OPTIMISING CONTROL ALGORITHMS IN BIOFEEDBACK-SYSTEMS

First Steps Towards Model Identification Adaptive Controllers

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Abstract: We explore the potential of model identification adaptive controllers (MIAC) within a biofeedback system. Through the application of an adaptive control algorithm, the system performance could be optimised with respect to time. In a series of experiments the galvanic skin resistance of test subjects playing a computer game was recorded. On this data, a system identification was performed, utilising an Adaptive-Network-based Fuzzy Inference System (ANFIS). The results serve as a basis for the development of the adaption laws of the MIAC and allow conclusions about suitable controllers.

1 INTRODUCTION

Current demographic surveys indicate a shift in the population structure of Germany, where especially the relation between younger and elderly people is affected by decreasing birth-rates and increasing life expectancy. In the year 2060 one third of the population is expected to be over the age of 65 (Plötzsch, 2009). As a direct result of these demographic changes, the share of people living in their familiar environments even in old age will increase accordingly. As aging is a process which has a negative impact on the physical and cognitive capabilities of the human body, activities of daily living are not only becoming more difficult to perform but the risk of accidents, medical emergencies and age-related diseases increase. This poses new challenges for research areas like telemedicine and ambient assisted living (AAL).

In the former, the user's physiological conditions are monitored, with the aim to detect alarming trends, emergency situations or to provide preventive measures. In the latter, the aim is to create environments which support people during their activities of daily living while simultaneously being capable of recognising emergency situations.

In both cases, physiological signals are either mandatory or an additional source of information about the user's current state.

Preventive measures which fight the onset of frequently encountered health conditions in elderly people, like loss of balance, chronic obstructive pulmonary disease, heart failure or dementia, are often implemented in systems which actively incorporate the user through the promotion of physical and mental exercise (Morris, 2006), (Chiari et al., 2009), (Bosch et al., 2009), (Oswald, 2007). One approach to designing these systems is using biofeedback, where the term *biofeedback* describes a loop consisting of capturing physiological data and the feedback of this data to the person.

The captured physiological signals are generally imperceptible to the person on a conscious level, especially their dynamic properties. Hence the signals are pre-processed for the feedback and presented to the person in an easily perceivable manner. Based on the knowledge about the dynamic physiological signals, the person is to apply strategies to purposefully alter his/her physiological state. The most common styles of presentation are auditory and visual signals (Rief and Birbaumer, 2006).

In this paper we present a biofeedback system designed as a game-like computer program which guides the user into a predefined affective state, so that the measured data can be utilised as reference values for later inference processes. Our work is based on (Rachuy et al., 2011) where we proposed a wearable sensor device which is able to measure physiological signals and provide these measurements as input data for successive inference steps about the user's affective state.

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2 BIOFEEDBACK-SYSTEM DESIGN

When designing a biofeedback system, two key factors are of significance: how to represent the captured data and how to map the dynamics of the data to the chosen representation.

The decision on how to represent the physiological measurements is guided by multiple objectives. Foremost, the representation should enable the users to consciously perceive the state of their physiological signals and the changes these physiological states undergo. This can be achieved through a visual representation of the data as a factual line plot or numerical value, but the devised requirement of perceptibility also allows for many more and more abstract diagram styles, up to the representation in a game-like virtual environment (WildDivine, 2010), (SomaticVision, 2009). Further design objectives are to motivate the user to engage with the biofeedback system on a regular basis, despite the repetitiveness of the task. This deserves particular attention if the biofeedback system is used as a preventive measure, since the motivation can not be drawn from the user's desire to get relief from a medical condition.

When representing the data in a game-like environment the proximity to entertainment technology facilitates the motivation of continuous engagement. In these environments a combination of auditory and visual presentation components can be utilised. Parameters for the representation of the physiological states and their dynamics can for example be colour attributes like chrome or hue, sound attributes like tempo or volume or the position and movement of objects. The choices which parameters to use are generally based on implicit expert knowledge about the aesthetics of computer games, formal criteria do hardly exist (Nacke, 2009).

In addition to the choices of how to represent the measured values there is the question of how to map the dynamics of the measured values to changes of the visual and auditory parameters. The most straight forward and intuitive method is a proportional mapping. While this approach will lead to a functional biofeedback system, it is not necessarily the optimal system configuration. The application of time-optimising strategies holds the potential to create a system which will allow for the user to achieve faster progress in the alteration of his/her physiological states.

In purely technical systems, the optimisation of the control strategy is usually done on the basis of a mathematical description of the system. In a biofeedback system, such a description would have to include a mathematical modelling of the physiological reaction of the user. Since this reaction can be subject to the conscious exertion of influence by the user, it is highly complex and an analytical approach for a mathematical modelling is not a feasible strategy. An alternative lies in the application of model identification adaptive controllers (MIAC), schematically depicted in figure 1.

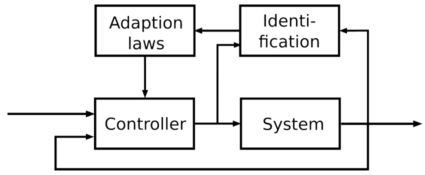

Figure 1: Block diagram of a MIAC.

A MIAC can be implemented with very little a-priori knowledge about the system's behaviour (Isermann, 1987). Contrary to classical control theory, the identification of the system and the optimisation of the controller is not done sequentially, but at the same time. This approach is of advantage if there is uncertainty of the quality of the identification, which can e.g. be due to stochastic disturbances inhibiting the convergence of the identification algorithm. In the case of biofeedback systems, online identification also allows for the incorporation of interpersonal differences between individuals, since the system behaviour does not have to be generalised.

The keyword *adaptive* describes the property of the control system to adapt its behaviour according to the changing properties of the controlled process. With an adaptive controller a system can be run in a stable condition, as long as certain preconditions concerning the identification method and structure of the control algorithm are met.

To test and optimise the performance of the chosen identification model, adaptation laws and control structure, the system has to be operated in a closed loop. In the case of a biofeedback system, this means it is necessary for a test subject to be present throughout the optimisation process. To minimise the testing period, we propose an off-line system identification, to be able to better estimate applicable controller structures and adaption laws.

3 SYSTEM IDENTIFICATION THROUGH ANFIS

The physiological reaction of a person within a biofeedback loop can be described as dynamic and non-linear. Therefore, a suitable identification method should be able to approximate dynamic and non-linear behaviour. Since the system structure and internal states of the system "human" are not clearly definable or measurable, the identification is implemented as a so called "black-box-model" (Schröder, 2010). The identification is done on the basis of experimentally gathered data.

In this paper, we describe the implementation of a Adaptive-Network-based Fuzzy Inference System (ANFIS), which is a hybrid of fuzzy-logic and neural networkc, capable of dealing with ill-defined and uncertain systems (Karray and Silva, 2004).

In an ANFIS, a Sugeno-type fuzzy model is put into the framework of an adaptive neural network, enabling the application of network learning algorithms (Jang et al., 1997). When implemented as a first-order Sugeno model, the algorithm basically approximates the dynamic non-linear output function as a weighted superposition of local linear (time-invariant) models. The weight assigned to each local model is dependant on the value of activating parameters, which make up the input space of the net. Which of the input parameters are to appear in the local linear models is an adjustable design parameter. It is therefore possible to incorporate time-dependency into the activation variables, but avoid it in the linear models. Also, the input space can contain parameters which are not controllable, but involve an information gain for the validity area and period of the linear models. If the identification of the overall system behaviour as a piecewise linear, time-invariant function is successful, the online identification within the MIAC can be implemented as linear time invariant functions. As a consequence, the control algorithm can also be linear, allowing for the application of well defined design and optimisation tools.

4 IMPLEMENTATION

Our biofeedback system was designed as a computer game. The game was purpose-made for the experiments in order to be able to easily control all relevant variables and integrate measured values in real time. It was implemented in Java3D. The game genre was chosen considering the following requirements: (1) For the adaptive control algorithm it is advantageous if the system is influenced as little as possible by disturbance, since the goal of the control algorithm is a good reference transfer behaviour and not noise rejection. Therefore the game should contain little elements which influence the user, but are not actuating variables. (2) The game should be able to influence the user constantly through the same actuating variables. This is facilitated by game mechanisms which provide for the execution of a single task over a longer time period. (3) The user should not have the opportunity to define and pursue meta-goals. If the user strives to fulfil a goal different from the one predefined by the game design, the control efforts will be noneffective or even counter-productive. The game should leave the user little room for manoeuvre, meaning it should be of limited complexity. (4) The game needs to include dynamic elements, whose variation during the game will not interrupt the game flow.

Based on these criteria, the game was designed as a racing game. The user is challenged to steer an avatar, depicted as a large sphere, keeping it within a marked track, see figure 2. The actuating variable to be controlled by the algorithm is the velocity of the avatar. Synchronous to a change in velocity the colour scheme of the game is manipulated. A certain velocity corresponds to a certain colour, improving the perceptibility of the actuating variable. As an incentive to perform well on the assigned task, points are awarded to the player for the position of the avatar. The inclusion of this mechanism facilitates a higher immersion of the subjects into the game (Fairclough, 2009). High immersion ensures that the recorded physiological reaction is caused by the game, not environmental influences.

5 EXPERIMENT SETUP

In a series of experiments we recorded the physiological reaction of test subjects playing the game as input-output tuples for system identification. The physiological parameter examined was the galvanic skin response.

The group of test subjects consisted of 14 people, 8 male and 6 female. The test subjects volunteered for the experiments and did not receive any reimbursement. All subjects had an academic background, the mean age of the group was 27,3 years (Min=20, Max=33, with two subjects refusing to give precise information). Upon invitation, the users were informed about health preconditions for participation. Prior to the experiment and immediately after, the participants were asked to fill out a questionnaire regarding personal information and the subjective game experience.

The users were asked to steer the avatar and try actively to relax during the game. The instructions were given in written form. The game was presented on a 22" LCD-computer monitor, type Samsung SyncMaster 2233RZ: 120Hz, and speakers placed on the left and right of the monitor. The user was seated on a comfortable office chair. The experiments were con-

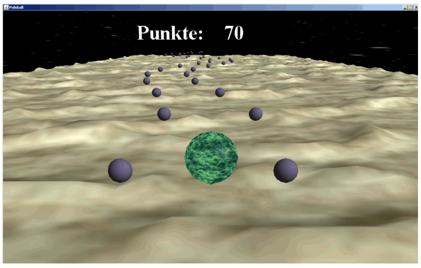

Figure 2: Practise game screen.

ducted in a university laboratory.

The user controlled the movement of the avatar by acceleration sensors, placed on the back of her/his dominant hand. Through the rotation of the hand along the arm axis the avatar was moved horizontally, from left to right. The velocity of the avatar was the actuating variable and could not be influenced by the user. Prior to the experiment, each user had up to two minutes to familiarise him-/herself with the game controls. The game was run in practise mode, with a constant velocity of 0,6 m/s and the design seen in figure 2. After the user felt confident about the controls, but not later than 2 min, the experiment started. The variable training time was implemented to accommodate the varied experience of the users with computer games and control through motion.

6 INPUT PARAMETER SPECIFICATION

Ideally, the experiments should incorporate all possible states of the actuating variable, so that the system model covers the entire input space. Due to the fact that it is a dynamic system, the order of presentation of the actuation states is of significance.

For the first set of experiments, we assumed the model order to be two. For the time-step k, the system output $y(k)$ is dependant on the state of the actuating variable $u(k-1)$, the previous state of the system output $y(k-1)$ and the previous state of the actuating variable $u(k-2)$. The physiological reaction to a stimulus in the galvanic skin response is subject to latency (Stern et al., 2001). This latency d_t has to be taken into account in the model formulation. With these assumptions the local linear models become:

$$y(k) = b_1 u(k-1-d_t) + b_2 u(k-2-d_t) - a_1 y(k-1) + c$$

The variation of the actuating variable *velocity+colour* during the experiments followed a predefined schedule. The limits of the range of values for the actuating variable were determined in preliminary tests. The continuous range of velocity values was discertised into 10 equally distanced values. Out of these values a complete parameter set of 100 combinations was constructed, consisting of two consecutive velocities. The tuples were sorted to form a consistent succession of all possible velocity changes. During the experiment each velocity was held constant for 10 seconds, resulting in a total experiment time of approx. 17 minutes. For each experiment the succession was permuted. The galvanic skin response was measured on the index and ring finger of the subject's dominant hand. Additionally to the physiological reaction, we recorded the exerted acceleration, the position of the avatar, the state of the actuation variable, the absolute game time and the awarded points.

We evaluated this data prior to the system identification to examine which parameters should make up the input space of activating parameters to determine the validity area and period of the linear models. For this evaluation we made use of questionnaires and performed a correlation analysis between the answers given by the test persons and the recorded data. The correlation analysis allowed for the following conclusions: (1) The test subjects were under the impression that their performance in steering the avatar and keeping it on track improved over the duration of the experiment. This is in accordance with the recorded values of the avatar position. Therefore, the absolute game time is likely to posses an information content for the validity period of the local models. (2) The test subjects stated that the position of the avatar (on track or off track) has had an influence on their ability to relax during the game. This supports the hypothesis that the position of the avatar in reference to the track should be part of the system model's input space. (3) The test subjects were influenced by the dynamics of the background music. Initially designed as an element to improve the immersion in the game, the background music was perceived as having "fast" and "slow" passages. Therefore, the relative volume of the background music should be assessed regarding its information content for the validity area. Based on these conclusions, the input space of the system identification model was set as:

$$u_{in} = \begin{bmatrix} y(k-1) \\ u(k-1-d_t) \\ u(k-2-d_t) \\ onTrack(k-1-d_t) \\ music(k-1-d_t) \\ time(k-1-d_t) \end{bmatrix} \quad (1)$$

7 RESULTS

For the training of the ANFIS a training data matrix is constructed. Every row of the matrix contains the input data for the simulation time step k and in the last column the measured system output $y(k+d_t)$ incorporating the latency d_t. After training, the performance of the net is evaluated using a validation data set, which has the same shape as the training data. The quality criterion is the average percentage error with:

$$Err_{ap} = \frac{\sum |y_{measure} - y_{net}|}{\sum |y_{measure}|} \cdot 100$$

In order to obtain a unique solution when optimising the ANFIS through the method of linear least squares, the number of training data tuples P should be at least equal to the number of optimised parameters m_ϕ (Jang et al., 1997). Considering the likeliness of a noise-induced error, it is beneficial to have $P \gg m_\phi$. The number of parameters depends on three variables:

- the shape of the local models
- the number of net inputs u_{in}
- the number of membership functions $MBFn$

The number of membership functions determines the granularity of the discretisation of the input range of each parameter. With the defined shape of the local models and the input (as eq. (1)), the maximum number of MBFs is given by:

$$P \gg 4 \cdot \prod_{i=1}^{6} MBFn(u_i)$$

The first ANFIS was trained with the structure in table 1:

Table 1: Structure ANFIS No.1.

u_{in}	6
$MBFn$	$[3,3,3,2,3,3]$
rule base	full
activating function	generalised bell
number of training tuples	108928
number of validation tuples	8379
tuples/parameter ratio	56

The average percentage error amounts to $Err_{ap} = 16,53\%$, with nine-fold cross validation. The results are summarised in table 2. The change in the galvanic skin resistance after the presentation of a stimulus lies at about 5-50% (Stern et al., 2001). Therefore, it would be desirable to achieve an average percentage error of less than 5,0 % with every net. All but one validation produces error values $\leq 10\%$. The reason for the significantly worse performance of V9 could not be determined. It could be due to a faulty attachment of the sensors or the test subject might a person whose skin conductance does only very weakly respond to the affective state.

Table 2: Validation results.

	ANFIS 1		ANFIS 2
	Err_{ap} $\frac{P}{m_\phi} = 56$	Err_{ap} $\frac{P}{m_\phi} = 47,5$	Err_{ap}
V6	$3,76\%$	$39,4\%$	$1,6\%$
V7	$10,28\%$	$275,4\%$	$1,7\%$
V8	$5,22\%$	$20,9\%$	$1,2\%$
V9	$110,02\%$	$247,2\%$	
V10	$4,75\%$	$21,2\%$	
V11	$2,78\%$	$20,0\%$	
V12	$1,64\%$	$5,0\%$	
V13	$4,86\%$	$22,1\%$	
V14	$5,47\%$	$86,2\%$	
Mean	$16,53\%$	$81,9\%$	$1,5\%$

In figure 3 the best performing and in figure 4 the worst reasonably performing validation is depicted.

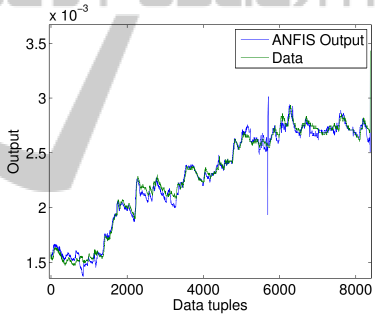

Figure 3: Best performing validation ANFIS 1.

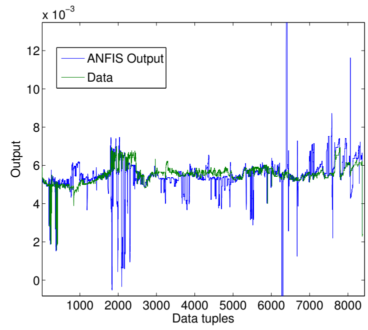

Figure 4: Worst performing validation ANFIS 1.

Taking a closer look at the results of the validation with the worst but reasonable performance, V7, it becomes evident that the net's performance is not uniform. There are some input value combinations for which the approximation error is comparatively larger. This points towards the conclusion that the partitioning of the input space through the chosen number of membership functions is not yet ideal and should be explored further.

To evaluate the influence of the data tuple/parameter ratio, we trained ANFIS 1 with the data of 11 out of the 14 experiments, which equates to a data/parameter ratio of 47,5 (see table 2). The resulting mean average percentage error amounts to $Err_{ap} = 81,9\%$, which is significantly larger than for the first training. Increasing the number of membership functions by one for one input would result in a data/parameter ratio of 41,9. The improvement gained by a higher input space resolution would be negated by the low data/parameter ratio, therefore increasing the number of membership functions was postponed until further data is available.

To further improve the simulation results and to examine the information content of the chosen activation variables, ANFIS 2 was trained. Its structure remained the same as ANFIS 1, except for the input space, where the parameter *time* was omitted.

This modification improved the net performance significantly, leading to an average percentage error of only $Err_{ap} = 1,5\%$ after three-fold cross validation. Evaluating the resulting linear functions revealed however that this is achieved by modelling the output as constant, with the superposition of all linear functions taking approximately the form $y = u_1$.

8 CONCLUSIONS

We designed and implemented a biofeedback system as a game-like computer program to guide the user into a predefined affective state. As a first step towards the development of a model identification adaptive controller which will optimise the biofeedback system with respect to time, we conducted a series of experiments.

Our goal was the approximation of the system as linear time-invariant models, allowing for the application of well defined and efficient optimising tools when designing the control algorithm and the adaption laws. While being able to generate models with average percentage errors below 2%, the examined model structure did not yet reveal a correlation between the skin conductance and the controllable variables of the biofeedback game.

However, since the data/parameter ratio showed to have a high influence on the net's performance, we conclude that for an exhaustive analysis of the influence of the input partitioning, more data is necessary. With the higher granularity of the input space, the generalisation requirement of the linear models is reduced. This could result in more accurate models better suited to depict the correlation between skin conductance and game parameters.

Further research is suggested to determine whether an ANFIS can be trained to approximate the system's behaviour and to find a suitable foundation to construct a MIAC in which the system is identified online as a linear time-invariant model.

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