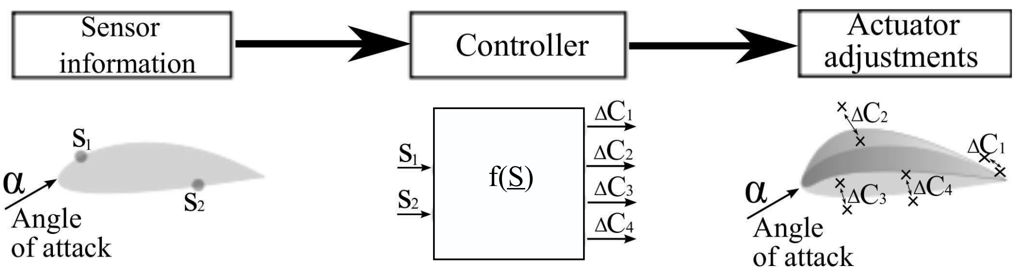


Figure 5.4: Schematic view of the overall control structure

In Fig.5.4 s_i represent one example of two pressure sensors of the adaptive airfoil distributed over the surface. The controller processes the pressure values to the actuators reactions ΔC_j - splines control points, based on previously described B-rational NURBS splines construct. If sensors detect the change of the angle

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

of attack, controller calculates the necessary offset of the control points ΔC_j to its current position to optimize the system performance. An example of shape morphing through actuators is presented in Fig. 5.5

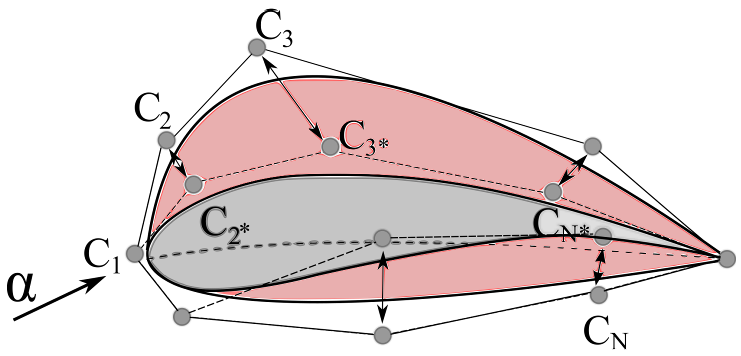


Figure 5.5: Controller actions, (gray) initial airfoil shape, (red) airfoil after actuators actions

After the change of the angle of attack, the controller goes through three cycles of adaptation. The experiments have shown that for the given system organization in average three iterations of airfoil adaptation after the single environmental change (ex. change of angle of attack from 2° to 4°) were required to reach the stable state of the adaptive airfoil system. The system goes through a set of partial update steps until the optimal geometry is reached. Fig.5.6 shows exemplary surface modifications during the adaptation process for the scenario of two different angles of attack. After three controller actions, the optimal airfoil shape for the angle of attack α_1 has been found. In the example simulation scenario given in the Fig. 5.6 the angle of attack α_1 changes to α_2. Since for the changed environmental condition the current system state is not optimal any more, the controller calculates again the required reactions of the actuators in three steps.

The overall system is designed in a way that the position as well as the number of sensors and actuators can be changed freely. The maximal number of possible pressure sensors is limited to the CFD resolution. The described setup serves a test framework for the simulation of the interactions between control structure and morphology during the operation of the control structure as well as during their evolutionary development.

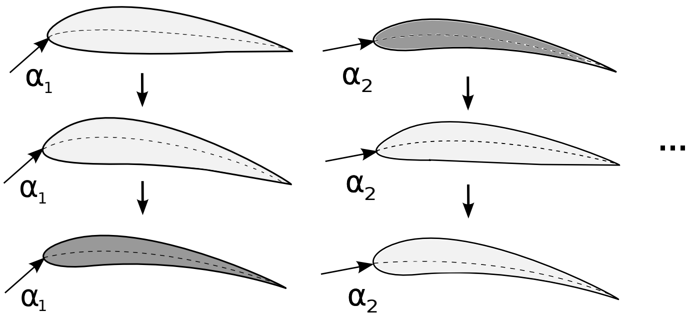


Figure 5.6: Example of 3 steps of controller actions for each angle of attack

5.1.3 Evaluation of system adaptivity

The task for the controller was to improve the airfoil drag after a variation of the inflow angle. Therefore, the drag coefficients of the current airfoil state before

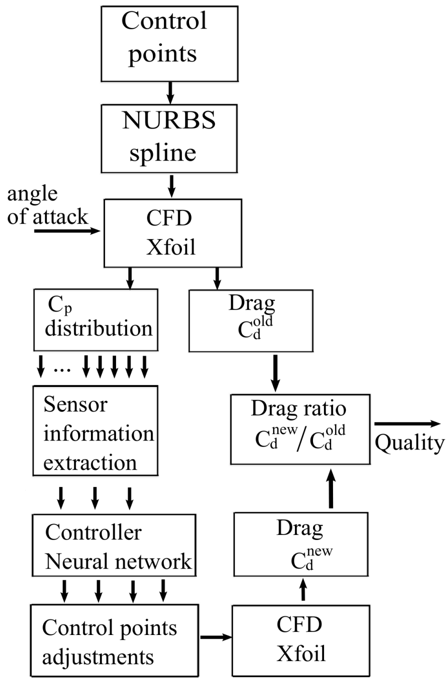


Figure 5.7: Overview of the system evaluation

C_d^{old} and after C_d^{new} the modification of the airfoil surface are calculated in the CFD simulation. The ratio of these two values indicates if the controller outputs realizing an actuator adjustment, performed well and could reduce the airfoil drag and additionally create the required lift value for the new angle of attack. Fig. 5.7 depicts basic evaluation algorithm of the adaptive airfoil system. The described evaluation takes place in each cycle of controller actions and during overall operation time of the evaluated system. An additional objective is the amount of created lift, which has been considered as a constraint.

5.2 Experiments overview

The presented adaptive airfoil application utilized the pressure sensors for the detection of the change of inflow angle of attack, actuators for morphing the wing shape and the neural controller to generate the appropriate reactions to the changing environment. The application provided a suitable testbed for the investigation and research on the growth concept based on the coupling of both morphology and signal processing dynamics during the combined evolutionary process, proposed in the previous chapter. In the scope of the thesis a several series of experiments has been performed. Below the major groups of the experiments and its main objectives have been summarized.

- The first series of experiments targeted investigation on the feasibility of standard evolutionary algorithms to optimize the morphology and signal processing of proposed adaptive wing design in a single optimization scope [97].
  - Evolutionary algorithm has been used to optimize the fixed number of pressure sensors and the controller of the entire adaptive airfoil under random environmental conditions, permanently changing in each generation.
  - During the evolutionary process the position of the sensors on the airfoil's surface and the weights of ANN have been co-evolved.
  - The airfoil system has been evaluated according to its ability to adapt to the changing environmental conditions.
  - The major focus of the first experiments - investigation of the influence of environment on the coordination of the entire system development between sensory and controller systems during single optimization progress as well as the detection of the expected performance disparity according to the amount and quality of the perceptual information from the environment.

  - Experiments investigated the influence of the complexity and dimension of actuation system and sensory on the quality of possible adaptations.

- The next series of experiments referred to detection of the airfoil shapes with minimal drag and required amount of lift [97].
  - The experiments were important for the generation of a baseline which allowed the comparison of the airfoil shapes generated by the adaptive system solutions found in the previous experiments with the airfoils of maximal achievable quality.
  - Standard evolutionary strategy has been used to optimize the shapes of the airfoils - straight design optimization with fixed number of spline control points for the individual angles of attack with lift constraint.

- The next experiments concentrated on the application of proposed growth method on the development of the sensory system and controller of the adaptive airfoil [98].
  - Main objectives of experiments: First, realization of developmental stages of the sensory and controlling systems design, defined as a growth process and investigation of the ability of the sensory-controller growth process to detect optimal inputs and the corresponding controller for the adaptive wing system. Secondly, comparison of the differences in structures of the systems developed through the presented evolutionary growth method and of evolved systems, having fixed set of sensory elements.
  - Noise and variance reduction: The random variations of the environmental conditions in each generation of previous experiments resulted in extremely noisy fitness landscape with high variance of final solutions. Instead of randomly changing the angle of attack each generation, one complex scenario of environmental changes has been introduced for all generations which covered a sufficiently high number of angle changes. With that, the effect of noise could be removed while keeping the time necessary for the evaluation within a reasonable range.
  - New controller: To enable the developmental process of the system which starts with an initially simple set-up growing into a system of higher complexity, the complexity of the controller has been reduced by replacing it with a linear recurrent model.

  - To verify the functionality of the new linear recurrent controller experiments with fixed sensory and controller dimensionality has been revised.

- The next experiments targeted the extension of the evolutionary growth method to the optimization of variable adaptive airfoil system, free of any morphological or controller system limitations on the early developmental stages and evolve all functional parts of the system simultaneously [99].
  - Experiments included the introduction of cost factors for the sensory and actuation elements. Costs factors for the morphological elements could achieve a limited growth of the system dimensionality, unlike the previous experiments, since extra actuator or sensor has been added by the evolutionary process only if it could bring significant performance improvement.

- Final experiments validated the performance of the solutions with three sensors found by the co-evolutionary growth method on the unknown scenario of 100 angles of attack.

5.3 Co-evolutionary optimization of signal processing and sensor positions

The co-evolutionary approach of adaptive systems, described in detail in Chapter 4, implies the concurrent evolutionary development of both morphology and control. The presented adaptive airfoil application with its pressure sensors for the detection of the change of inflow angle of attack, actuators for morphing the wing shape and the neural controller was used to test the proposed growth method with the focus on synchronization of the design of a sensory, actuation and signal processing system parts during entire optimization process.

The first carried out experiments referred to the optimization of the position of fixed number of pressure sensors and the controller of the entire adaptive airfoil morphology under permanent changing random environmental conditions. Though the position of the sensors on the airfoil's surface and weights of ANN have been co-evolved. The target of the experiments was the investigation of an influence of random environment on the coordination between sensory and controller systems during the optimization progress as well as the detection of the expected performance disparity according to the amount and quality of the percepted information from the environment.

The optimization task was solved with an Evolution Strategy (ES), developed by Bienert, Rechenberg and Schwefel as well as with a CMA Evolution Strategy [89], [90]. The results of an ES were significantly better than the results of CMA-ES algorithm, with mutative step size adaptation. It can be explained by the fact, that the optimization algorithm had to deal with the variation of the objective function since the series of angle of attack the system was tested on has been randomly changed each generation. In this case, the result of the evolutionary algorithm was rather robust than the specialized solution, which could deliver sufficiently good performance at any unknown environmental condition. The applied ES(50,200) had two different self-adapted step sizes, for sensor positions and neural network weights adaptation.

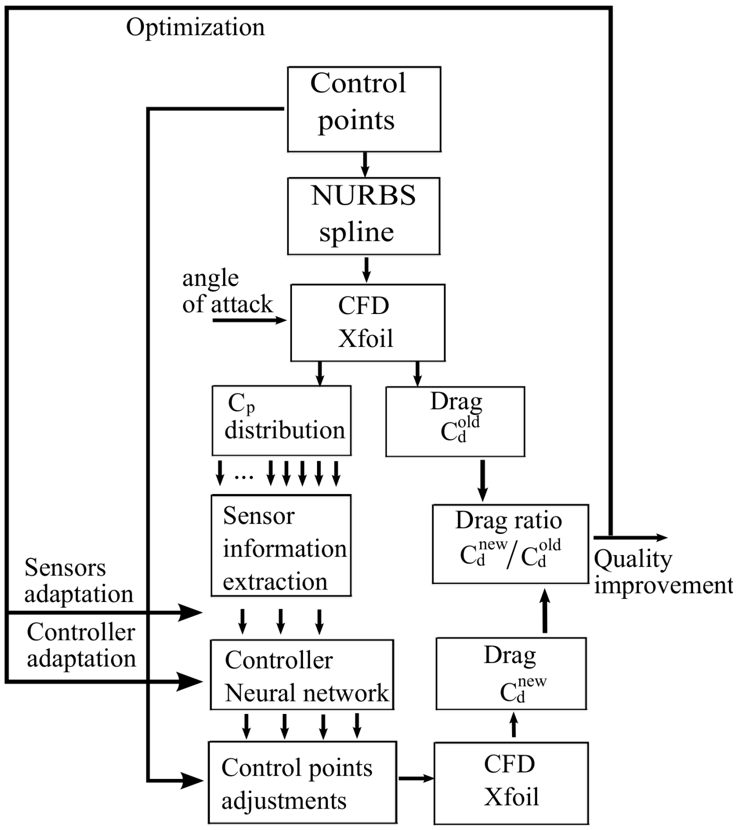


Figure 5.8: Overview of the system evaluation

As described previously the task of the controller was to improve the airfoil drag after a variation of the inflow angle. Therefore, the drag coefficient of the airfoil before any modifications took place is evaluated and after the modification of the airfoil blade. The ratio of these two values shows if the neural network outputs realizing an actuator adjustment, perform well and reduce the airfoil drag. The total fitness of the individual has been defined as the sum of the drag coefficient value ratios summed over the set of different angles of attack given in the experimental setup. Fig. 5.8 shows the structural diagram of the individual evaluation and the scope of evolutionary optimization of the neural weights and the position of the pressure sensors.

The optimization started with randomly initiated sensor positions between 0 (trailing edge, wing upper-side) and 2 (trailing edge, wing underside) and neural network weights, uniformly randomly initialized between -0.01 and 0.01.

The final fitness value of the individual is calculated as the sum of drag value ratios over all tree steps of spline control point adjustments for a single angle of attack and additionally over a cascade of different angles of attack. In each generation, a set of angles of attack has been randomly changed between 2° and 4°. The random change was introduced to avoid that only shape transitions which are predefined by the set of given inflow angles are possible.

The size of the controller was defined by the number of neurons in the input layer which is equal to the number of sensors. The number of neurons in the output layer is equal to the number of actuators and a fixed number of 20 hidden neurons, with sigmoid activation function (Fig. 3.5 in Chapter 3). Fig. 5.9 shows the filtered fitness curves of the robust optimization averaged over 10 runs. The fitness function was defined as following:

$$Fitness(Individual) = \frac{\sum_{\alpha=1}^{N} \sum_{i=1}^{M} \frac{C_d(\alpha,\text{changed airfoil})}{C_d(\alpha,\text{unchanged airfoil})}}{N * M} \tag{5.7}$$

where M is a number of controller actions for the same angle of attack ($M = 3$), α is the angle of attack, N is the total number of angles of attack applied and the individual has been evaluated on, C_d is the drag coefficient. The number of optimization parameters results from the size of system controller (number of neurons in a hidden layer), the number of sensors and actuators (control points of the spline). The total number of parameter is

$$N_{Param} = N_i * N_h + (N_i + N_h) * N_o + N_h + N_o + N_i + N_s \tag{5.8}$$

where N_i is the number of sensors, N_h the number of neurons in the hidden layer (was fixed to $N_h = 20$), N_o is the number of actuators (was fixed to $N_o = 6$) and N_s is the number of optimization step-sizes ($N_s = 2$). As an example, for the system, using 5 sensors, 283 parameters need to be optimized.

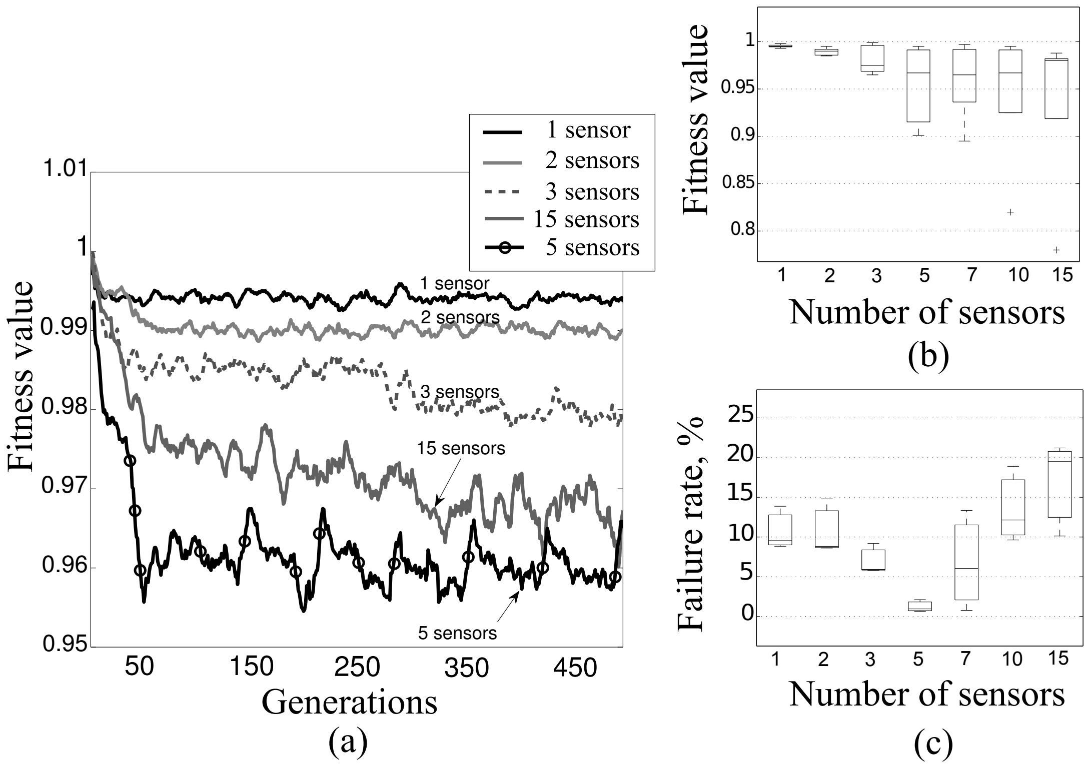


Figure 5.9: (a) Robust optimization results filtered with moving average over 10 generations. Fitness curves has been averaged over 10 runs with different starting parameters. (b) Box plot of the optimization runs for each number of sensors, (c) Percentage of the cases in which controller lead to a failure performance, for scenario of 10 random angles of attack between 1° and 7°

The results show that the system development progress depends on the number of sensors. For the systems, using between 1 and 5 sensors, the clear trend of averaged performance improvement takes place with an enlargement of the sensory system (see Fig. 5.9 (a) and (b)). Starting with 7 sensors the averaged performance does not improve. Additionally, in Fig. 5.9 (c) is demonstrated that on average the failure of controller actions, defined as an action, that leads to an invalid solution, increases gradually for the systems with more than 5 sensors, although the maximal achievable quality given in Fig. 5.9 (b) is better with a larger sensor number. Invalid solutions have been the airfoil shapes, which failed to be calculated by XFoil simulation.

According to Fig. 5.9 (b) high variance of the quality of the final solutions for the same number of sensors can be observed. The random variations of the environmental conditions in each generation as well as the high number of the optimization parameters resulted in extremely noisy fitness landscape with high variance of final solutions due to the permanent changing objective function during the optimization process. The example of two optimized solutions having the same number of sensors but significantly different performance is presented in Fig. 5.10 and Fig. 5.11.

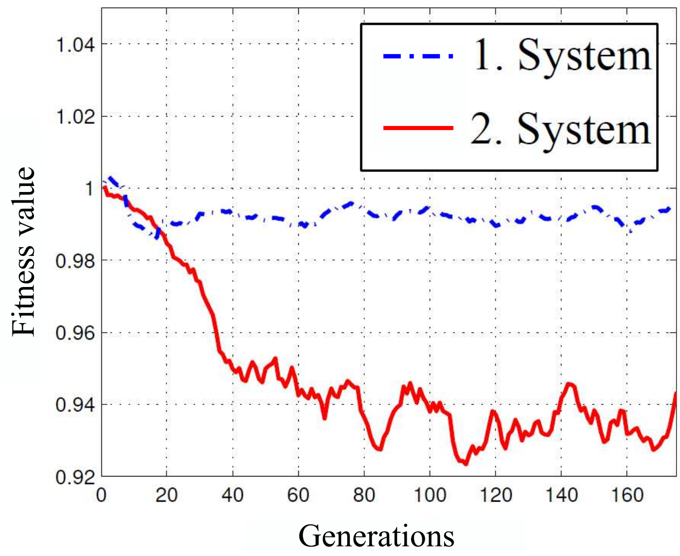


Figure 5.10: Fitness function development of the 1. and 2. system both having 5 pressure sensors during optimization

Fig. 5.10 demonstrates the optimization process of two systems both using 5 sensory inputs to control the adaptive airfoil with differently initialized starting parameters. The initial performance the system is comparable and improves in the first phase of the optimization process, discerning significantly after 20th generation. The insight in the internal system organization shown in Fig. 5.11 demonstrates, that significant performance difference lies in the totally different organization of sensory systems.

A typical drawback of the neural networks is the difficulty of its detailed analysis. To investigate the internal structure of the neural controller, the converted network connections between sensors and actuators of the adaptive airfoil, omitting the non-linearity of the hidden layer, has been calculated according to Eq. 6.2 and visualized. The connection strengths between neurons have been calculated as following:

$$S_{io} = \frac{\sum_{j=1}^{N_h} W_{ij} V_{jo}}{N_h} \tag{5.9}$$

The variable S_{io} is the converted connection strength between input i and output o, N_h is the number of neurons in a hidden layer, W and V - input and output weights of the neural network. For visualizing of the converted neural connection strengths S_{io} a Hinton diagram has been used [100]. The size of the boxes corresponds to the value of the connection strength. The boxes color (green and red) represents a positive or negative sign of the connection strength respectively. The values of the connection strengths lie between zero (no box) and one (box of maximum size).

According to Fig. 5.11 (a) and (b) 5 sensors of both systems converge to their positions after 160 generations. Whilst all the sensors of the first system are positioned on the upper-side, the sensors of the second system are distributed over leading and trailing edge as well as on the upper and lower-side of the airfoil.

The subsequent experiments presented in Fig. 5.12 investigated the influence of the complexity of actuation system - the number of spline control points, on the maximal achievable quality of the final solutions. In the design optimization runs with only tree control points per airfoil very high improvement of the blade quality in an early phase of the optimization was observed, however with a low final quality. With a higher number of spline control points, the airfoil quality improved slower, but the final quality of the airfoil was significantly higher.

The presented results of the experiments indicated a strong impact of actuator dimensionality on the achieved performance of the final solution. For this reason, it is highly essential to utilize the variable number of actuators of the adaptive wing during the optimization process, which has been carried out in final experiments. The results of the optimization experiments with the variable configuration of both sensory and actuation systems are presented later in this chapter, whilst next experiments targeted the investigation of internal coordination between the development of signal perception and processing structures during the entire evolutionary process.

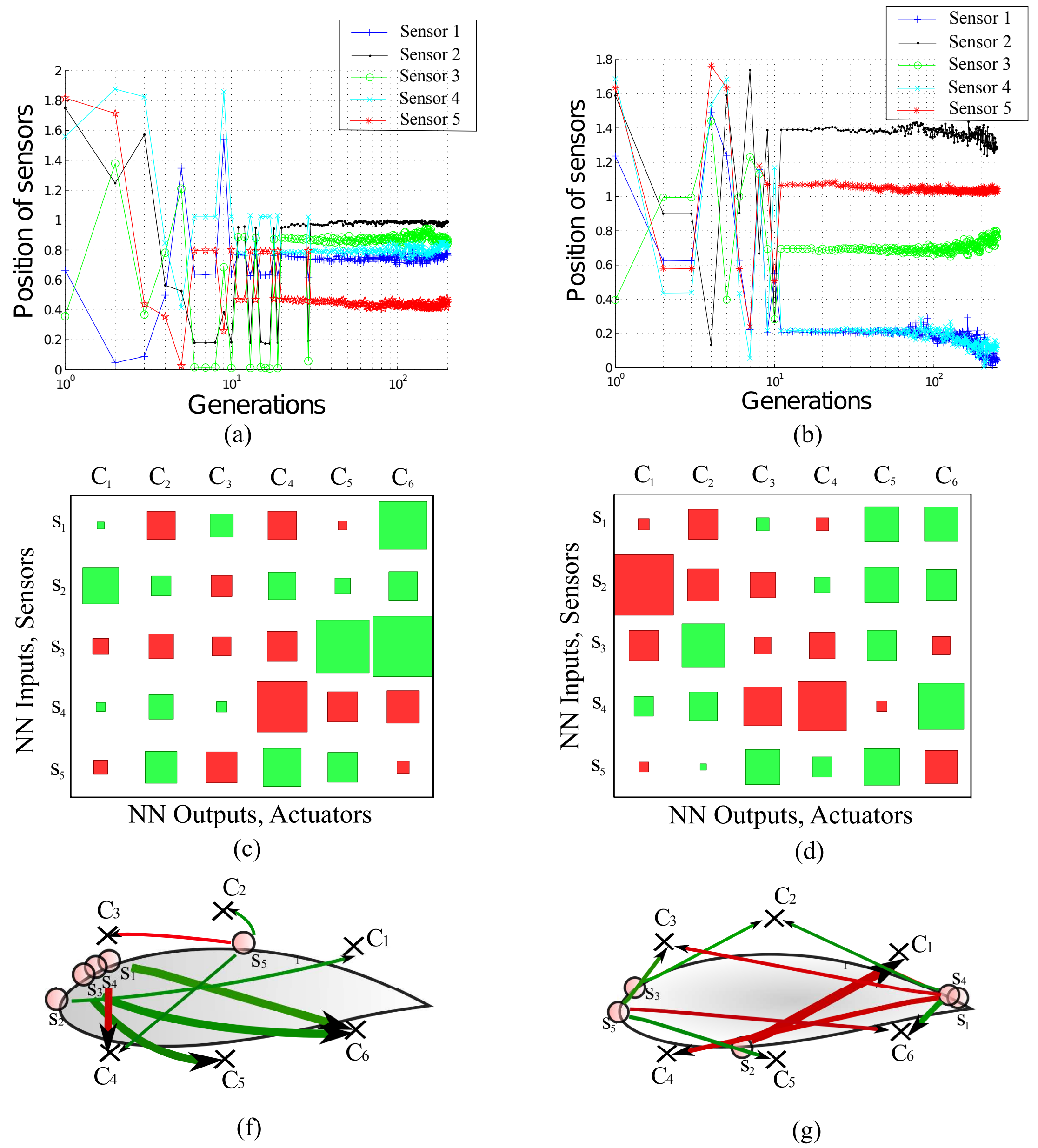


Figure 5.11: Optimizations results shown in Fig.12. (a) and (b) Position of sensors of the 1 and 2. system , (c) and (d) Hinton diagrams of the converted weights of the neural networks, 1. and 2. system at 160. generation (f) and (g) major connections between sensor information and actuators, 1. and 2. system at 160. generation, thicker lines mean a stronger connection

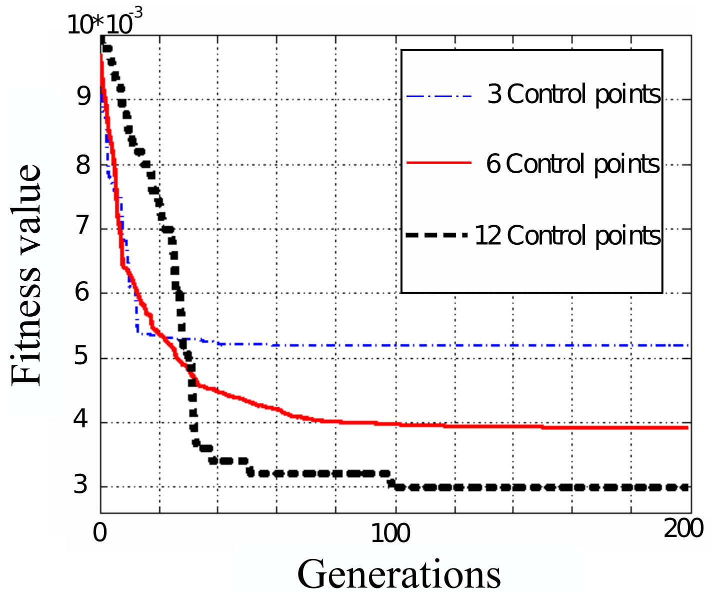


Figure 5.12: Averaged quality history of CMA optimization runs for a different number of spline control points. Angle of attack was set to 3°, slightly different start airfoils were used in all 5 of the otherwise identical simulations which were used for averaging.

5.3.1 Precise co-adjustment of sensory and controller systems during optimization process

The next series of experiments targeted the innvestigation of the correlation in development between the sensor morphology and the signal processing structures as well the quality of the information gathered from the environment during entire optimization process. An example of the dynamics of the concurrent sensor-controller adjustment during the optimization experiment is given in Fig. 5.13.

Fig. 5.13 (c) and (d) show corresponding diagrams of the neural strengths of the system at the 800th and 900th generation. The boxes color in Hinton diagram here (gray and black) represents a positive or negative sign of the connection strength respectively. The values of the connection strengths lie between zero (no box) and one (box of maximum size). In Fig. 5.13 (b) we see a significant performance improvement at the generation 900. Fig. 5.13 (a) shows the development of the sensory system configuration. Sensor 3 changes its position gradually at around the 900th generation. The corresponding change in the controller system can be observed in Fig. 5.13 (c) and (d). Compared with the controller at generation 800, a significant change of the controller connection strengths at generation 900

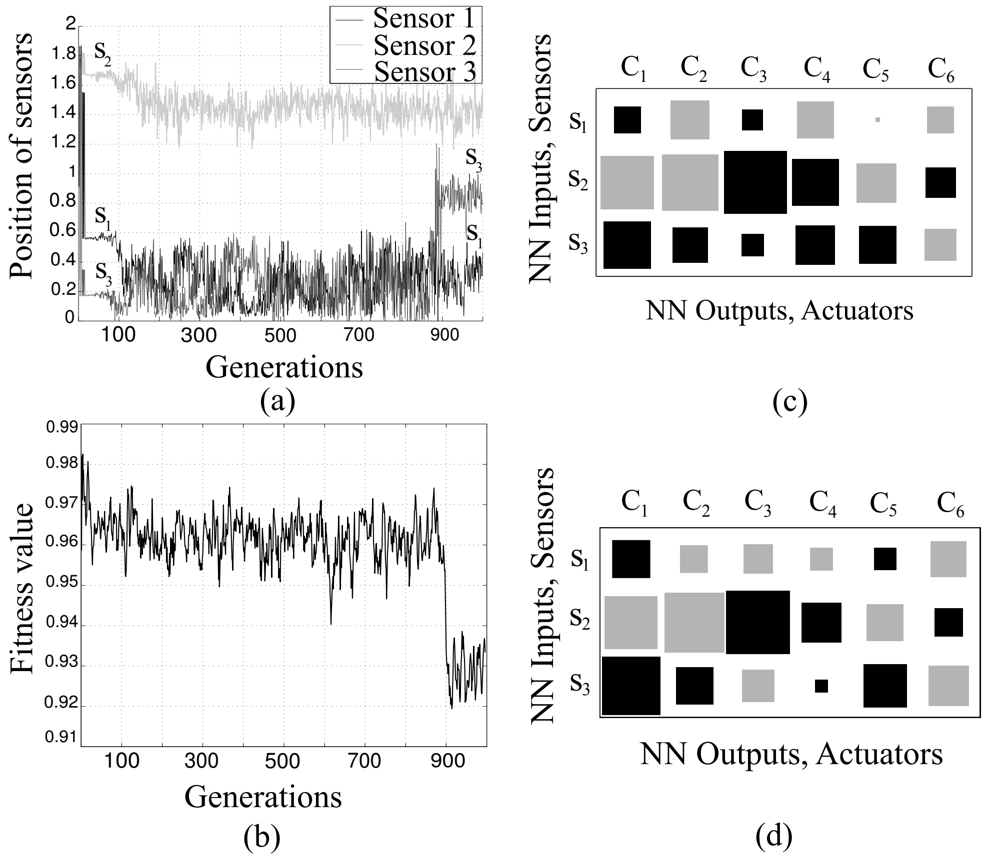


Figure 5.13: (a) Development of the position of the sensors during the optimization (b) Optimization of the robust system, using 3 sensors. Evaluation on the random angles of attack between 1° and 5°, Hinton diagrams of the neural controller of the system at generation 800 (c) and 900 (d)

for the first and the third sensor can be observed. The connections of the second sensor stay nearly constant. Regarding Fig. 5.13 (a), (b), (c) and (d), a precise sensor-controller co-adjustment takes place. These results in this example establish that the development of the signal perception and signal processing modules are tightly coupled and precisely coordinated.

5.4 Baseline airfoil design

The target of the baseline optimization has been to find the shapes for the airfoils with minimal drag in order to generate a baseline which allows the evaluation of the blade shapes generated by the adaptive system. To determine the maximal achievable quality of the airfoils conventional evolutionary design optimization was performed. Standard CMA-ES(4,8) evolutionary strategy with adequate population size [90] was used to find the optimal shapes of the airfoil for the individual angles of attack with lift constraint. A minimal lift constraint has been set to a lift coefficient of NACA 2410 airfoil, $C_l^{min} = C_l^{NACA2410}$. NACA airfoils are the aircraft wing shapes, developed by the National Advisory Committee for Aeronautics in 1948 [93] and define since that time a set of standard airfoil shapes.

Fig. 5.14 shows the result of the design optimization with fixed number of spline control points, $C_n = 6$. The maximal thickness of the airfoil was set to the maximal thickness of the NACA 2410 airfoil which is equal to 10% of the chord. For a set of 5 angles of attack, the optimal airfoil shapes have been determined experimentally with the resulting drag and lift coefficients given in Table 5.1. The specialized optimal solutions have been found for each angle of attack, which have significantly lower drag and higher lift than a single NACA 2410 airfoil being rather robust for a wide range of different angles of attack.

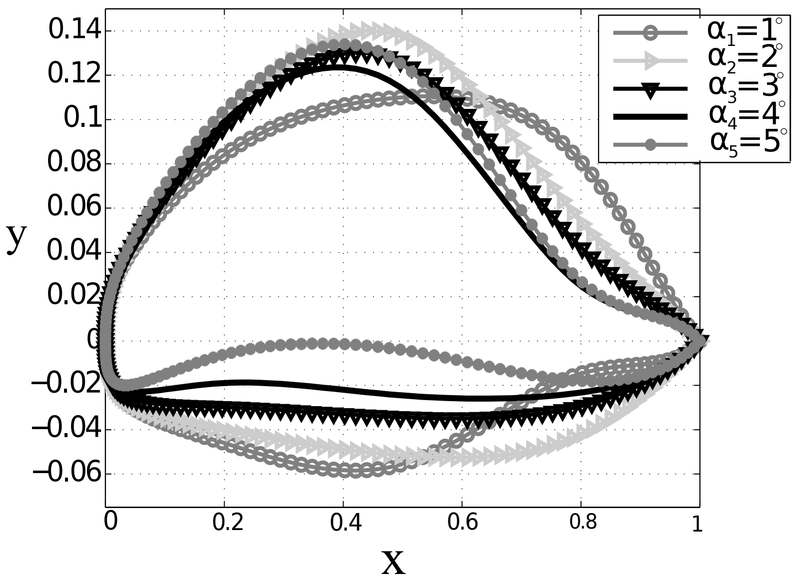


Figure 5.14: Optimized airfoil shapes

The results of the baseline optimization runs indicate maximal achievable performance for the given settings and form the baseline for the evaluation of all further experiments.

Table 5.1: Best baseline performance with 6 spline control points, compared with NACA 2410 airfoil.

$\alpha, degree$	$C_d^{opt} 10^{-3}$	C_l^{opt}	$C_d^{NACA2410} 10^{-3}$	$C_l^{NACA2410}$
1°	3.091	0.401	4.950	0.355
2°	3.192	0.497	5.070	0.467
3°	3.391	0.617	5.390	0.576
4°	3.434	0.845	5.910	0.686
5°	3.860	0.931	6.140	0.791

5.5 Sensor-controller growth experiments

In the previous experiments the controller was realized as a feed forward neural network with one input layer, a single hidden layer with sigmoidal activation function and one output layer with a linear activation function. The neural controller used 20 neurons in the hidden layer and showed good performance. However the high number of neurons in the hidden layer, especially when having a high number of sensors, slowed down the optimization process considerably due to the high number of optimization parameters.

Since the focus of this work is to analyze the developmental process of the system which starts with an initially simple set-up growing into a system of higher complexity, the complexity of the controller has been reduced by replacing it with a linear recurrent model. Additionally, the simplified controller allowed a significant reduction of the computational costs. The simulation time could be reduced from 500 on average to 200 generations(see later results in this chapter). The schematic model of the controller is shown in Fig. 5.15

$$\begin{aligned} C_o(t+1) &= C_o(t) + \Delta C_o(t) \\ \Delta C_o(t) &= \sum_{i=1}^{I} (s_i(t) - s_i(t-1)) K_{io} = \sum_{i=1}^{I} C_{io} \\ s_i(t) &= f(C_1, \ldots, C_O) \end{aligned} \tag{5.10}$$

The controller input signals are the changes of the pressure coefficients s_i over one time step of controller processing. The outputs of the controller are the actuator signals C_{io} and describe the position of the virtual actuators in two-dimensional space. The actuator adjustments ΔC_o are calculated as a sum of the signals of all sensors of the system multiplied with the corresponding linear controller coefficients K_{io}. The current state of the actuators C_{io} defines the pressure coefficients s_i by

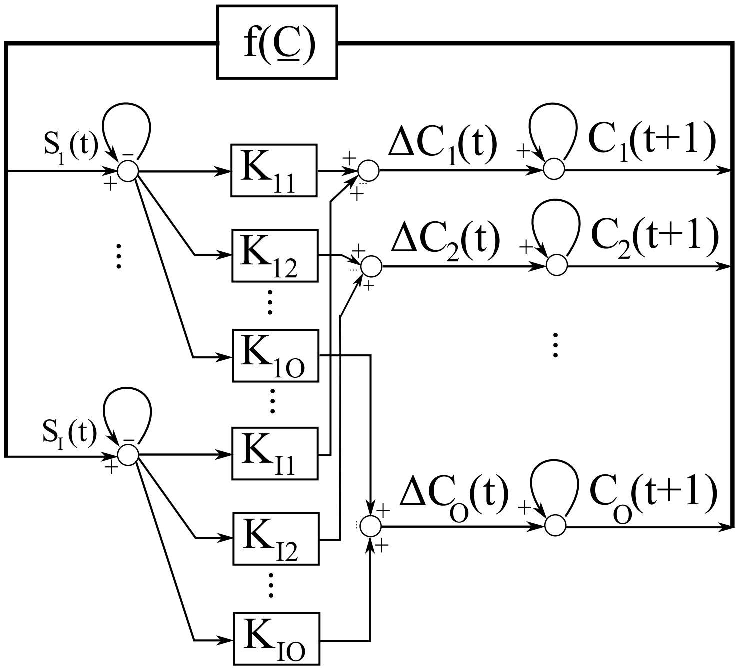


Figure 5.15: Model of linear recurrent controller

the nonlinear air flow function f, simulated with Xfoil solver described earlier.

The ascertained high correlation between the development of the sensory and the control systems has been demonstrated in Fig. 5.13. These results support the idea of the benefits in concurrent morphological and control systems development. The results of the first experiments with different fixed dimensionality of the sensory system additionally assume the existence of the optimal number of implemented pressure sensors. These number is defined as optimal since it presents the minimal number of information required to fulfill the given task.

The next experiments concentrated on the application of proposed growth method on the development of sensory and controller system of the adaptive wing and its ability to detect a minimal set of sensory inputs required to create requested lift while producing minimally possible drag. The implemented system growth method synchronizes the design of a sensory and a signal processing system parts during the optimization process and additionally frees the system of early structural limitations of the sensory system, giving it a possibility to develop autonomously to a system with an optimal number and position of the sensors and the related optimal controller. One further significant advantage of the growth process, is a minimal requirement on the priori knowledge about the system at hand.

Equally to the previous experiments with fixed dimensions of sensor morphology, the system was evaluated according to its ability to reduce the drag of the airfoil to its minimum while changes in the inflow angle of the air occur. Therefore the ratio in drag coefficient before C_d^{old} and after C_d^{new} a change of the inflow angle is evaluated. The ratio of the changed and unchanged drag values indicates the performance of the controller through actuators adjustments. Fig. 5.16 shows the extended structural diagram of individual evaluation in the optimization scope of sensor positions and additionally its number as well as the system controller parameters.

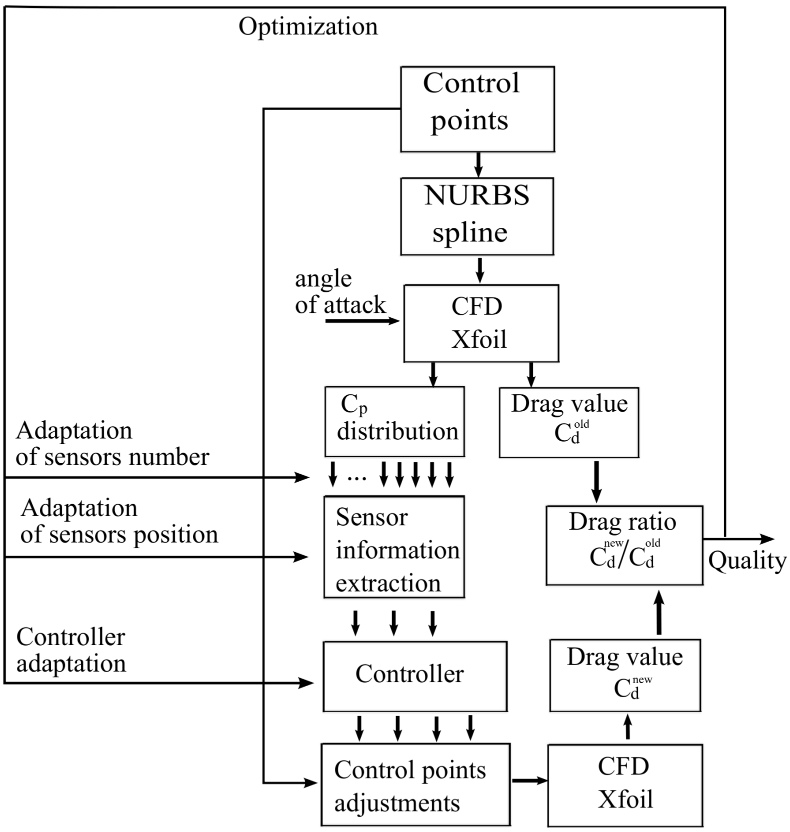


Figure 5.16: Overview of the system evaluation

The fitness of an individual was defined again as a sum of drag value ratios over tree steps of controller actions for a single angle of attack and additionally over a cascade of angles of attack shown in Fig. 5.17 accordingly to 6.2.

In order to reduce the influence of the initial condition of the wing geometry and in order to test the system for a sufficiently high number of angle changes each system is evaluated for 16 different angles, shown in Fig. 5.17. With that, the effect of noise is removed while keeping the time necessary for the evaluation within a reasonable range. The maximal thickness of the airfoil was again set to the maximal thickness of the NACA 2410 airfoil which is equal to 10% of the chord length. In addition, the constraint on the lift coefficient has been set to the lift of a

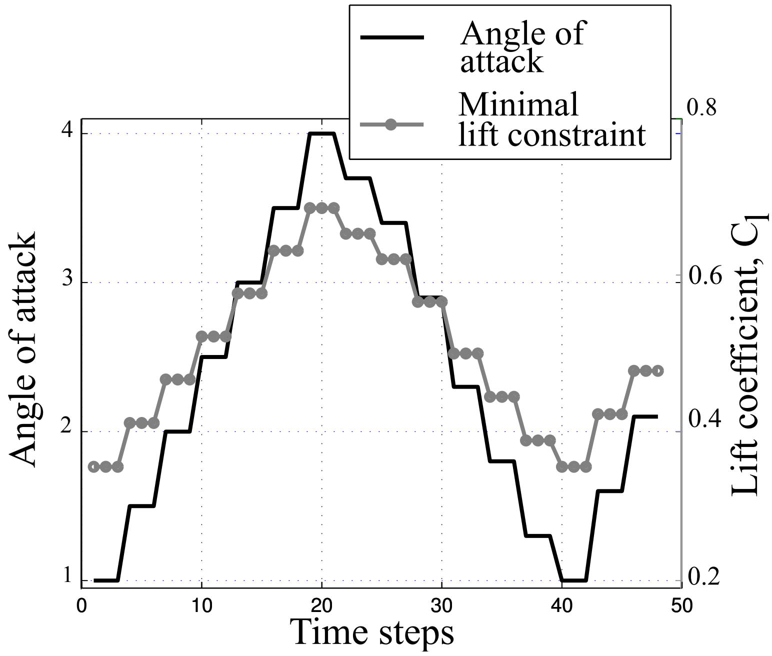


Figure 5.17: Training scenario of different angles of attack(in black) and lift coefficient of NACA 2410 airfoil (in gray) for the individual evaluation

standard NACA 2410 airfoil at a corresponding angle of attack. The lift coefficients of the NACA 2410 airfoil are shown in Fig. 5.17.

5.5.1 Revision of results with new controller and fixed dimensionality of sensory system

To verify the functionality of the linear recurrent controller presented in 5.3 experiments with fixed morphological and controller dimensionality has been revised. The concurrent optimization of sensor positions on the airfoil surface and the optimization of controller coefficients, described above, has been implemented with a standard ES with reduced population size compared to the robust optimization runs in section 5.3. The implemented ES(15,100) uses two different self-adapted step sizes, for the sensor positions and the linear controller connection weights adaptation.

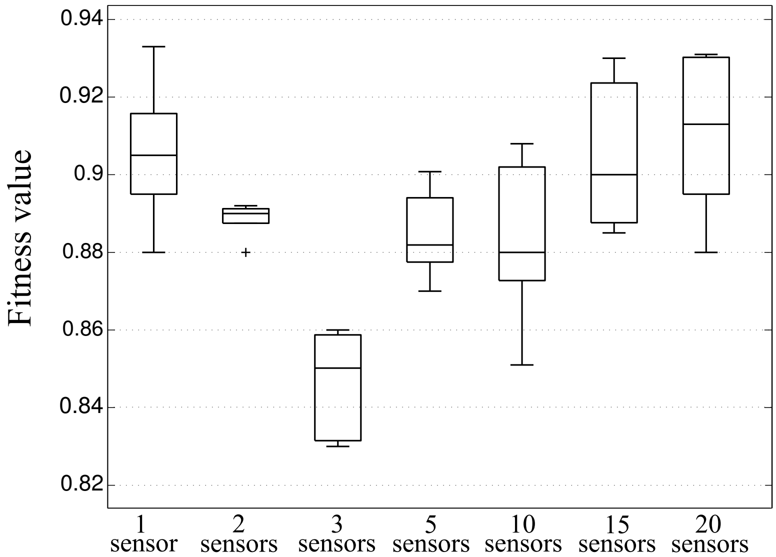


Figure 5.18: Final quality of the sensor-controller optimization runs after 45 generations. 10 optimization runs for each fixed number of sensors with different starting parameters.

The optimization starts with the randomly initiated sensor positions between 0 (trailing edge, wing upper-side) and 2 (trailing edge, wing under-side) and controller coefficients, uniformly randomly initialized between -0.2 and 0.2.

Two mutation step sizes are defined. One for the position of the sensors and one for the connection strengths of the controller. The parameters are initialized with 0.1 for the sensor positions, and 0.01 for the controller connections. The results of the concurrent sensor-controller optimization with different morphological dimensionality, which remain constant during the optimization process, are presented in Fig. 5.18 and 5.19. The results indicate the existence of an optimal number of sensors (3 pressure sensors) for the selected conditions of the framework and optimization strategy. Systems using one or two pressure sensors show a low performance compared with the systems using 3 sensors, due to the fact that the key information about the change of angle of attack measured indirectly through pressure sensors is missing. The relatively bad performance of the system with a

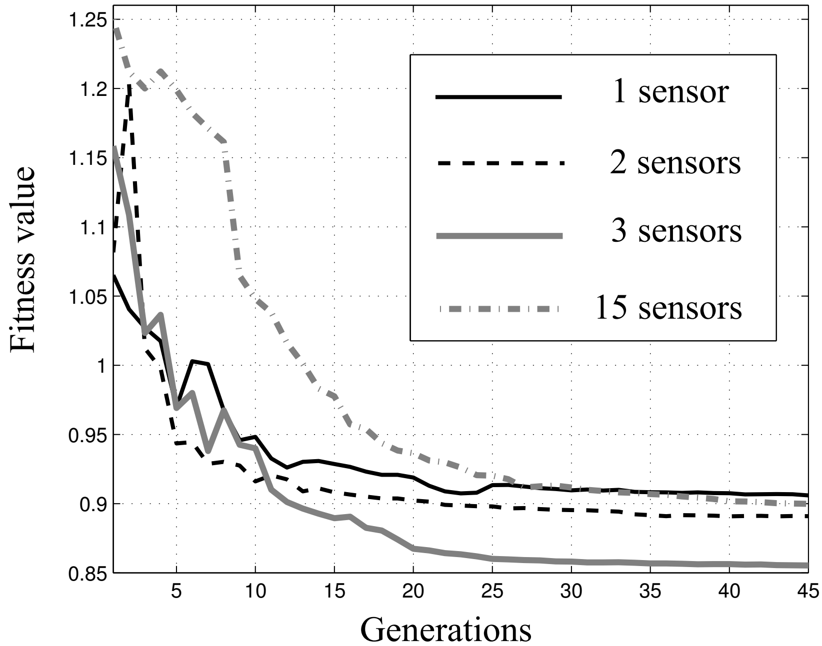


Figure 5.19: Averaged fitness curves of the results in Fig.5.18. Fitness curves has been averaged over 10 runs with different starting parameters

higher number of sensors results from the inability of the chosen optimization algorithm to optimize the resulting number of optimization parameters for the given complex aerodynamic fitness landscape. Theoretically, the similar performance as for the low dimensional search space could be expected also for high dimensions if the number of iterations is not limited. However, the computational costs, in this case, increase exponentially. In the scope of realistic simulation time frame, large-scale optimization problems get at some point infeasible with an increase of search space. In this case, the optimization is very slow or converges too early and does not reach the global optimum.

5.5.2 Development of optimal sensor-controller configuration by growth process

In this section, the applicability of a concurrent evolutionary growth process proposed in chapter 4 for the design of the optimal sensory and controller parts of a system for the example of an adaptive wing is demonstrated. The focus is twofold. First on the realization of developmental stages of the sensory and controlling systems design, defined as a growth process, and second on the comparison of the differences in structures of the systems developed through the presented evolutionary growth method and of evolved systems, having fixed set of sensory elements. Furthermore, the required conditions on the evolutionary set-up of the system growth method to find the optimal system configuration have been specified and researched in detail.

5.5.3 Application of growth process on adaptive airfoil design

The task of the sensory-controller growth process has been to detect the optimal inputs and the corresponding controller of such an aerodynamic test problem as proposed morphing wing in the scope of combined evolutionary process. The optimization of the controller inputs dimensionality represents a special case of controller topology optimization, despite the fact that applied linear recurrent model is fully connected since the inputs number is variable during the optimization. The gradual growth of the sensory system and controller structures takes place during the evolutionary process. Concurrently the environmental conditions, defined as changing angle of attack according to Fig.5.17 and the given task of generation of required lift for the given angle of attack influence the growth process of the system acting in this environment. The optimization couples the interactions between control system, morphology and the external aerodynamic. All these parts of the dynamical system have a strong impact on each other and are co-evolved during the entire optimization process.

The expected advantage of the growth process versus an optimization with a fixed number of sensory elements has been the possibility to detect the optimal number and the configuration of controller inputs as well as optimal resulting signal processing structure during the combined optimization process.

As described earlier the achieved quality of the final system depended strongly on the timing and the method of system enlargement as well as on the current values of the mutation step sizes at the time of structural changes. Since the idea of the growth process has been to use optimized solutions in the previous search dimensions as a starting point in the next searching space dimension, it is decisive to maintain benefit solution despite the structural change. The neutrality of the mutation has been achieved through initialization of the coefficients of new sensor elements with zero. Additionally, a new sensor elements and the corresponding controller connections get individual mutation step sizes, which allows the new structural elements to develop individually while keeping the previously optimized system setup intact. The good results have been achieved using insertion probabil-

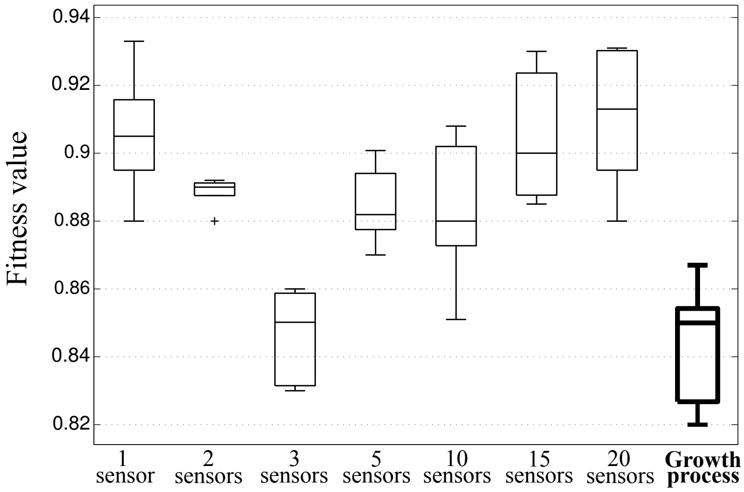


Figure 5.20: Comparison of the final quality of the sensor-controller optimization runs with the quality of the growth method (in bold) averaged over 10 optimization runs.

ity value of $p = 0.05$, which means that statistically 5 out of 100 individuals in the population get a new sensory input.

5.5.4 Experimental results of growth process compared with optimization of systems with fixed morphological dimensionality

Fig. 5.20 shows the results of the described growth method in comparison to the optimization results with fixed morphological settings. The results demonstrate, that the systems developed with our growth method show similar good performance as the systems optimized for 3 sensors.

Fig. 5.21 shows the comparison of averaged development process of the systems through growth and of the systems with 3 and 10 sensory elements. The average system constructed through growth process developed 10 sensors after 100 generations and converged close to the average quality of the system using 3 sensors. In comparison to the results of the growth method, the evolved systems with fixed number of 10 sensors get trapped into local optima after 40 generations and end up with the similarly bad performance of the system using two sensors. The re-

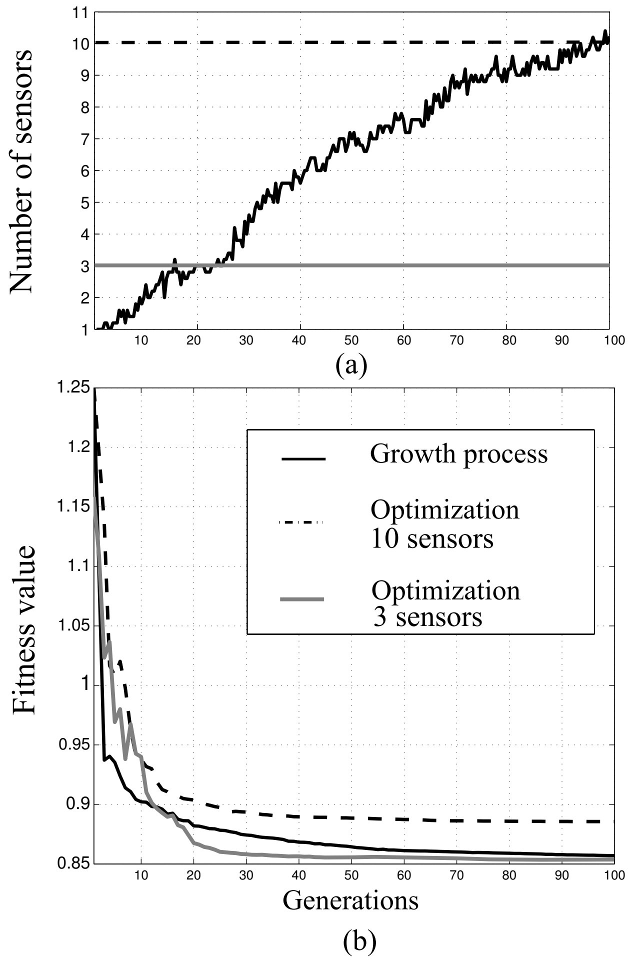


Figure 5.21: (a) Number of sensors during the optimization averaged over 10 runs with different starting parameters (b) Corresponding averaged quality development.

sult of the growth method has been a system using 10 sensors on average. Since the expectation have been to obtain a system with optimally placed 3 sensors, the results of the growth method has been unexpected. However, a detailed insight of the controller system organization generated by the growth method gave the explanation on the achieved results.

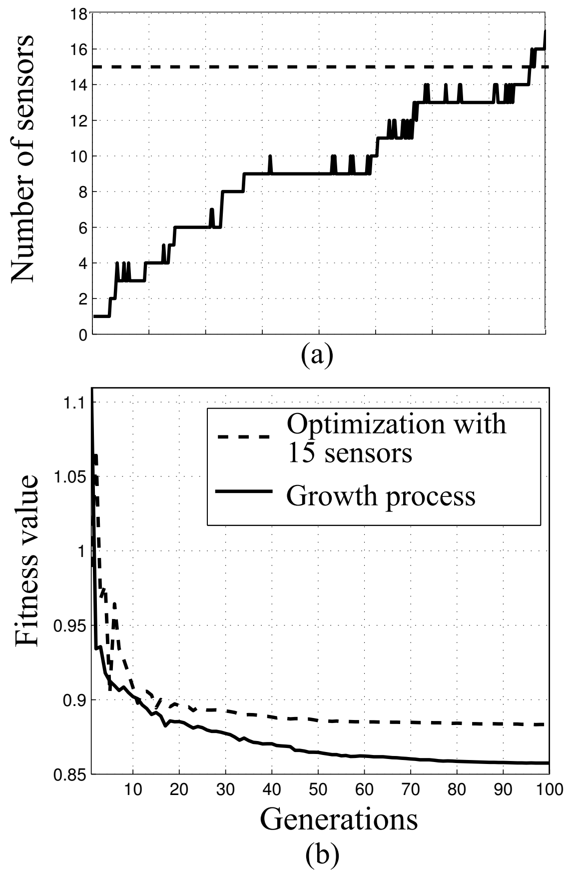


Figure 5.22: (a) Number of the sensors during the optimization of the systems presented in Fig. 5.26 (a) and (c), (b) Corresponding quality development.

5.5.5 Strong hierarchy of system organization produced by growth method

Fig. 5.23 and 5.22 demonstrate the differences in the functional controller organization and its impact on the system performance. Fig. 5.22 (a) and (b) compare the corresponding performance progress of two differently developed systems in Fig. 5.23 (a) and (c) during the optimization. The example system shown in Fig. 5.23 (c) has been optimized for 15 pressure sensors. It has been ascertained, that the controller of the system is organized in such a way that each sensor has a comparable influence on the control strategy. The organization of the control strategy of the example system developed by our growth method in Fig. 5.23 (a) is cardinal different. Due to the gradual step-wise system enlargement during the optimization,

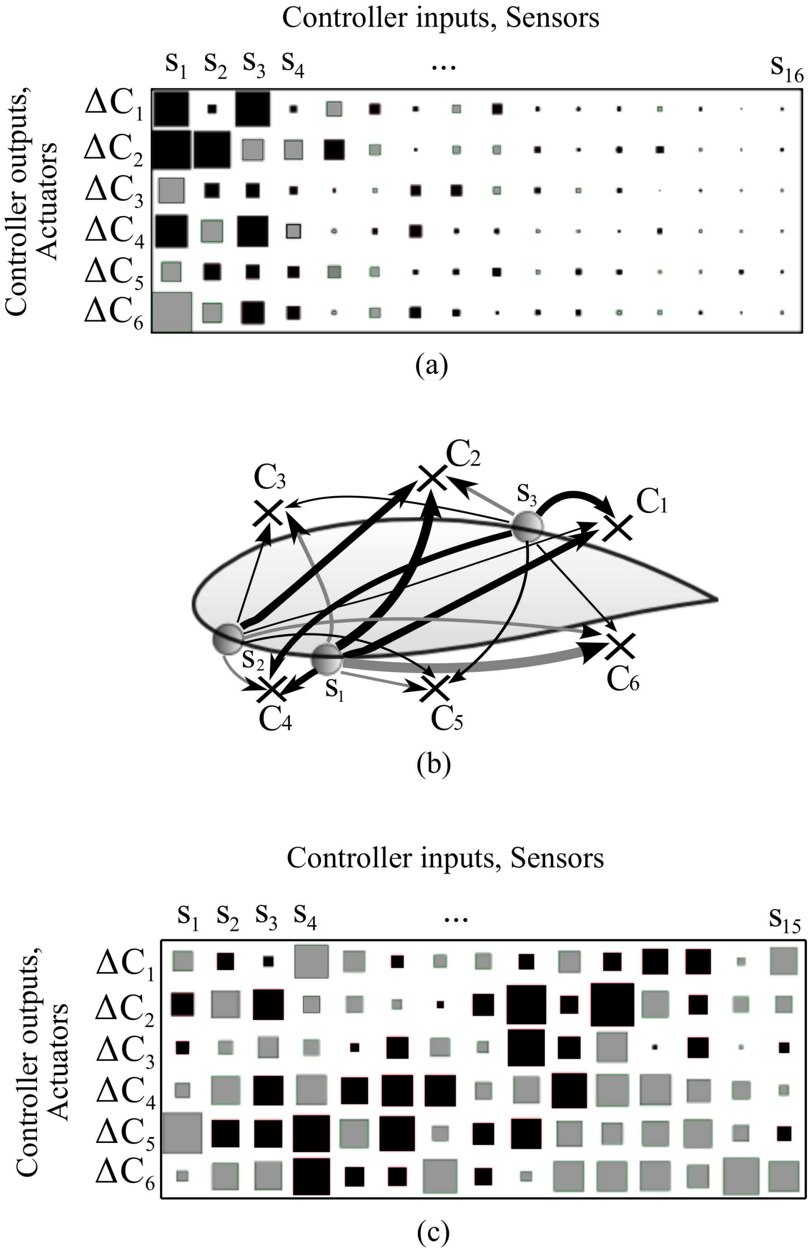


Figure 5.23: (a) Hinton diagram of the system controller, developed by growth process at 100th generation, (b) Schematic airfoil controller with 3 major controller connections between sensors and actuators of the system in Fig. 5.23 (a). Thicker lines mean a stronger connection, (c) Hinton diagram of the system controller optimized for 15 sensors at 100th generation

the clear arrangement of the sensors according to their importance for the system could be observed, where the first sensor s_1 has the strongest and the last sensor s_{16} the lowest impact on the system performance. The first 3 sensors of the system have a major impact on the system, which matches the results of the optimization in 5.3.

5.6 Growth process of adaptive airfoil overall morphology and controller

The promising results of the experiments with growth process of sensory and controller systems of adaptive wing design motivated to expand the research to the combined development of all functional parts of the system to additionally increase the quality of evolved solutions. The drawback of the growth method ascertained in the last experiments has been usually high dimensionality of the sensory structures of the evolved solutions. The reason could be the absence of regulation terms like evolutionary sensors removal mechanisms or negative effect of additional sensors. This means, once the additional sensor has been selected by the evolutionary process, there exist no removal mechanisms in the further progress. Therefore, a cost factors for sensors and actuators has been introduced, which worked as regulation mechanisms and supported limited growth of the system dimensionality.

$$Fitness(Individual) = \frac{\sum_{i=1}^{N} \frac{C_d^{t+1}(\alpha_i)}{C_d^t(\alpha_i)}}{N} + w \cdot S + v \cdot A \quad , \tag{5.11}$$

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. 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, the constraint on the lift coefficient has been included - equal or higher than a lift of a NACA 2410 airfoil at a corresponding angle of attack. In this case, a system gets new sensor or actuator only if it gives a significant benefit to the system performance.

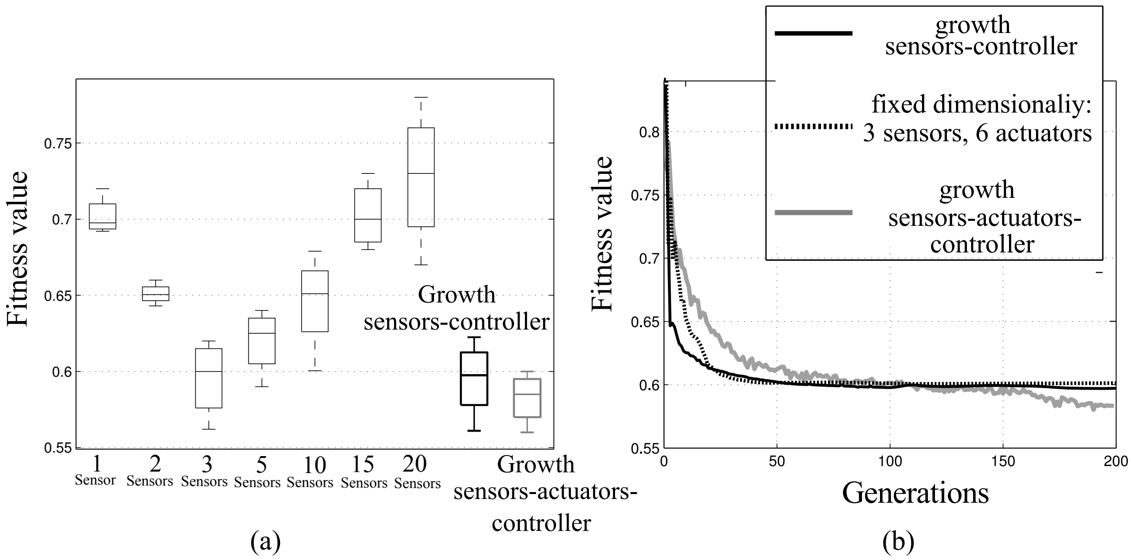


Figure 5.24: (a) Final quality of sensors-controller and sensors-actuators-controller optimization runs, compared with results of the runs with a different fixed morphological configurations. 10 optimization runs with different starting parameters, (b) Comparison of the averaged fitness curves

5.6.1 Impact of integration of cost factors on final dimensionality of sensory, actuation and controller systems

In this section experimental results of the presented sensor-actuator-controller growth method of the adaptive wing are demonstrated and compared with the previous experimental results.

Fig. 5.24 (a) depicts the comparison of the optimization results for different systems. First, the results of the systems, having different fixed number of sensory elements and equally positioned fixed 6 actuators has been presented. The optimization results for the sensors-controller and sensors-actuators- controller growth method has been presented and compared. The detailed explanation for the difference in the final performance is given. Generally, the performance of the final system is expected to improve, the more sensory information about the environment is available. Indeed Fig. 5.24 (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 is the high number of sensory elements. For experiments with fixed morphological dimensionality decline of the performance of the systems, having more than 3 sensors has been established. In the 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.

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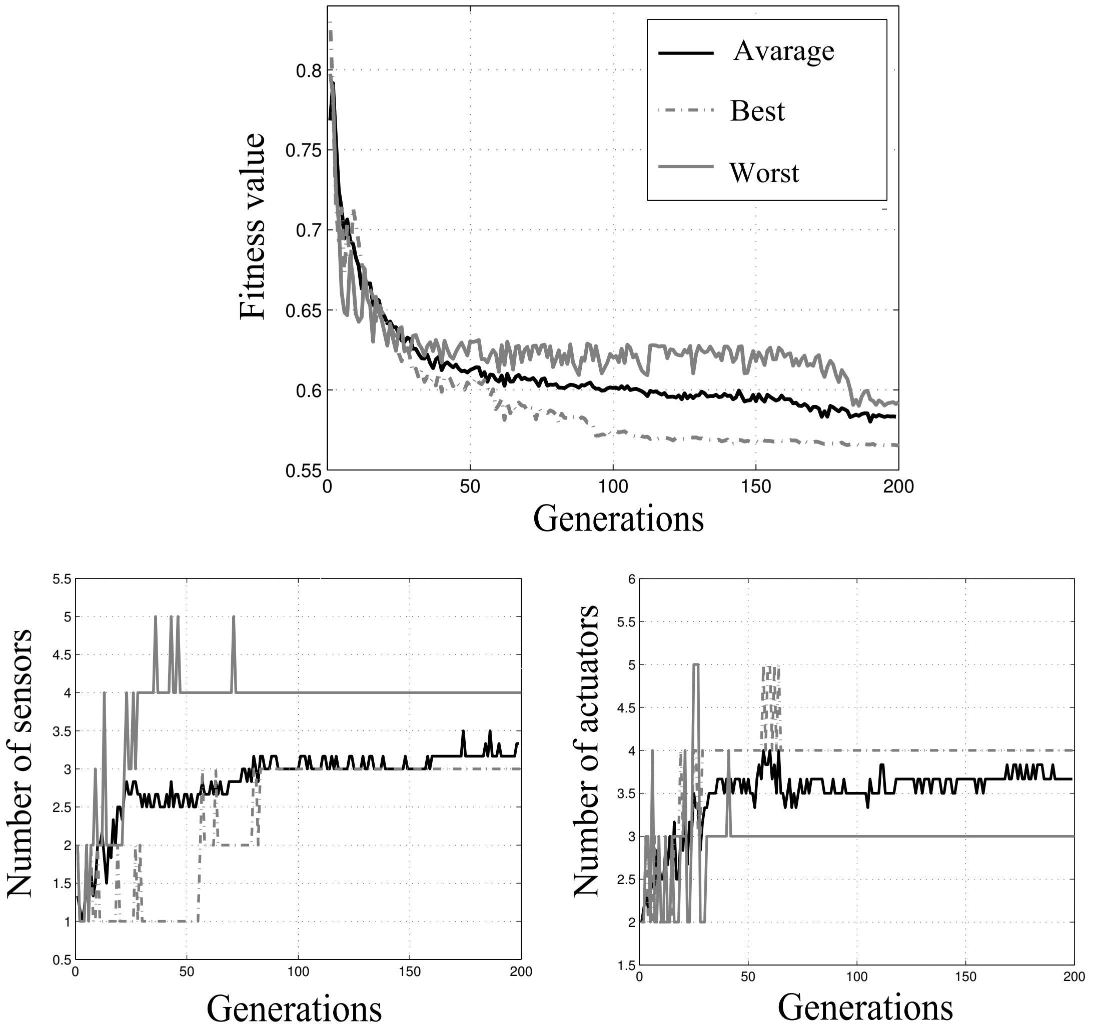

Figure 5.25: (a) Average (10 runs), worst and the best fitness progress of the sensors-actuators-controller optimization, (b) Development of the number of sensors over 200 generations, (c) Development of the number of actuators

According to the optimization results, systems with 3 pressure sensors represent a sufficient solution for morphological setting for given optimization strategy, since it reached the best final quality on 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. The growth method generated a system, having on average about 3 sensors and between 3 and 4 actuators. According to the average achieved quality of the fully

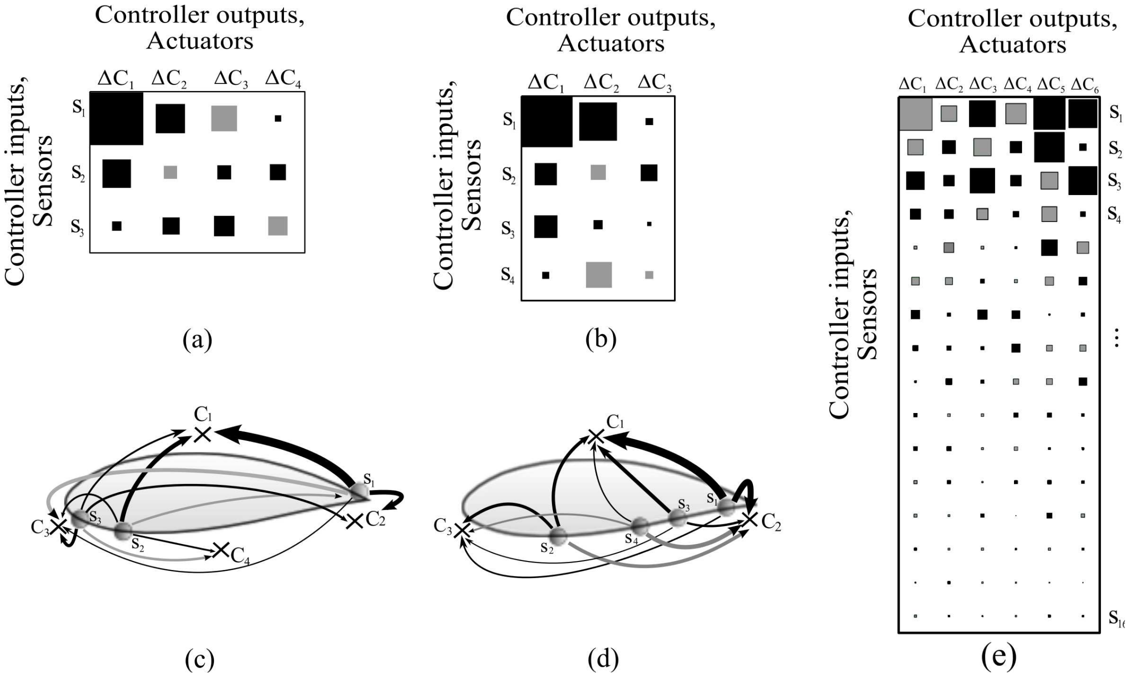

Figure 5.26: Hinton diagrams of the system controller of the worst (a) and the best (b) system in Fig. 5.25, developed by the sensors-actuators-controller growth process at the 200th generation, (c) and (d) Position of the sensors and actuators of the systems and schematic airfoil controller with the 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.

variable system design, presented as sensor-actuators-controller growth method, which starts the optimization with initially minimal system configuration, evolving during the optimization through gradual step-wise complexification is significantly more beneficial in terms of performance and computation costs. 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. 5.25.

To analyze the functional configuration of the controller a Hinton diagrams has been used [100]. 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 connection strengths are scaled between minimal (no box) and maximal values (box of maximum size). Fig. 5.26 demonstrates the final controller structures of the worst and the best system, developed with the growth method after 200 generations. Fig. 5.26 (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 in 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.

5.7 Test of final system functionality under unknown environmental conditions

Fig. 5.27 demonstrates the comparison of the baseline and NACA 2410 airfoils for 16 different angles of attack shown in Fig. 5.17 with the performance of the best system developed with a growth process, tested on a scenario of 100 different angles of attack, generated randomly between 1 and 4 degrees. As expected, an adaptive airfoil system developed with the growth method shows significantly better performance than a single standard NACA 2410 airfoil. It also gets close to the maximal possible quality of specialized baseline solutions for single angles of attack presented previously, but performs less good for the marginal angles of attack.

5.8 Potential realizations of adaptronic structures

Shape control and thus actively influencing the flow of aerodynamic profiles is a challenging target in aerospace. The previously described growth method produced solutions for adaptive airfoil design for that purpose, including multiple pressure sensors, shape-morphing actuators and the internal control structure capable of

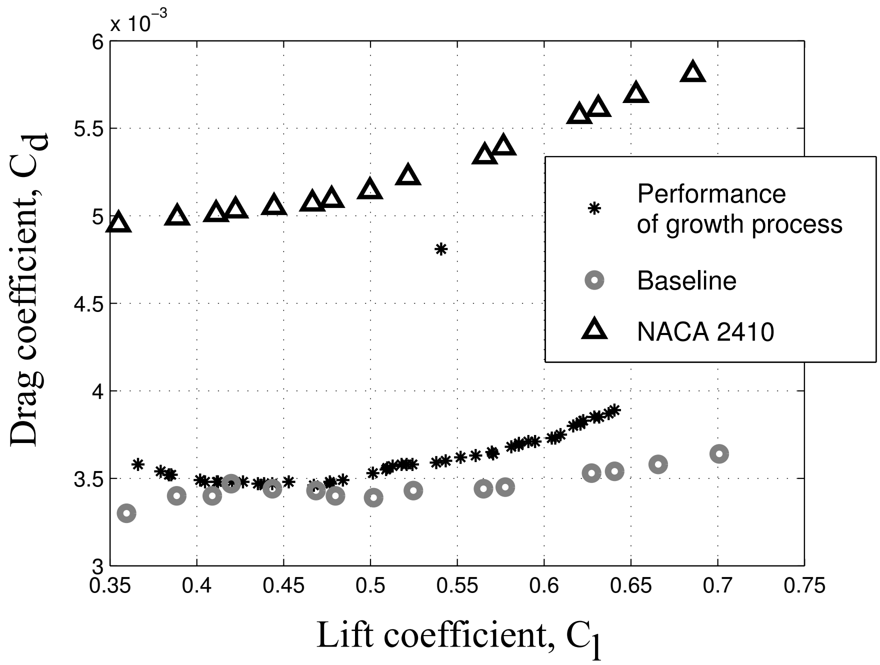

Figure 5.27: Performance validation: Performance of the baseline airfoils, NACA 2410 standard airfoil and the system developed through growth

controlling the resulting morphology for different flight conditions (different angles of attack). One example of the evolved system in the scope of the last experiments is given in Fig. 5.28.

The evolved system in Fig. 5.28 disposes of 4 pressure sensors and 3 actuators. The morphology and control of the system have been evolutionary co-optimized and could achieve excellent performance in the simulations. Thereby a significant part of the engineering design process of adaptive systems like a selection of morphology and control has been automated and simplified with considerable reduction of computational costs and personal effort. The next step in the design process is the realization of the simulated system in a real system of soft and hardware components. The recent development of a novel sensory techniques allows almost disengaged integration of almost weightless sensory elements in the airfoil structure [101]. Modern ECUs dispose of powerfull microprocessor which can process the sensory inputs from the pressure sensors in real-time. The main difficulty of the entire system realization is the construction of appropriate actuators. In the framework of the synthesis of a shape-adaptable structural system, mechanical design deals with the task of choosing the properties of actuators to fulfill amoth others:

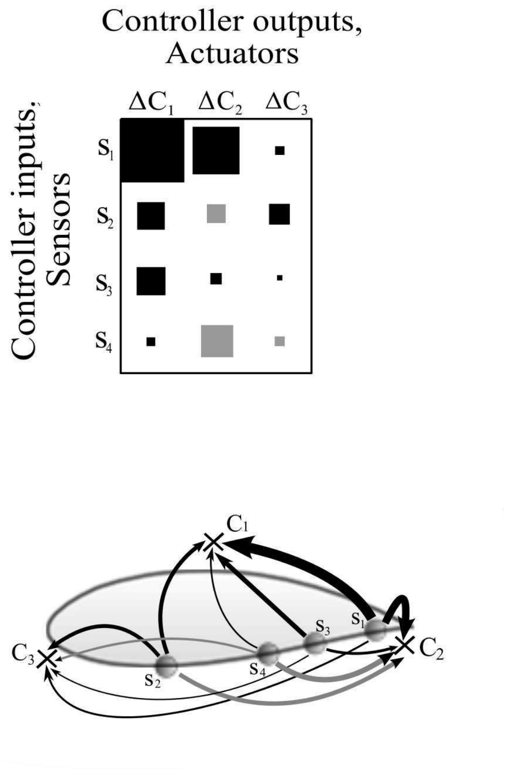

Figure 5.28: Optimized morphology and controller of adaptive airfoil system

- a set of deformability requirements specifying the geometrical changes which the system must be able to perform according to simulation results;
- a set of stiffness requirements which define the allowed deviations from the desired shape under given loads;
- activability requirements which state that the desired deformation is achievable by loading through the actuator system;
- a set of further requirements which define limits for the systems weight and energy consumption etc.

The control points of a non-uniform rational B-splines (NURBS) surve as virtual actuators of the adaptive airfoil. NURBS are mathematical models, excluding the above-mentioned constraints like e.g. stiffness or deformability. The precise simulated deformations of the airfoil shape optimized in the scope of the evolutionary process could be heavily achieved through the fixed already existing actuation mechanisms. The proposal of the problem solution is the investigation of possibilities to integrate the deformation constraints of realistic actuators characteristics in the optimization, to achieve the results applicable to the hardware components of existing actuation solutions.

One example of the possible solution for actuation system widespread in the area of the avionics is shape memory alloys (SMAs). SMAs are metallic alloys which undergo solid-to-solid phase transformations induced by appropriate temperature and stress changes and during which they can recover seemingly permanent strains [102]. An example of possible SMA actuators integration in the airfoil design serves a study of Strelec and Lagoudas [103]. The authors build the airfoil prototype based on the simulation results and have shown that integration of smart actuators such as SMAs can successfully increase the overall performance and efficiency of the aerodynamic solutions.

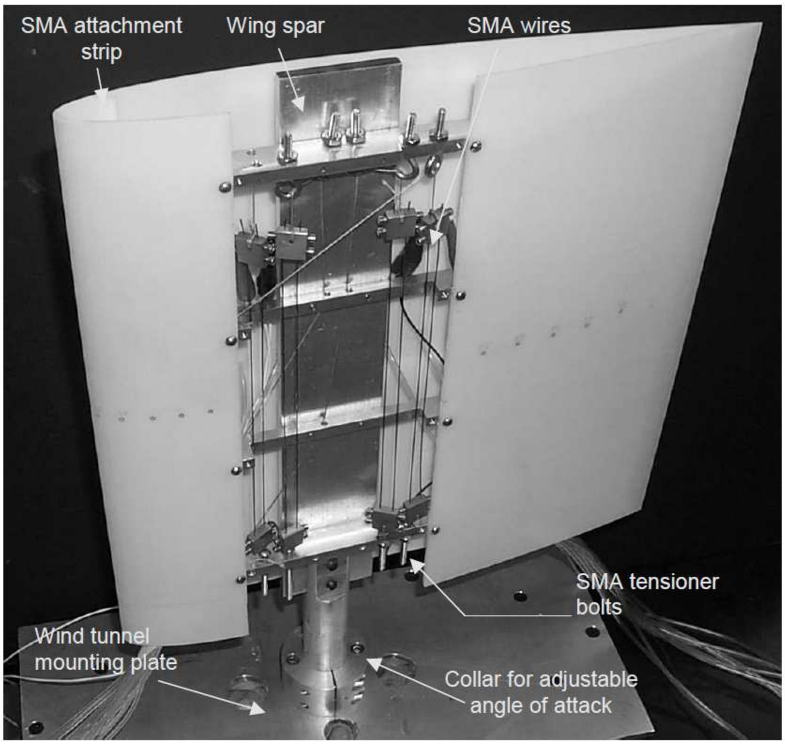

Figure 5.29: Adaptive airfoil prototype using SMA actuators for shape morphing, picture from [103]

An SMA component, being both structural and active, can effectively reduce the complexity of a system when compared to the same system utilizing conventional actuation technology. The material constraints of SMA actuators could be integrated in the evolutionary growth process proposed in the scope of this thesis and allow the development of such a realistic intelligent integrated structures as adaptive airfoil system.

6 Application of co-evolutionary system design method on virtual autonomously driving vehicle

Advanced driver assistance systems and at the end fully autonomous driving cars is a big challenge and a fast growing sector in the automotive domain. The driver assistant systems and fully autonomous vehicles represent the future of the automotive industry and are expected to help to make the car driving more safe and comfortable and allow more effective use of the traffic infrastructure and efficient fuel efficiency. A modern intelligent vehicle can perform many driver-assistance tasks, such as avoiding and preventing accidents and reducing the severity of accidents.

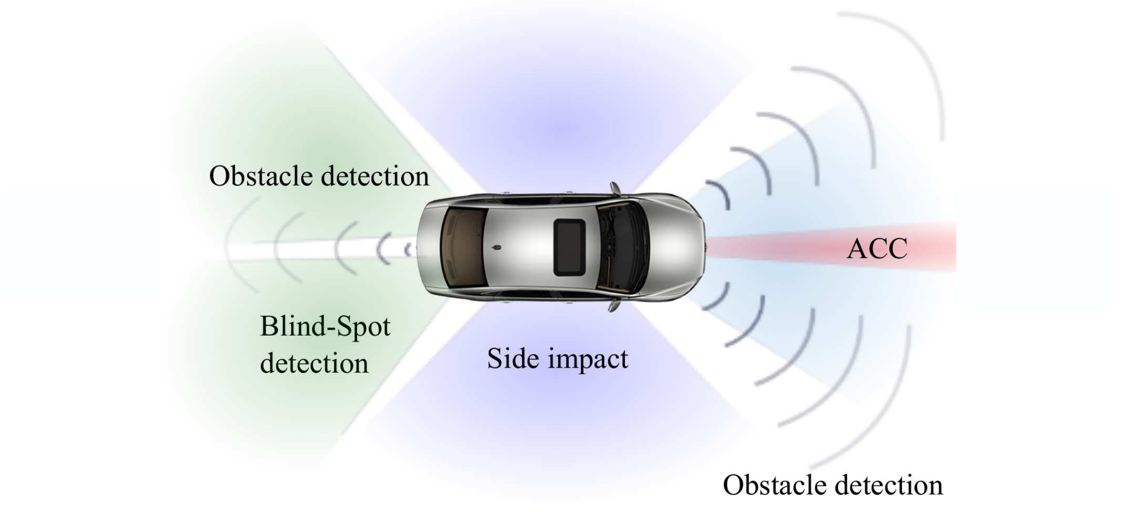

Figure 6.1: Example of different car range sensors with diverse function

6.0.1 Automotive range sensors

To perform intelligent driver assistance tasks, the vehicles include not only passive safety systems, such as airbags and seat belts but will additionally include more and more active safety systems, such as electronic stability control, adaptive suspension, and yaw and roll control and driver-assistance systems, including adaptive cruise control, blind-spot detection, lane-departure warning, overtake assist and parking assistance etc. These systems require automotive range sensors like for example ultrasonic sensors, radar, LIDAR systems, and vision-imaging cameras [104] etc. is used for its own localization in the case of temporary GPS unavailability, the localization of relative obstacles, pedestrians and other traffic participants. Fig. 6.1 shows the example of common range sensors in the vehicle. Range sensors can also deliver the information about the relative velocity of the detected vehicle measured by the means of different physical measurement principles, like for example the Doppler effect. Fig.6.2 shows different range sensor types used in automotive industry with its physical active principle.

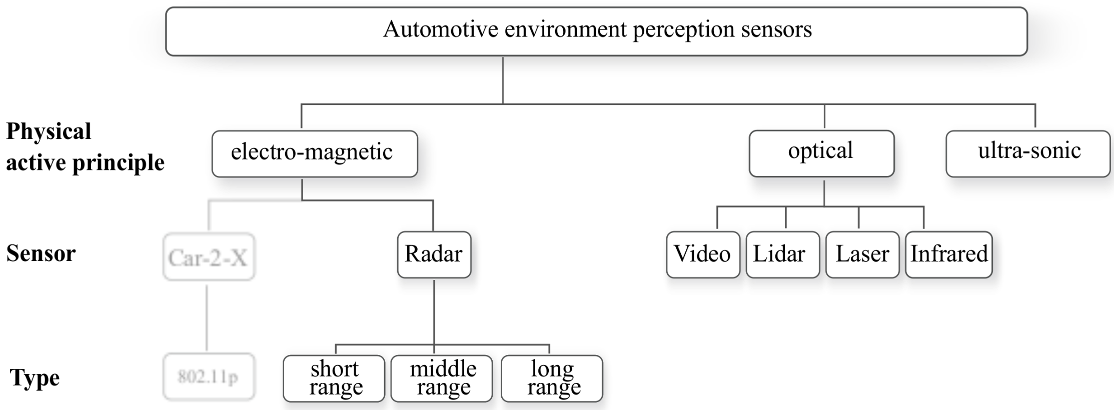

Figure 6.2: Example of different vehicle range sensors

Over the last two decades, there have been started numerous projects with the target to develop autonomously driving vehicles. Perhaps the most well-known is DARPA Urban Challenge, where international teams designed the hard- and software for autonomous vehicles for example for the collision avoidance of dynamic obstacles, driving over intersections and merging. Over 50 vehicles drove simultaneously on a closed route for an entire day. Six autonomous vehicles completed the race successfully. As an example, the Technische Universität Braunschweig started in June 2006 as a newcomer in the 2007 DARPA Urban Challenge [105].

Significantly supported by industrial partners, five institutes from the faculties of computer science and mechanical and electrical engineering equipped a 2006 Volkswagen Passat station wagon named Caroline to participate in the DARPA Urban Challenge. The sensory equipment of the Caroline, for example, has been: in front, two multi-level laser scanners, one multi-beam lidar sensor and one radar sensor cover a field of view up to 200 meters for approaching traffic or stationary obstacles, four cameras detect and track lane markings in order to allow precise lane keeping, the stereo vision system behind the windshield and another color camera combined with two laser scanners mounted on the roof to provide information about the drivability of the terrain in front of the vehicle, one multi-level laser scanner, one medium range radar, one lidar and two radar-based blind-spot-detectors enable Caroline to detect obstacles at the rear. The detailed sensory configuration of the experimental vehicle has been shown in Fig. 6.3.

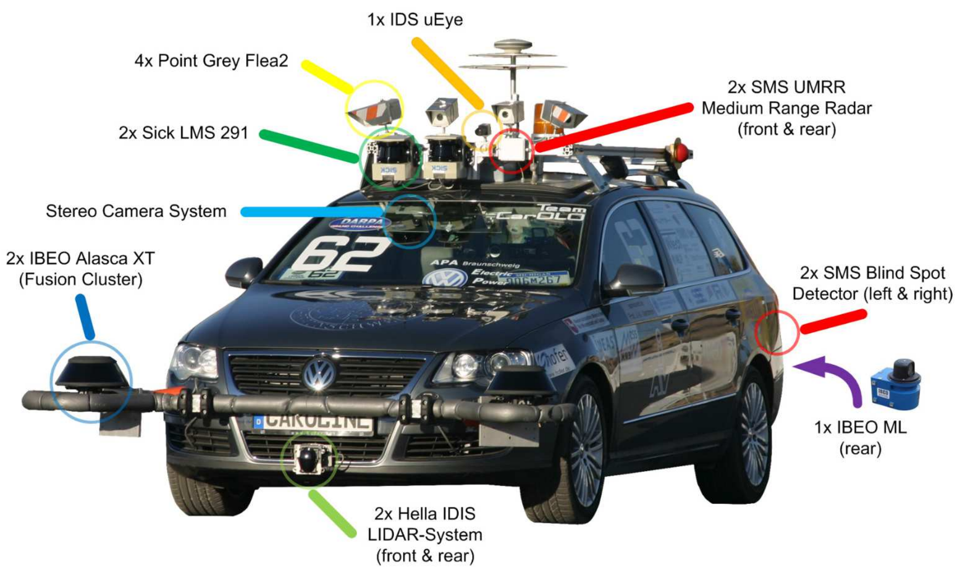

Figure 6.3: Detailed sensor set of the Caroline experimental vehicle, figure from [105]

6.0.2 Cost factors of automotive environment perception sensor system

The total price of the sensors used for Caroline project amounts to several hundred thousand US dollars. This price is still excessively high to be realistic for a serial-production of an autonomously driving car. On the one hand, the high costs of the project cars are linked to the high prices of some special sensor types and on the other hand to the high number of sensors used in the vehicle, many of which are redundant to ensure the robustness in the case of malfunction. Similar to other project cars, the process of selection of the number, type and the configuration of the range sensors is not explained fully. Since the important milestone in the development of the autonomously driving car would be the possibility to make it affordable for a normal customer, the optimization of the sensor set of the car in terms of the minimization of required number of the vehicle's range sensors is promising. The controller of the vehicle uses the input signals gained from the environmental sensors and processes it to the outputs, in the case of the autonomous driving car - lateral and/or longitudinal acceleration. It disposes of sensors, which acquire information about the current environmental state like, for example, detection of obstacles, actuators - lateral and longitudinal acceleration and controller and central signal processing structure. As it has been shown in the former section, that the controller parameters strongly correlate to the configuration of sensor and actuation systems. This implies, that effective optimization of the vehicle's overall configuration could be achieved, if the controller would be concurrently optimized in the same optimization scope as its sensory and actuation subsystems. The previously presented morphology-control growth method, successfully applied on adaptive airfoil design, can be also tested on one further application in a completely different domain - on the co-evolution of the sensors and controller of the autonomously driving vehicle. Guided by the contribution, that the inspiration from natural body-brain co-evolution could make the design process of adaptive structures efficient in terms of functionality and actuation and sensor resources, the co-optimization of range sensors and lateral control of the autonomously driving vehicle has been carried out in this work and described in detail in the further chapter.

6.1 EvoCarD optimization framework

In this chapter, the framework for the co-evolution of morphology and information processing structure for the optimal control of an automatically driven vehicle is described. Although the generation of the optimal sensory system with control for cars is not in the main focus of this research, this problem is a suitable test bed for the research on the co-evolutionary design of developing adaptive systems. Similar to the application of adaptive wing in chapter 5, the sensory and actuation systems as well as a central controller, processing the input signals to the outputs, can be easily considered for the autonomously driving car as well. Autonomous driving over the road intersection, regulated by right of way rules, represents non-trivial traffic situation and requires a complex controller capable of performing a correct situation analysis and a reliable sensory system. An example of such a traffic situation is given in Fig.6.4.

Figure 6.4: Common traffic situation with left-turn lane and minor road

The ego vehicle is equipped with multiple range sensors. Each sensor, depending on the type, has its specified characteristics. Typical automotive radar sensor can be short-, middle- or long-range and is described by the maximum range of measurement in meter. A further parameter is the lateral opening angle (LOA). A typical value of the LOA of a long-range radar for the adaptive cruse control is about 8°. For stop-and-go assistance are LOA values up to 80° common. Mostly the maximum range and the lateral opening angle of the radar are in a trade-off relation. According to the given characteristics of the radar sensor, it can detect the oncoming vehicle at the earliest at the corresponding maximum range and measure its relative distance to the ego vehicle and the relative velocity of the detected car, like in the experiments performed in this thesis described later. In this application, the virtual range sensors are realized as simplified radars with a fixed lateral opening angle of 10°. The maximum range and the relative orientation of the sensor in the car geometry are variable and represent one part of the optimization parameters of the sensory system.

In the real traffic, an autonomous vehicle faces street scenarios where the dynamics of other traffic participants has to be calculated explicitly. Examples of such a complex, but common everyday situations are merging into the traffic flow, passing with oncoming traffic, changing lanes, turn to the major from the minor road and avoiding a collision by these maneuvers. In the experiments performed in this thesis the virtual road cross-section with two lanes minor and 4 lanes major road, regulated by right of way rules, serves as a test-platform, where the described traffic situations occur and has to be managed by the autonomously driving traffic participants. The reaction of the vehicle to the unpredicted current traffic situation is achieved through the controller actions, which process all sensory inputs into the breaking or acceleration. An artificial neural network (ANN) based control of an autonomous vehicle is proposed in [106],[107] since it is capable of generating the strongly non-linear behavior of arbitrary complexity, like for example decision making to accelerate or break, which depends on the sensory inputs from the environment. In this work a model of a standard feed-forward multilayer perceptron (MLP) artificial neural network (ANN) has been utilized to control the acceleration and deceleration of the ego vehicle. The relative distance and the velocity of the vehicle classified as the target object represent the inputs of the ANN controller, which implies minimum two neural inputs per sensor, as shown in Fig. 6.5. The ANN controller used one single hidden layer with 10 neurons with standard sigmoidal activation function. The output layer of the neural network consists of one single neuron for the acceleration, where negative acceleration(deceleration) correspond to for breaking intervention.

Similar to the previous application of the adaptive airfoil, the entire system consisting of sensors, actuators and signal processing has to be evaluated in the context of its adaptivity under variable environmental conditions. As described before, the typical road cross-section with two lanes minor and 4 lanes major road, regulated by right of way rules, has been chosen, since it generates complex traffic situations like merging into the traffic flow, lane change, change of major to minor roads, collision avoiding etc. To be able to calculate the adaptivity of the autonomously driving vehicle, the appropriate simulator of virtual road environment and traffic participants had to be found. An important aspect has been to be able to integrate the platform for multiple diverse sensors and controller models within the simulator. The choice of the simulator has been made in favor of the CarD simulator, which has been developed by Matthias Platho.

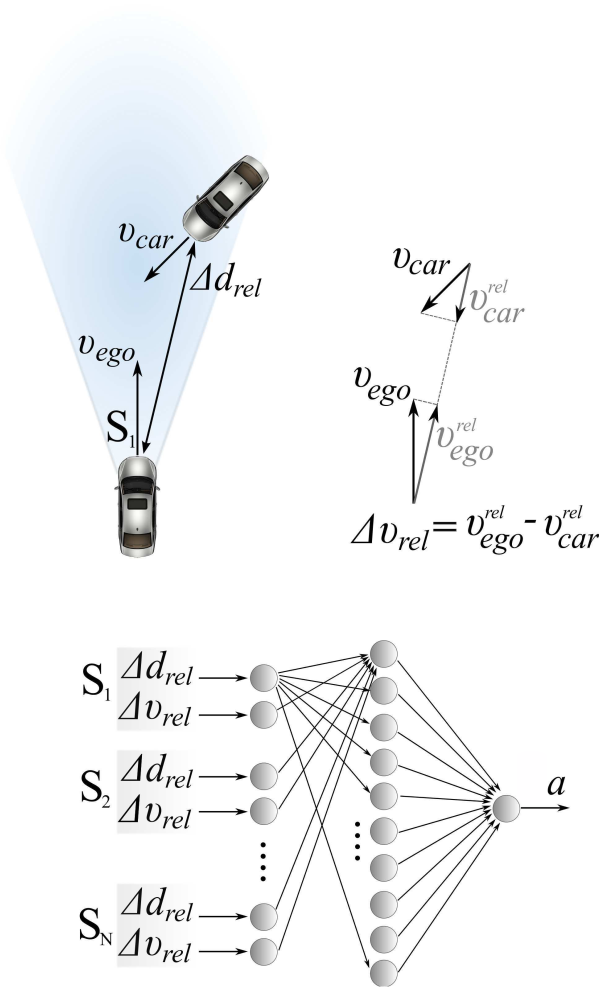

Figure 6.5: MLP controller of the autonomous vehicle

6.1.1 Traffic simulator platform CarD

The CarD simulator has been originally developed for generating sufficient and suitable driving data, which can be used to benchmark newly developed methods [108]. CarD is capable of generation and simulation of complex urban multi-lane intersection scenarios with vehicles that interact, collide, adhere to traffic lights and follow right-of-way rules. The vehicles are not controlled by a central instance and each driver decides individually depending on its personal traffic situation, route and target. The traffic simulator is microscopic, which means that it models traffic on entity level. Each vehicle is controlled by a behavior model, which reacts to other traffic scene participants, regulation rules or traffic lights [108]. The main advantage of the CarD compared to commercial microscopic simulators such as

AIMSUN [109], VISSIM [110], PARAMICS [111] or INTEGRATION [112], is that the behavior models can be accessed and modified directly.

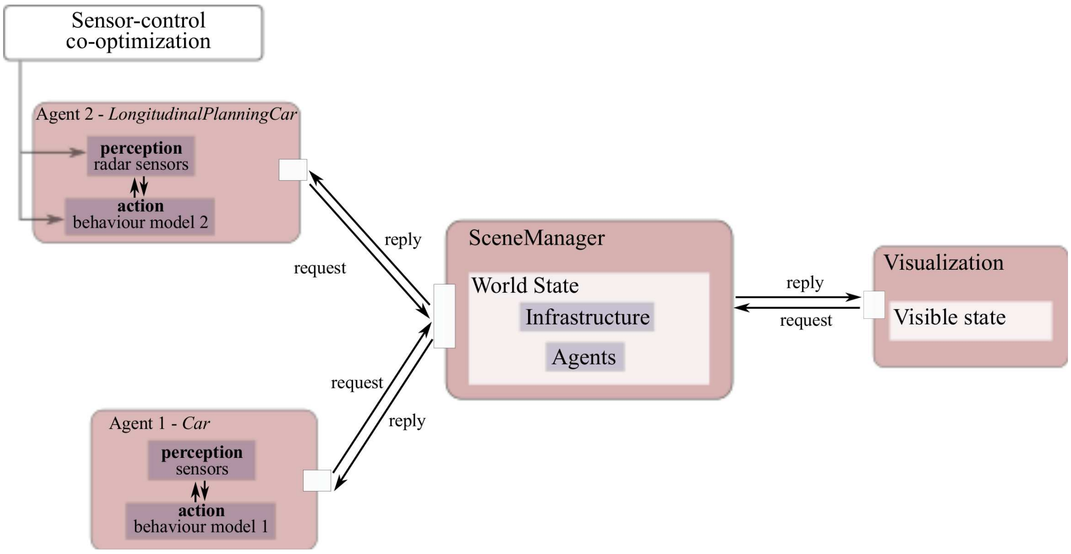

Figure 6.6: CarD architecture

Traffic arise from the interactive behavior of road users. Each traffic participant is acting autonomously and has its starting point in the environment and final destination. The vehicle acts as an intelligent agent *Car*, which can sense the environment with its sensors and plan its action according to the current traffic situation. The *Car* agent is equipped with the fixed basic sensors and simple predefined reactive model. Although each road user plans and acts autonomously, a coordinating instance, called *SceneManager* is needed for the update of the current situation and the parameters of the agents. The *World* contains all information about both infrastructural conditions and existing agents in the scene. Infrastructural conditions are information about the layout of the road network, the positions of traffic lights including their assignment to individual lanes or whether a road is a minor or major road.

The original version of the CarD simulator has been extended in this work for implementation of the co-evolutionary sensor-controller optimization. Besides existing intelligent agent *Car*, one extra agent has been developed. The additional agent, called *LongitudinalPlanningCar* is a derivative of the original *Car* agent and inherits its basic driving dynamics. Though *LongitudinalPlanningCar* has its own controller, realized through an MLP ANN described above and own radar sensors. For the original *Car* and new *LongitudinalPlanningCar* agent, sensing takes place by the means of message exchange pattern, in which the perception module requests information about the current environmental state. *SceneManager* provides complete information about the current world state and process its changes by calling the *update* function. Two different agent types *Car* and *LongitudinalPlanningCar* and its relation to central coordination instance *SceneManager* is presented in Fig. 6.6.

The sensors of *LongitudinalPlanningCar* differ from a fixed set of *Car* sensory elements. The virtual radar sensors of *LongitudinalPlanningCar* are defined by the means of a specific construct, where the entire *World* state is filtered through the current characteristics of the given sensors. The sensed information about the environment is defined by the sensor's parameters and is an extraction of the information about both infrastructural conditions and existing agents in the scene.

The presented application is the realization of concurrent development of sensory system and control for an autonomously driving agent. The optimization works on the parameters of *LongitudinalPlanningCar* agent. At the same time, the behavioral model and the sensors of the *LongitudinalPlanningCar* instance are the objectives of the optimization. Compared to the optimized agent, the sensors of *Car* and its reactive model do not change during the optimization process. The interaction of these two different agent types at the road intersection results into the traffic situations of arbitrary possible complexity.

6.2 Evolutionary co-optimization setup for development of sensor morphology and control

In this chapter the evolutionary optimization setup and the integration of CarD simulation in the embedded optimization platform is described. As already mentioned, the main focus of his thesis is not primarily the generation of optimal sensory system and control for autonomous driving, but rather a research on the potentials of automatic co-evolutionary design methods of complex adaptive systems. The application is concentrated on the investigation of effects of gradual system complexification during the optimization process on the concurrent development of both morphological and controller functional parts of the entire system. Since an autonomous vehicle driving over the road cross-section, regulated by right of way rules, is non-trivial traffic situation, it requires a complex controller capable of correct situation analysis and reliable sensory system. The concurrent evolutionary development of these two subsystems could make the design process more efficient, similar to the former application of adaptive wing. The contribution is that evolutionary methods are able to generate systems which can optimally adapt to environmental conditions while at the same time shedding some light on the precise synchronization of such system parts as morphology and control during the developmental process. As it has been shown on the example of optimization of the previous application, biologically inspired growth process can give the possibility to coordinate the development of morphology and control without its dimensional limitation in the early stages of structural development. In this manner, the systems stay evolvable in many scales during the entire optimization process. The result of the optimization is then simple systems with the sensory and controller systems optimally suited and highly organized.

Optimization starts with the radar sensors with a fixed lateral opening angle of 10° and random initial range, randomly initiated orientation between -180 and 180 degree (positive mathematical meaning) and uniformly neural network weights, uniformly randomly initialized between -0.1 and 0.1. Combined co-evolutionary method described in detail in Chapter 4 and Chapter 5 has been applied to dynamic optimization of the sensory and controller systems of the autonomously driving *LongitudinalPlanningCar* agent. The proposed co-evolutionary growth approach has been realized by the concurrent development and gradual complexification of the sensory and corresponding controller systems. Equally to the optimization strategy for adaptive wing design, standard ES(15,100) developed by Bienert, Rechenberg and Schwefel [89] has been used to optimize the overall system configuration. The characteristics of the sensors, such as radar orientation, its maximum range as well as the controller parameters, in this case, the weights of ANN are coded in one genome explained in detail in Chapter 4. The mutation rates are additional optimization parameters and play an important role in the success of the optimization process. The former application results demonstrated the need of individual mutation rates for a new appearing structural element, like a new sensor, actuator and its corresponding neural connections. The mutation rate decreases during the progress of the optimization of existent morphology. The individual mutation rate of the new elements must be selected to be higher than the mutation rate of the older elements and allows them to develop faster in the further optimization process. The neural connections of the new sensors are initially zero. This ensures the required neutral mutation during the growth process and achieves the maintenance of the previously found beneficial solutions and realization of solutions in many scales.

In the scope of the co-evolutionary growth process, the optimization of the described adaptive structure starts with the configuration of minimal complexity. Ideally, the systems have initially one radar sensor, which automatically results into the low dimensional controller. The output of the controller is the acceleration of the vehicle. The addition of new sensors during the evolution is realized identically to the previous application through probability-based approach, which is a triggering method of system enlargement. The insertion probability is an important meta parameter which should lie in certain boundaries to ensure successful growth and has to be tuned for different applications individually. More precisely it means, that each single individual in a population has a fixed probability to get a new sensor and subsequently a new controller connections during the mutation phase. In the case, the probability is too high, the new elements are introduced before the former system converged. Otherwise, if the probability has been selected too low, it slows down the optimization and increase the computational costs unnecessary, since a higher total number of iterations is needed. Experiments not shown here were conducted and indicated the optimal value of probability $p = 0.1$ for this application.

6.2.1 Evaluation algorithm of adaptive behavior of virtual vehicle

An individual, representing an intelligent autonomous driving vehicle, is evaluated according to its ability to safely pass a given intersection, avoiding collision with other traffic participants through keeping reasonable distance to other vehicles during straight lane drive and turn maneuvers. Additionally, the individual is evaluated according to the covered mileage it achieved in the given period of simulation time.

The fitness of an individual describes the risk of the drive which is in this study proportional to the relative distance of the vehicle to other road users. The risk is high when the relative distance between the fast vehicles is low. The target of the optimization is to find the optimal sensory configuration and the corresponding controller to minimize the risk of the drive.

$$Risk(Individual) = \sum_{n=0}^{N} \frac{1}{\|p^{car} - p^{LPcar}\|} + \frac{s^{max} * c}{s_{ind}} \quad , \tag{6.1}$$

where $\|p^{car} - p^{LPcar}\|$ is euclidean distance between the evaluated and the closest detected vehicle through the radar sensors of $LongitudinalPlanningCar$, s^{max} is maximally possible covered distance during the simulation time, s_{ind} - distance covered by the individual, c - distance constraint coefficient, N - number of simulation time samples ($N = 2000$). The value of distance constraint coefficient c has a strong impact on the driving strategy of final solutions. By increase or decrease

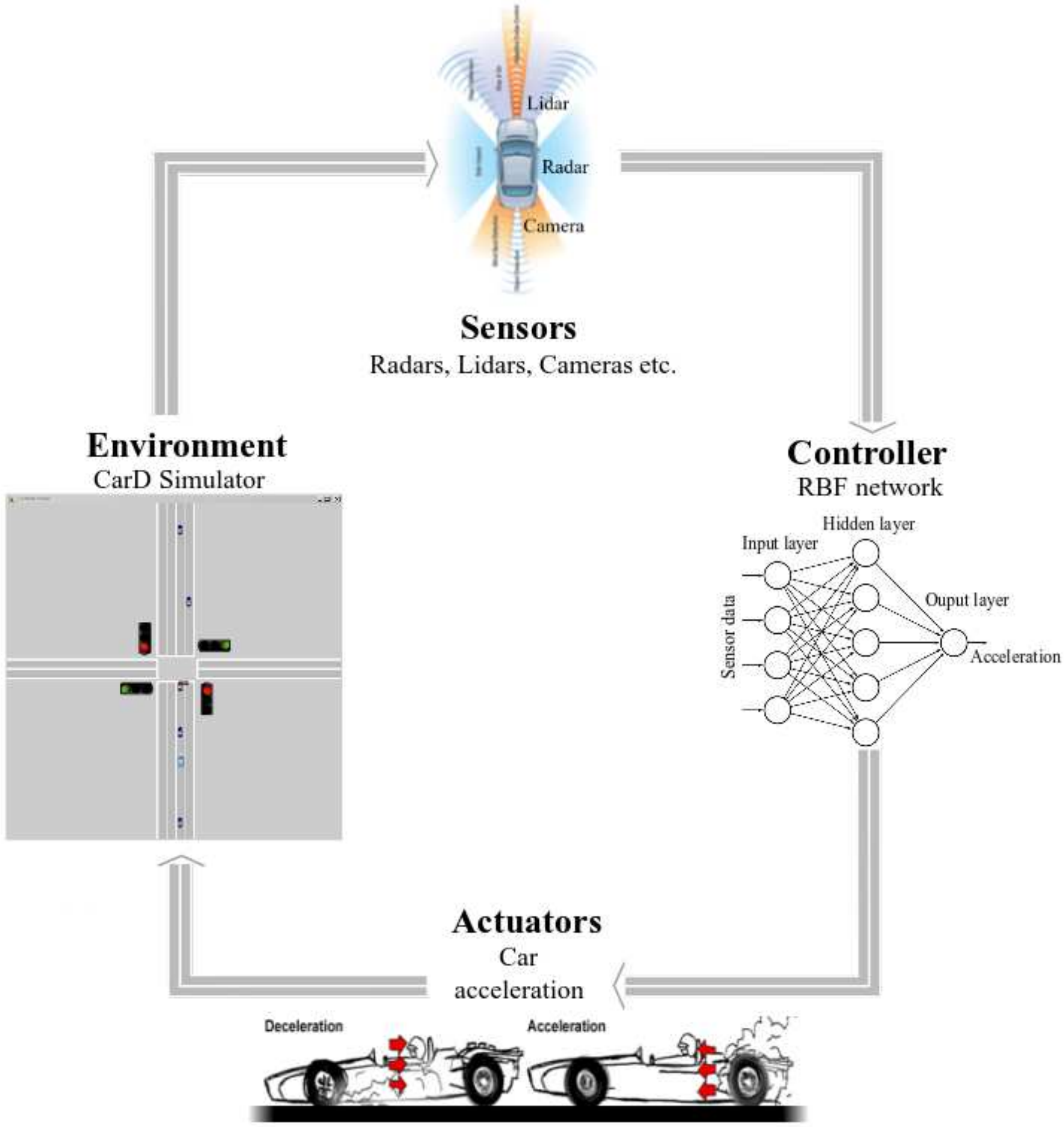

Figure 6.7: Schematic view of the simulation environment

of the influence of the mileage coverage, the evolved behavior of the virtual vehicle can be shifted during the evolutionary process between riskier in a high-speed and rather conservative in a low-speed range. The evaluation algorithm of the CarD simulation is depicted in Fig. 6.7.

6.3 Simulation results

6.3.1 Evolvability of solutions with differently rich sensor systems

The first experiments with ES(15,100) have been the concurrent optimization of sensor orientation in the car structure and the neural network weights. The fitness function is defined according to 6.1. It concentrated on the investigation of the impact of a different number of radar sensors on the optimization progress and the final fitness quality. The number of the sensors in the first phase of experiments was constant during the optimization process and serves as a benchmark for the comparison of the further results of the growth method. Fig. 6.8 and Fig. 6.9 present the result of the optimization of a single sensor orientation and its maximal range and the corresponding neural controller.

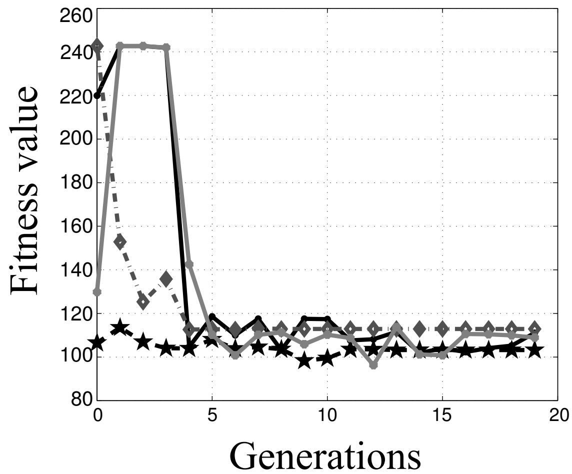

Figure 6.8: Example of optimization runs of the systems having a single radar sensor with different initializations. Optimization parameters: direction and the maximal range of the virtual radar sensor.

The systems converged very fast, in only 5 generations, to completely different solutions as shown in Fig. 6.9. This brings to the assumption, that each of evolved sensors is important to ensure a lower drive risk of the vehicle. This means that the system needs rich sensory set-up distributed in the vehicle structure.

The next series of the experiments has been optimization of the system with differently rich sensory system. The results of the experiments are summarized in

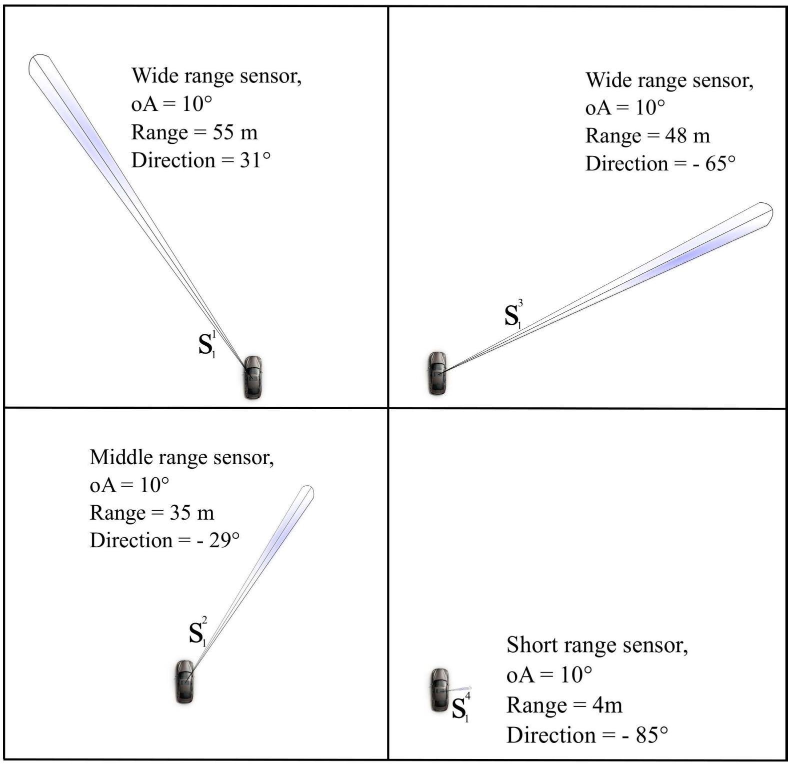

Figure 6.9: Corresponding phenotypical realization of the optimized systems in Fig. 6.8. Direction of 0 degree is ideal frontal driving direction.

Fig.6.10

According to Fig. 6.10 the evolutionary strategy finds good solutions for the given number of sensory elements in the most cases up to 10 radar sensors, which is indicated by the low variance of final solutions. The risk of the drive for the systems having more than one radar could be significantly reduced. The optimization progress of the systems having significantly more than 10 radar sensors looks different. With a larger number of sensors the progress first stagnates and then gets even negative compared to the systems having fewer sensors. Once again a further example of the evolvability problems of the large-scale optimization problems can be demonstrated. The optimization has to deal with a large number of parameters in the complex fitness landscape with multiple local optima, which causes a rapid decrease of the population diversity. As the result, the optimization converged to a local optimum. Similar to the results of the optimization of the adaptive wing in Chapter 6, there exists an optimal feasible number of the optimization parameters and minimal dimensionality of a sensory system required to sufficiently fulfill

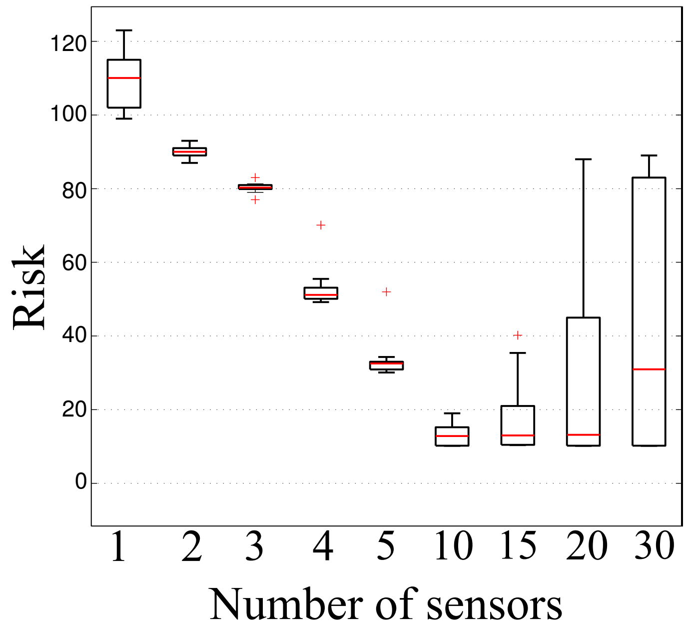

Figure 6.10: Final quality of the sensor-controller optimization runs after 50 generations. 10 optimization runs for each fixed number of radar sensors with different starting parameters.

the given task. The vehicles with 10 radar sensors showed on average the best performance. All the final solutions having 10 sensors on total had a high quality.

The detailed configuration of sensory system and the controller structure of one of the system, having 10 radar sensors as well as the history of the optimization process over the generations is presented in Fig. 6.11 and Fig. 6.12.

Over 50 generations a significant reduction of risk and, therefore, the performance increase can be achieved. 10 radar sensors have been positioned in the car structure by the evolutionary process as shown in Fig.6.11. The obligatory front and back view long range radars necessary for ACC are combined with the side view long, middle and short range radars. Using the optimal sensor set a virtual autonomously driving car could successfully drive over an intersection with significantly lower risk as in the beginning of the optimization with the unoptimized configuration.

The previous application has shown, that Hinton diagrams serve as an appropriate visualization tool for neural networks. Also, for EvoCard application Hinton diagrams has been used [100] to visualize the converted neural connection strengths consistently. The size of the boxes corresponds to the value of the connection strength. The boxes color (green and red) represents the positive or negative sign

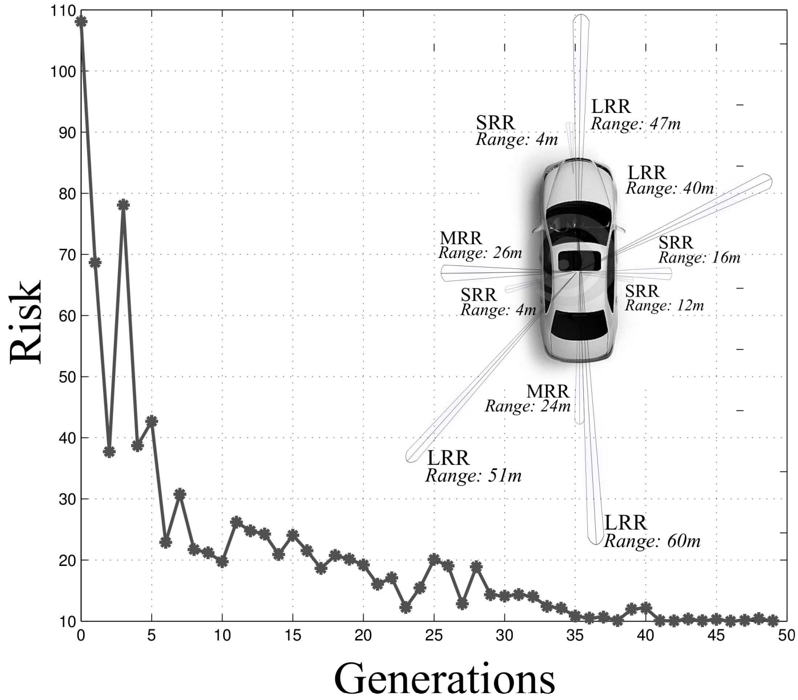

Figure 6.11: Example of optimization run for the optimization of neural controller and 10 sensors of the car, 10 neurons in a single hidden layer

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). To investigate the internal functionality of the neural network as a controller, the converted network connections between sensors and actuators has been visualized, omitting the non-linearity of the hidden layer. The connection strengths between neurons have been calculated according to equation defined in chapter 5:

$$S_{io} = \frac{\sum_{j=1}^{N_h} W_{ij} V_{jo}}{N_h} \tag{6.2}$$

The variable S_{io} is the converted connection strength between input i and output o, N_h is the number of neurons in a hidden layer, W and V - input and output weights of the neural network.

Fig.6.12 demonstrates that some sensors have a stronger influence on the acceleration than the others. The arrangement of the sensors according to its importance for the system is not ordered in the controller structure, since all 10 sensors develop concurrently during the optimization.

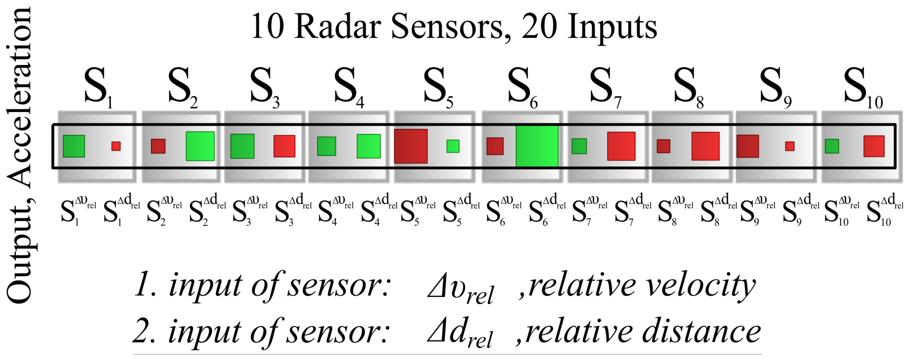

Figure 6.12: Neural controller organization of the system having 10 radar sensors in Fig. 6.11

6.3.2 Simulation results of EvoCarD sensor-controller growth method

The final experiments have been the application of the proposed growth method on the development of the sensory system and controller structure of the virtual autonomously driving car, simulated in CarD. Fig.6.13 demonstrates the result of the growth process. Similar to the results of the system's optimization with fixed morphology, significant risk minimization can be observed. The fitness function progress features big steps in the performance increase which correlate with the enlargement of the sensory system. The example optimization process, depicted in Fig. 6.13, resulted in the system having 18 sensors. In comparison to the optimization of the system having initially high fixed number of sensors during the development, the growth method produces feasible solutions. Particularly the statistics of the results of the growth method shown in Fig. 6.14 illustrates the ability of the proposed system development method to overcome the broadly discussed evolvability problems of high dimensional optimization problems. Although the average quality of the final solution of the system with 10 radar sensors is slightly higher than the average quality of the solutions found by the growth method, the overall performance of the growth method is good. This statement can be supported by the fact, that the results produced by the applied system growth method have a low variance of the solutions. Once the appropriate parameters of growth method have been set, each single growth process produces a solution of sufficient quality, which reduces the computational costs of the search for optimal system dimensionality tremendously. Similar to the results of the growth method of adaptive wing

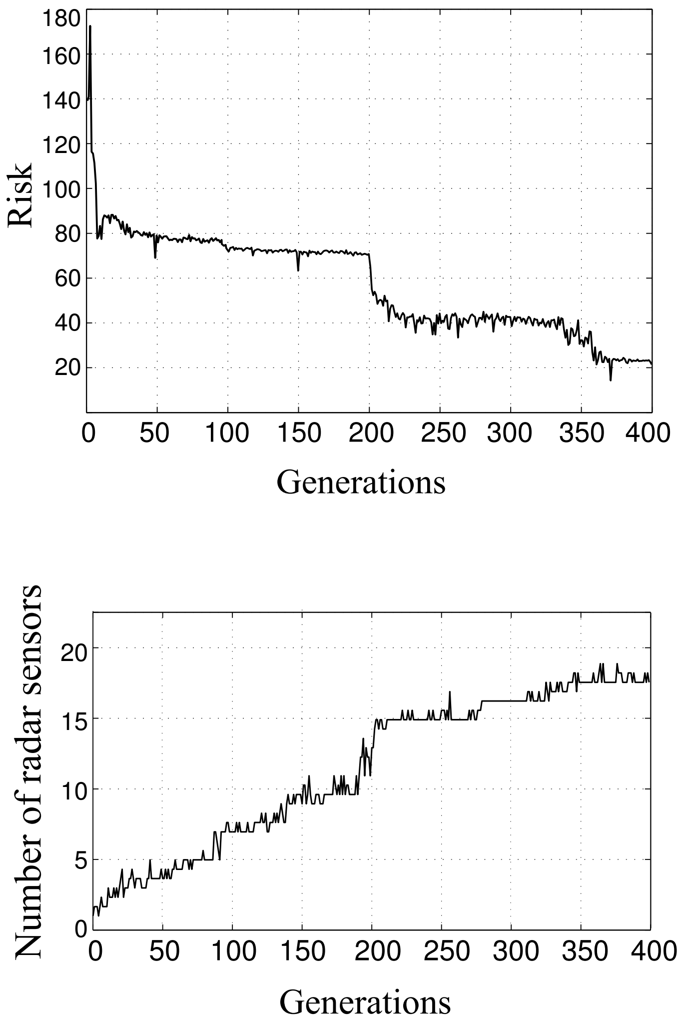

Figure 6.13: Result of sensors-controller growth process of the virtual vehicle. Lower values of risk correspond to higher performance.

controller in Chapter 5, is the organization of the virtual vehicle controller strategy developed by growth totally different compared to the controller optimized for the fixed number of radar sensors. The controller of the system with fixed dimensionality of the sensory inputs is organized in such a way that each sensor has a comparable influence on the control strategy as shown in Fig. 6.15 (a). The organization of the control strategy of the example system developed by the growth method in Fig. 6.15 (b) is completely different. Due to the gradual step-wise system enlargement during the optimization, a clear arrangement of the sensors according to their importance for the system can be observed, where the first sensor s_1 has

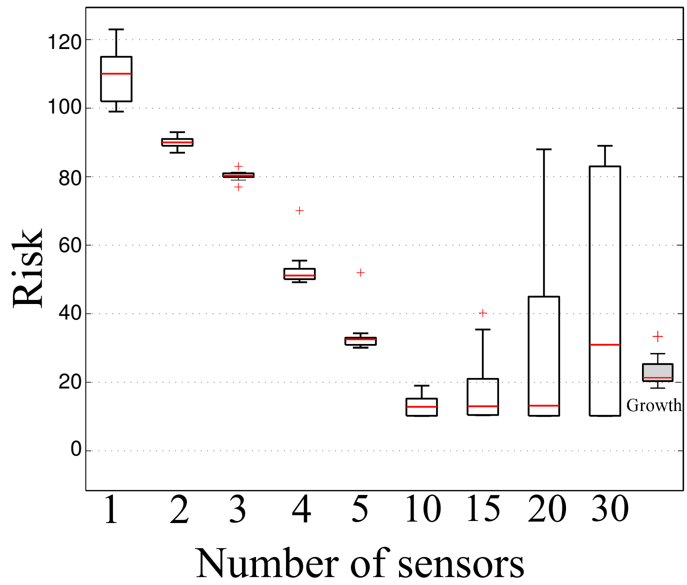

Figure 6.14: Comparison of the final quality of the sensor-controller optimization runs with the quality of the growth method (in gray) averaged over 10 optimization runs.

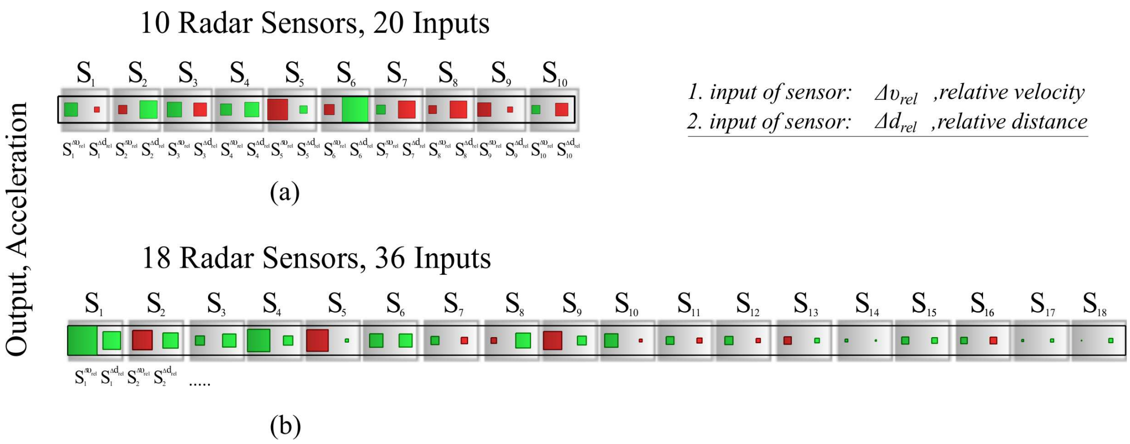

Figure 6.15: (a) Example of the neural controller organization of the system with 10 radar, (b) Example of neural controller organization of the system produced by sensor-controller growth method

the biggest and the last sensor s_{18} the smallest impact on the system performance.

In following short summary of the results of the CarD application is presented. Sensors as well as the control structure of the virtual autonomously driving vehicle are defined during an evolutionary process, resulting in a concurrent and coordinated development of the overall system architecture. The experimental results indicated a strong influence of the number of the environmental sensors, which is related to the amount of information which is available to the control structure, and the final performance of the system. On the one hand, the system needs sufficient sensory information defined by the number and position of the radar sensors for an optimal control strategy in the complex intersection environment. On the other hand, the achieved quality of the optimized solution degenerates with very high numbers of optimization parameters, which are determined by the complexity of the control structure which in turn is defined by the number of sensory inputs. Both aspects can be observed in the experimental results. A small number of sensors results in simple and low-dimensional control structures which converge quickly in the evolutionary process to a local optimum, yet having an overall low quality measured by a high risk of the drive due to insufficient sensory information. In the case of a high-dimensional sensory input of the system low convergence speed toward an optimum can be observed due to the high dimensional optimization problem or even an early convergence to local optima. These results suggest the existence of the optimal number of system parameters for the evolutionary design process. Unfortunately neither the optimal dimensionality of the sensory input nor the optimal number of optimization parameter is known for the problem at hand. The utilization of automatic design through the sensor-controller growth method can improve the design process since it targets the automatic identification of the optimal system configuration during the evolutionary process. Furthermore, the system development through the presented growth method results in a structured system organization, with a strong hierarchical arrangement of the elements of sensor and controller structures. Thereby, the described arranged system organization provides information about the importance of the present sensor elements of the system. Such highly organized systems should be beneficial in terms of traceability and fail-safe characteristics.

7 Conclusion and future work

This work presents a research in the area of developmental approaches applied to adaptive structures. Chapter 2 started with the introduction of the research area, which describes the possible transfer from biology to engineering. This allows the designers to create novel adaptive solutions with high performance and efficiency, due to the fact that the living creatures has been evolved over extremely long time of the evolution and, therefore, suited to the required task. An organism is an embodied system that lives and acts in an environment. It has been an assumption that complex adaptive behavior of the living organism could be the result of the interaction between the control system, the body and the external environment, and is difficult to be analytically described by trying to identify components with rather independent functions. The precise coordination between form and function during the evolution (body-brain co-evolution) produced such creatures, which are capable of impressive adaptivity, although having often relative simple morphology. The intelligence of the behavior of entire organism emerges through the evolutionary optimized interaction between morphology and signal processing structure.

The first application utilized an aerodynamic example and investigates the autonomous generation of an optimal adaptive system with the variable dimensionality of sensing and signal processing structures as the overall system optimization. The adaptive system has been realized by a virtual adaptive wing, which consists of sensors and actuators as well as a related control structure. The virtual adaptive wing reacts autonomously to the changes in its environment and uses the available virtual actuators to minimize the drag of the entire system. The changing environment has been simulated by variating the angle in which the air is approaching the airfoil.

The first experiments with an adaptive airfoil application targeted to demonstrate the applicability of evolutionary computation methods to co-evolve a sensor morphology and a suitable control structure to optimally adjust a virtual adaptive wing structure. In contrast to approaches in which the structure of a sensor configuration is fixed early in the design stages, the target has been the simultaneous generation of information acquisition and information processing based on the optimization of a target function. The following two aspects have been considered as main advantages. Firstly the ability to generate optimal environmental sensors in the sense that the control structure can optimally utilize the information provided and secondly the abdication of detailed prior knowledge about the problem at hand.

The experimental results demonstrated the expected high correlation between the development of the sensory system and the control systems. Furthermore, a strong influence of the number of the environmental sensors has been observed, which is related to the amount of information which is available to the control structure, and the final performance of the system. On the one hand, the system needs sufficient sensory information defined by the number and position of the sensors for an optimal control strategy in the changing environment. On the other hand, the achieved quality of the optimized solution degenerates with very high numbers of optimization parameters, which are determined by the complexity of the control structure which in turn is defined by the number of sensory inputs. Both aspects can be observed in the experimental results.

The second series of experiments focused on the investigations of a simultaneous evolutionary design of sensor and actuator configuration and control structure for the example of an adaptive wing configuration implemented as a structural growth process. The results have been compared with the optimization of the system with fixed morphological settings. The experimental results of the adaptive wing optimization have shown that implemented system growth method synchronizes the design of a sensory, actuation and a signal processing system parts during the optimization process and additionally frees the system of early structural limitations, giving it a possibility to develop autonomously to a system with an optimal number and position of the sensors and actuators as well as the related optimal controller.

Furthermore, the results demonstrate the expected existence of optimal dimensionality of the system and the ability of the presented growth method to detect this optimal morphological and controlling system configuration. The extension of the system growth approach has been the integration of cost factors for the number of sensors and actuators of the adaptive airfoil. Combined with cost factors for a morphological dimensionality, the growth approach was able to produce the morphological configuration of low dimensionality able of fulfilling a given task of drag reduction and maintenance of a required lift. Therefore, an optimization process supports the generation of the preferably low dimensionality of morphological and controller units, which is still sufficient to react optimally in a simulated changing environment.

Additionally, it has been ascertained that the system development through the presented growth method results in a structured system organization, with a strong hierarchical arrangement of the elements of the sensor, actuator and controller structures. Thereby, the described arranged system organization provides information about the importance of the present sensor elements of the system.

It has been established, that the result of the growth process as a global system optimization depends strongly on the correct balance between the mutation rate of the initially existing and a new generated structural elements during the developmental process. New sensor and controller elements get individual strategy parameters, which values are higher than a current mutation rate of longer existent elements.

Motivated by the promising results of the growth method applied on adaptive wing design, one further application in the area of driver assistance systems has been considered. Similar to the application to an adaptive wing in chapter 5, the sensory and actuation systems as well as a central controller, processing the input signals to the outputs, can be easily considered for the autonomously driving car as well. Autonomous driving over the road intersection, regulated by right of way rules, represents non-trivial traffic situations and requires a complex controller capable of correct situation analysis and reliable sensory system.

The results of the sensory morphology-controller optimization of the autonomously driving car illustrate the general applicability of the growth method and the ability of the proposed system development method to overcome the broadly discussed evolvability difficulties of high dimensional optimization problems. The results produced by the applied system growth method have a low variance of the solutions and can give the system developer a reliable clue about the sufficient dimensionality of the sensory system. Once the appropriate parameters of growth method have been set, each single growth process produces a solution of sufficient quality, which reduces the computational costs of the search for optimal system dimensionality tremendously.

7.1 Future work

Promising results of the two presented applications show the high potentials of the proposed developmental approach. Nevertheless, there exists plenty of possible further development directions of the thesis. In following several possible extensions of the presented research are introduced.

The numerous experiments have shown that success of the realized growth process depends among others on the relation between the triggering methods and timing of the system enlargement and on parameter settings of the optimization strategy after a growth phase. The good values of these parameters have been found experimentally. The right ratio of the insertion probability, evolutionary strategy parameters of the new occurring elements and the method of its insertion in the structure represent a meta parameter and is decisive for the success of growth methods. Regardless the assumption, that the mentioned parameter of the developmental approach are strongly application dependent, the theoretical investigation and formulation of general requirements or rules to determine these important parameters would be an important step in the future and could achieve an improvement of the performance of the presented growth method.

One further extension of this work could be the previously mentioned combination of direct and indirect encoding by integration of ontogenetic growth. Combined with, for example, the gene regulatory networks, the evolvability of the growth method could be eventually further increased, since it allows the realization structures on many scales. Furthermore, the impact of the changing environment during the regulation of the system growth on the final solution could be researched more in detail.

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