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2014

Preprint:

This is an accepted article published in GECCO 2014. The final authenticated version is available online at: https://doi.org/[DOI not available]

Growth in co-evolution of sensor system and signal processing for optimal wing control

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ABSTRACT

The development of adaptive systems, which react autonomously to changes in their environment, require the coordinated generation of sensors, providing information about the environment and signal processing structures, which generate suitable reactions to changed conditions. In this work we demonstrate the applicability of a concurrent evolutionary design of the optimal sensory and controller parts of a system for the example of an adaptive wing design. The focus of the work 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. We ascertained that the 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.

Categories and Subject Descriptors

I.2.1 [**ARTIFICIAL INTELLIGENCE**]: Applications and Expert Systems;
I.2.8 [**ARTIFICIAL INTELLIGENCE**]: Problem Solving, Control Methods, and Search—*Heuristics*;
I.2.6 [**ARTIFICIAL INTELLIGENCE**]: Learning—*Parameter learning*;
J.7 [**COMPUTER APPLICATIONS**]: Computers in other systems—*Process control*

General Terms

Algorithms

Keywords

System growth, co-evolution

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1. INTRODUCTION

During the evolution of living beings, the sensory organs as well as the body morphology co-evolve with the brain development to adjust to the changing environment and to achieve competitive advantages. Additionally the evolution process forces the development of the animals organization towards complexification. Regarding these two evolutionary aspects of the biological design of complex living systems, we assume that the design process of technical solutions with high complexity could be improved by starting the system development with an initially simple system organization while performing parallel complexification of its functional parts. In contrast to biological body-brain co-evolution, the majority of the current engineering methods adapt isolated parts of the overall structure. The design of adaptive systems implies the development of sensors as well as actuators, which allow the improvement of systems in reaction to changes in their environment according to a predefined quality measure. The developers usually design the morphological part of the system separate from the controller unit. 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 the number and resolution of camera system of the robot, joints angles range etc., has been carried out by Brooks [3], Dorigo and Schnepf [6], Cliff, Husband and Harvey [5], Floreano and Mondada [8], Miglino, Nafasi, Taylor [12]. However the pre-selection of sensor-actuator configuration without considering the development of a control structure limits the global optimization task to the optimization of a part of the overall structure, in the case of fixed morphological configuration to a control structure optimization. The limits of the controller performance depend, however, on the suitability and the amount of sensor information, as well as on the actuator resources. This raises the problem that in the case the sensor data is insufficient to fulfill the given task, a more complex structure of the control system is needed to compensate the lack of sensor information. The development of the complex controller, however, still does not guarantee global efficiency, when the system does not get the key information about the environment necessary to fulfill a given task. On the other hand, if the system gets too much sensor information or has a large number of actuators, the optimization of the control structure might be not possible. In this case the optimization might get traped in a local optimum and does not reach the global optimum, due to the large number of the optimization parameters. Based on the described problem, an optimal adaptive behavior of in

a given environment seems to be a balance between the complexity of sensor, motor and control systems. The idea of a transfer of a biologically inspired growth process to a design process can give the possibility to coordinate the development of sensor and control structures without dimensional limitation of sensory setup in the early stages of structural development. Since the final system configuration is not pre-defined and is the result of the concurrent optimization process, we get an evolvable system and therefore enlarge the final search domain and potentially increase the chances of global optima detection. The found solution is expected to be globally optimal with maximal performance potential given minimal complexity. Since the growth process presents an optimization task with a regular enlargement of a search space domain, it is important to maintain a benefit solutions gained in a previous optimization step. In this way, the system growth method uses the optimal solution, found in a low dimensional search space, as an advantageous starting point for the search in a higher dimensional search space.
Gomez, Lungarella, Eggenberger, et al. [9] extended the principle of sensor-control balance to developmental enlargement of the system by simultaneously increasing the sensor resolution, the precision of motors, as well as the size of neural structure (controller). They showed with the experiments that a chosen system starting with a low-resolution sensory system, a low precision motor system, and a low complexity of controller, can learn a given task faster than a system with a complex configuration in the beginning. The coordination of the growth process was realized by internal learning mechanism where the active neural units controlling the robot were 'rewarded' or 'punished' depending on the improvement or aggravation in task fulfilling. The authors showed the advantages of concurrent optimization of the sensory and control systems as a dynamic developmental process of gradual complexification.
While the work of Gomez, Lungarella, Eggenberger et al. [9] has been done in a field of evolutionary robotics, we utilize the example of a virtual adaptive wing. 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 fact the manual design is generally challenging. In this work we demonstrate the simultaneous evolutionary design of sensor configuration and control structure for the example of an adaptive wing configuration implemented as a structural growth process and compare the results with the optimization of the system with fixed morphological settings. We also analyze the impacts on the organization of functional structure and the final performance of the optimized outcoming system, depending on the realization of triggering methods for system enlargement. The target for the development of the adaptive wing is the reduction of the drag the airfoil generates while still creating a minimum of lift. Environmental changes are realized by changes in the angle of attack of the airflow across a wide range.
A description of the framework of the adaptive wing with a detailed explanation of the functional set-up of the sensory and controlling systems is given in section 2. In section 3 we present the results of the optimization with fixed morphological settings. In section 4 we explain implemented growth realization, summarize the results of the optimization with a fixed morphological setting and compare them with the results of the growth method. Finally, we conclude the paper with a summary of the main findings of our work.

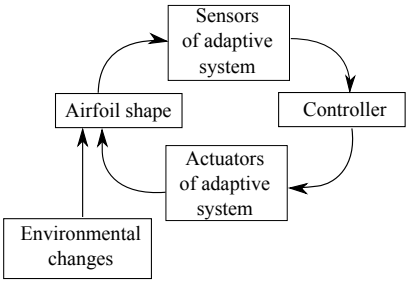


Figure 1: Framework of adaptive system

2. ADAPTIVE VIRTUAL WING SET-UP

In this work the adaptive system was implemented as a system which consists of virtual sensors, actuators and a signal processing unit. The controller of the adaptive system operates under changing environmental conditions by generating signals directed to the actuators, depending on the measured sensor values. The target is to generate a wing shape which has a minimal drag value for the actual environmental conditions. In addition a minimal lift value has to be guaranteed. In order to evaluate the airfoil shape a CFD (computational fluid dynamics) simulation is applied. The actuator signals correspond to changes of the NURBS [7] control points and define the current airfoil shape. The virtual sensors of the system have been defined as pressure sensors positioned 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. 1 gives a schematic overview of the system. The overall system is designed in a way that the position as well as the number of sensors and actuators can be changed freely. Therefore the system is able to adapt the wing shape optimally in reaction to environmental changes. 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.
In our work, we implemented the two dimensional airfoil by a non-uniform rational B-splines (NURBS) as shown in Fig. 2. 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 in 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.
For the simulation of the aerodynamic airfoil characteristics and pressure distribution we used the computational fluid dynamic solver Xfoil[1] because of its high speed which is decisive for optimization tasks Xfoil calculates different aerodynamic characteristics for the given airfoil geometry and environmental configurations, such as angle of attack, Reynolds number etc. In the simulation we change the angle of attack to generate variations of the airfoil environment since it has a major influence on its final aerodynamical characteristics. The Reynolds number has been fixed during the

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

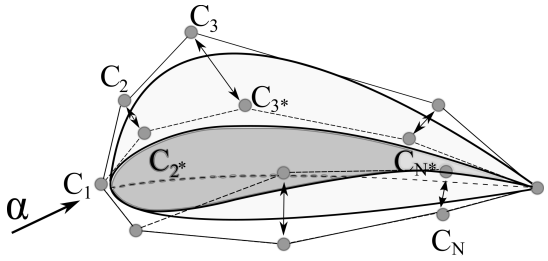


Figure 2: Example of the airfoil created with NURBS. Airfoil in white, defined by the initial positions of the spline control points. The airfoil shape change (in dark gray) results from the movements of control points

optimization($Re = 10^7$). To simulate the sensors we used the distribution of the pressure coefficient over the airfoil surface. The pressure coefficient, C_p is defined as following [1]:

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

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, V_∞ - 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. We used Xfoil to calculate the profile of the pressure coefficients C_p at 160 points on the airfoil surface. A sensor placed on the airfoil returns a sensor value corresponding to the pressure coefficient at the airfoil surface.

2.1 Adaptive wing controller

The task of the neural controller is to generate suitable actuator signals in order to minimize the drag of the airfoil by morphing the airfoil surface. A wide variety of controller designs for that purpose can be found in the literature. Parker and Nathan [14] as well as Bugajska and Schutz [4] implemented a controller as a reactive system which uses "if...then" rules to control a simulated robot. Haller, Ijspeert and Floreano [10] implemented a controller inspired by the central pattern generators underlying locomotion in animals. In our previous work [16] we implemented the controller as 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 a 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. The schematic model of the controller is shown in Fig. 3

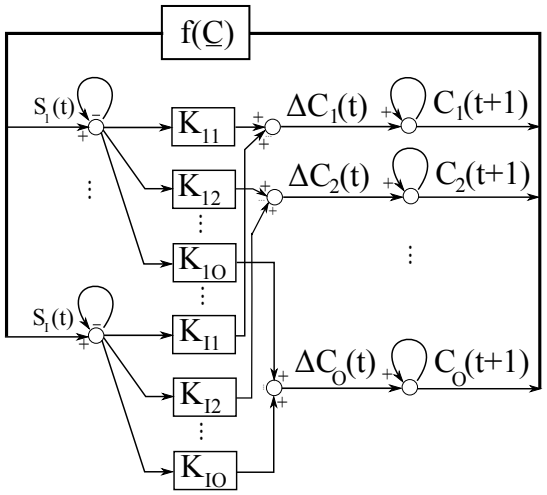


Figure 3: Model of linear recurrent controller

$$\begin{aligned} C_o(t+1) &= C_o(t) + \Delta C_o(t) \\ \Delta C_o(t) &= \sum_{i=1}^{I} (s_i(t) - s_i(t-1)) K_{io} \\ s_i(t) &= f(C_1, \ldots, C_O) \end{aligned} \tag{2}$$

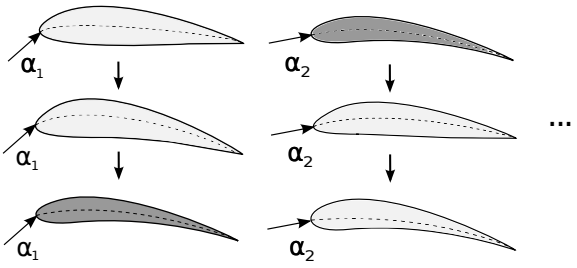


Figure 4: Example of 3 steps of controller actions for the same angle of attack

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 the nonlinear air flow function f, simulated with Xfoil solver. Three cycles of geometry change by the controller actions during the controller operation time for the same angle of attack has been implemented, in order to let the system to converge to a final state. Fig. 4 shows exemplary surface modifications during the adaptation process.

3. SENSOR-CONTROLLER CO-EVOLUTION

In this work the co-evolution process is realized by a concurrent optimization of morphological and controller struc-

tures of the described adaptive wing system. Although these two different functional units of the system are coded in a single genome, the described optimization process reflects the main aspect of co-evolutionary process, since both units are mutually co-adjusted during the entire evolutionary process. In [16] we ascertained a high correlation between the development of the sensory and the control systems. These results support the idea of the concurrent morphological and control systems development. In [16] we additionally demonstrated the existence of the optimal number of implemented pressure sensors. Due to these two main findings of our previous work we came up to the idea to transfer such an element of biological design as a growth process to the presented example of virtual adaptive wing. In work presented here we analyze the development of the system by a growth process. One of the advantages of the growth process, is a minimal requirement on the priori knowledge about the system. The growth process shows fast convergence in small search space, since it starts with an initially elementary system. Thereby we free the system from the early limitations and give it a possibility of coordinated development up to the system of minimal required complexity with maximal efficiency.

3.1 Evaluation algorithm

The system is evaluated according 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^1 and after C_d^2 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 shows the structural diagram of individual evaluation.

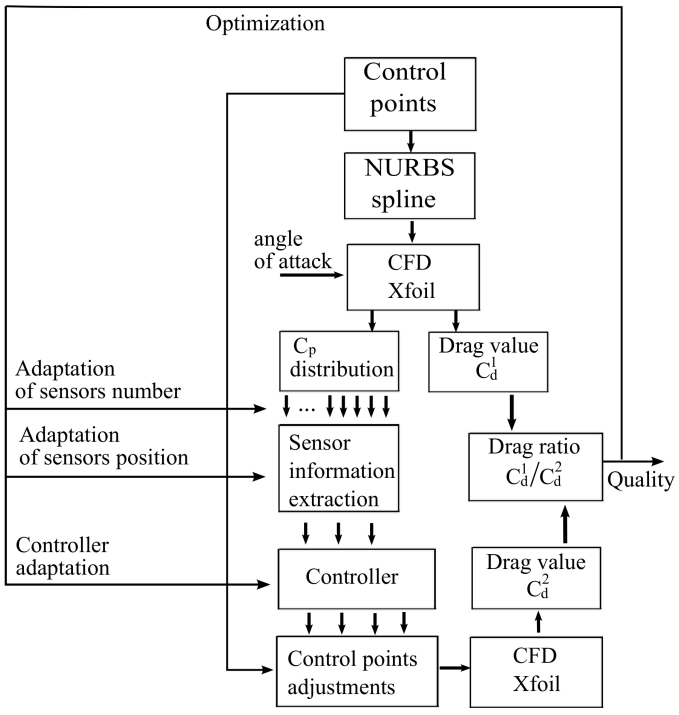


Figure 5: Overview of the system evaluation

The fitness of an individual was defined 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 as shown in Fig. 6.

$$Fitness(Individual) = \frac{\sum_{\alpha=1}^{N} \sum_{i=1}^{M} \frac{C_d(\alpha,\text{changed airfoil})}{C_d(\alpha,\text{unchanged airfoil})}}{N * M}, \quad (3)$$

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 on which the individual has been evaluated, C_d is the drag coefficient.
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 we evaluate each system for 16 different angles, shown in Fig. 6. 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 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

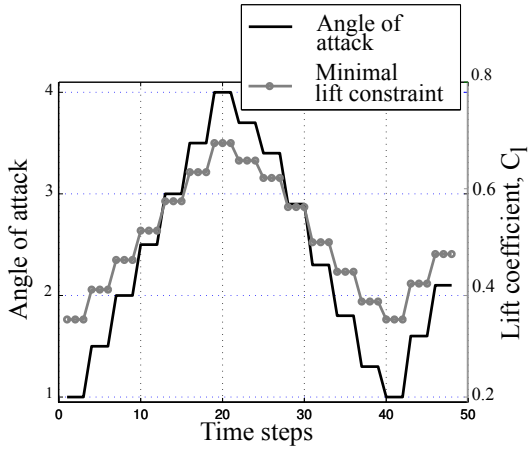


Figure 6: Training scenario of different angles of attack(in black) and lift coefficient of NACA 2410 airfoil (in gray) for the individual evaluation

been set to the lift of a standard NACA 2410 airfoil at corresponding angle of attack. The lift coefficients of the NACA 2410 airfoil are shown in Fig. 6.

3.2 Co-evolution of controller and position of sensors

To verify the functionality of the linear recurrent controller presented in 2.1 we revise the experiments with fixed morphological and controller dimensionality. The concurrent optimization of sensor positions on the airfoil surface and the optimization of controller coefficients, described above, has been implemented with a standard Evolution Strategy (ES), developed by Bienert, Rechenberg and Schwefel [15]. The implemented ES(15,100) uses two different self adapted step sizes, for the sensor positions and the controller connection weights adaptation. Although more sophisticated algorithms are available like CMA-ES [11] we stick to the comparable simple strategy which can be applied as well in the growth process. A single genome of the individual includes three chromosomes which code the position of the sensors, the controller parameters and the strategy parameters (mutation step sizes). Offsprings are the result of a single

point recombination and mutation of the parent individuals with the current mutation step size. The optimization has been implemented, using SHARK[2], open-source C++ machine learning library.

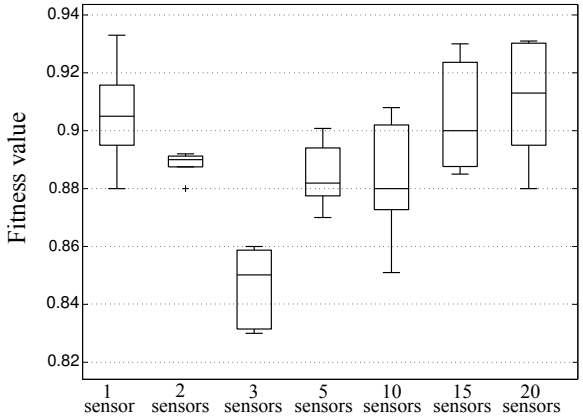


Figure 7: Final quality of the sensor-controller optimization runs after 45 generations. 10 optimization runs for each fixed number of sensors with different starting parameters.

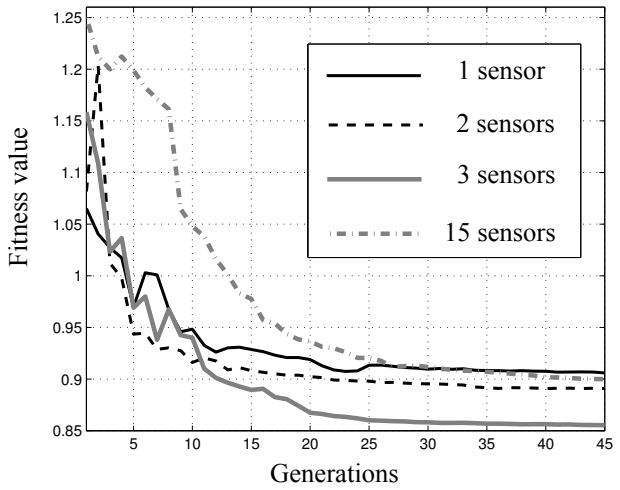


Figure 8: Averaged fitness curves of the results in Fig.7. Fitness curves has been averaged over 10 runs with different starting parameters

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. The trailing edge is defined as rear edge, where the airflow spited by the leading edge rejoins [1]. 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. 7 and 8. 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 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. In this case the optimization is very slow or converges too early and does not reach the global optimum.

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

4. DEVELOPMENT OF OPTIMAL SENSOR-CONTROLLER CONFIGURATION BY GROWTH

In this section we describe the implementation of the system growth method and specify the required conditions of the optimization set-up to find the optimal system configuration. We also compare the organization and functionality of the systems developed through the autonomous growth process with the results in 3.2.

4.1 Definition of growth process

The existence of the optimal system configuration shown in 3.2 motivated us to implement an optimization process that can detect the optimal solution for the system dimensionality during the entire optimization run. We solve this task through the system growth process which implies gradual enlargement of the initially elementary system by addition of the additional sensory and controller elements during concurrent sensor-controller optimization.

There exists a variety of approaches for the topology optimization of the processing structures in the neuro-evolutionary domain. An interesting work has been done among others by Moriarty and Miikulainen [13]. The authors implemented a new symbiotic, adaptive neuro-evolution algorithm (SANE) to optimize the topology of an artificial neural network. Stanley and Miikulainen [17],[18] developed also an approach for neural network topologies optimization named neuro-evolution of augmenting topologies (NEAT).

In this work we implement the topology optimization of the controller, realized by a linear recurrent model, as an optimization of the input dimensionality of the control structure. The input signals of the controller are fully connected with the outputs. The mentioned expected advantage of the growth process versus an optimization with a fixed number of sensory elements, is 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.

By implementing the growth process we found that 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

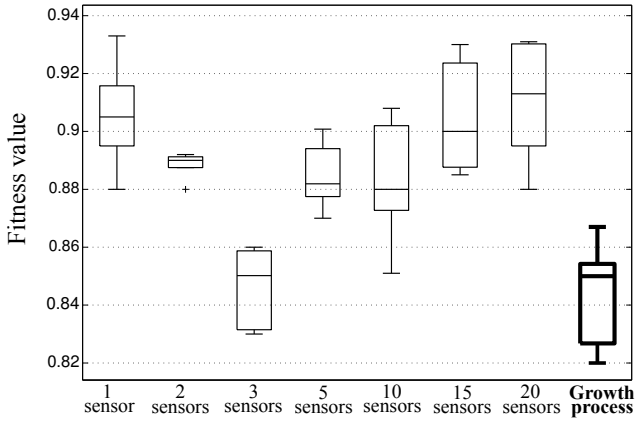


Figure 9: Comparison of the final quality of the sensor-controller optimization runs with the quality of the growth method (in bold) averaged over 10 optimization runs.

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. To ensure a neutral system mutation we initialize the weighting coefficients of a new sensor elements with zero. Additionally a new sensor elements and the corresponding controller connections get individual mutation step sizes. This gives a new elements a possibility to develop individually while keeping the previously optimized system setup intact. We use a probability based triggering method of system enlargement. This means that each individual in a population has a fixed uniformly distributed probability to get a new sensor element. We achieved good results using a probability value of $p = 0.05$, which means that statistically 5 out of 100 individuals in the population get a new sensory input.

4.2 Experimental results of growth process

Fig. 9 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. 10 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 similarly bad performance of the system using 2 sensors.
The result of the growth method have been a system using 10 sensors on average. Since we expected 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 of the systems developed by the growth method gave the explanation on the achieved

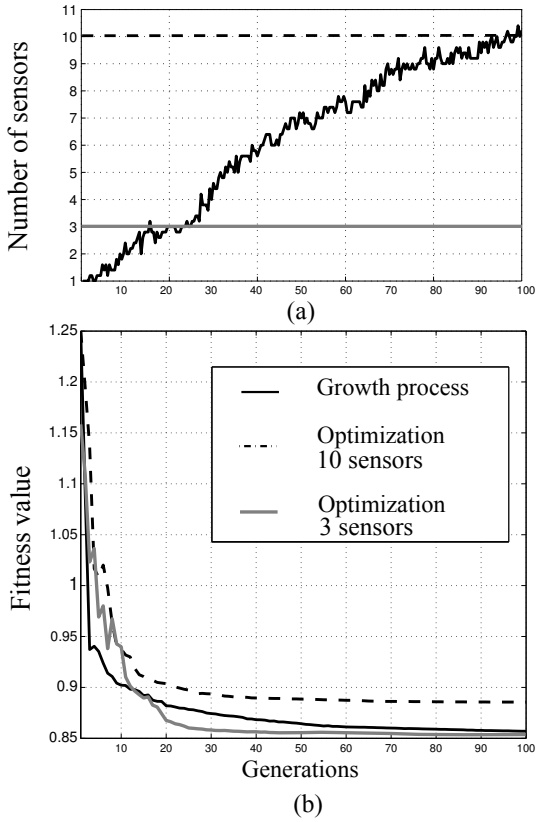


Figure 10: (a) Number of sensors during the optimization averaged over 10 runs with different starting parameters (b) Corresponding averaged quality development.

results. For visualizing of controller connection strengths a Hinton diagrams has been used [2]. The size of the boxes corresponds to the value of the connection strength. The box color (gray and black) represents a positive or negative sign of the connection strength respectively. The values of the connection strengths have been scaled between minimal (no box) and maximal controller connection strength (box of maximum size). Fig. 11 and 12 demonstrate the differences in the functional controller organization and its impact on the system performance. Fig. 12 (a) and (b) compare the corresponding performance progress of two differently developed systems in Fig. 11 (a) and (c) during the optimization. The example system shown in 11 (c) has been optimized for 15 pressure sensors. We 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. 11 (a) is totally different. Due to the gradual step-wise system enlargement during the optimization, we observe a clear arrangement of the sensors according to their importance for the system, where the first sensor s_1 has the biggest and the last sensor s_{16} the smallest impact on the system performance. We also noticed, that the first 3 senors of the system have a major impact on the system, which matches the results of the optimization in 3.2. These results confirm the applicability of the presented growth method for the detection of

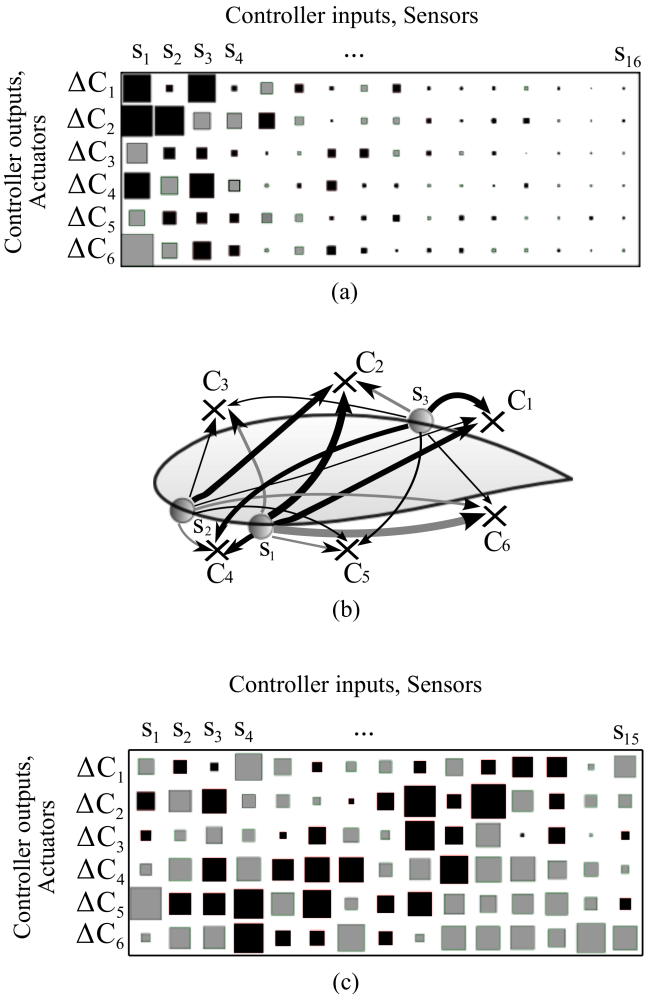


Figure 11: (a) Hinton diagram of the system controller, developed by growth process at 100th generation, (b) Schematic airfoil controller with 3 major controller connections between sensors and actuators of the system in Fig. 11 (a). Thicker lines mean a stronger connection, (c) Hinton diagram of the system controller optimized for 15 sensors at 100th generation

the optimal sensor and the signal processing systems.

4.3 Results validation

To get a baseline for the maximal achievable quality of the airfoils, conventional evolutionary design optimization was carried out. We used a ES(15,100) strategy to determine the optimal shapes of the airfoil for the individual angles of attack represented in Fig. 6 with a lift constraint of the lift coefficient of the NACA 2410 airfoil at corresponding angle of attack. Fig. 13 demonstrates the comparison of the baseline and NACA 2410 airfoils for 16 different angles of attack shown in Fig. 6 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

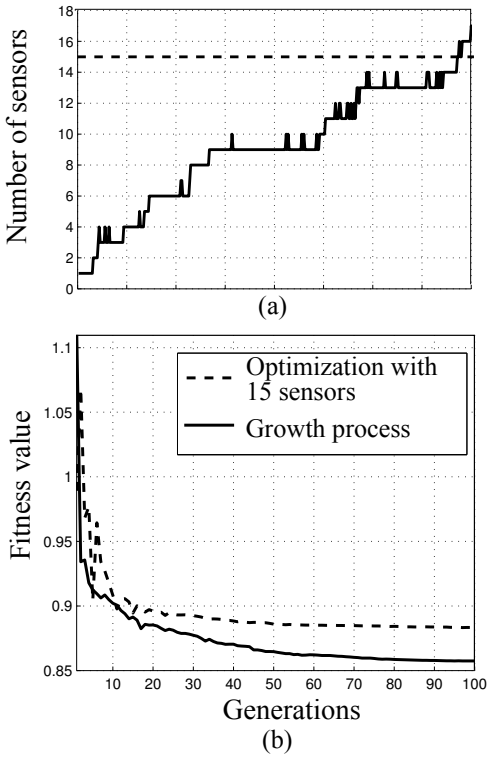


Figure 12: (a) Number of the sensors during the optimization of the systems presented in Fig. 11 (a) and (c), (b) Corresponding quality development.

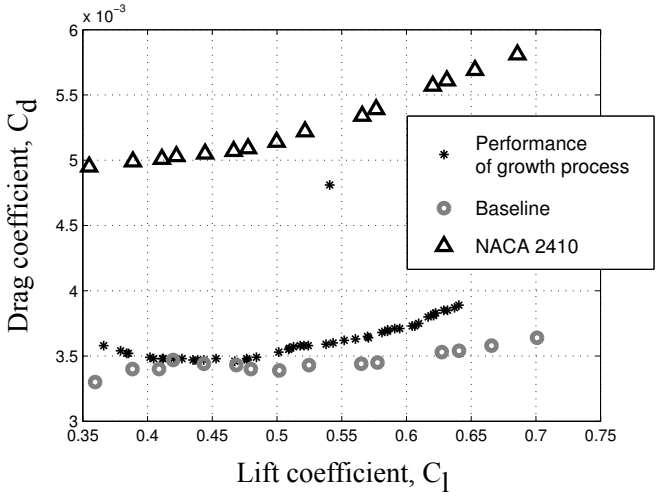


Figure 13: Performance validation: Performance of the baseline airfoils, NACA 2410 standard airfoil and system developed through growth, tested on 100 different angles of attack between 2 and 4 degrees, occurring in random sequence

also gets close to the maximal possible quality of specialized baseline solutions, but performs less good for the marginal angles of attack.

5. CONCLUSIONS

This work investigates the autonomous generation of an optimal adaptive system with variable dimensionality of sensoring 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 presented adaptive wing reacts autonomously to the changes in its environment and uses the available virtual actuators to minimize the drag of the entire system. We simulated the changing environment by variating the angle in which the air is approaching the airfoil. The implemented system growth method synchronizes the design of a sensoring 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 the related optimal controller. The experimental 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. Furthermore we 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 sensor and controller structures. Thereby, the described arranged system organization provides information about the importance of the present sensor elements of the system. We would like to emphasize, 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. This system enlargement construct gives new elements a possibility to develop individually while maintaining the overall system efficiency. Regarding our future work, we would like to include the development of the actuators of the system to the growth process, as well as to investigate a supposed trade-off relation between the number of the sensors and the complexity of the related signal processing structure.

6. ACKNOWLEDGMENTS

The authors gratefully acknowledge the support of Bernhard Sendhoff. Olga Smalikho thanks for the financial support from Honda Research Institute Europe GmbH

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