CONCEPT OF A CO-ADAPTIVE TRAINING ENVIRONMENT FOR HUMAN-MACHINE INTERFACES BASED ON EMG-CONTROL

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Abstract: Learning how to reliably operate HMIs is challenging and time-consuming especially if the underlying control signal is based on biosignals like myoelectric activities. This work describes a concept of a co-adaptive training environment. The human user performs a given task and various features are extracted for performance measurement. Based on single-objective optimization our concept looks for optimal parameters helping the user to improve the performance in the next tasks. Parts of the proposed concept were already implemented.

Keywords: Adaptive learning, HMI, EMG, biosignal control, training paradigms

Introduction

A human-machine interface (HMI) is a system which is controlled by human-generated signals and performs simulated or real actions based on algorithmic interpretation of input signals. Among HMIs controlled by intended biosignals, the dexterity level achieved by the user highly depends on both the nature of the HMI itself and the user's ability to deliberately modify the biosignals.

The reliability of a HMI could be improved by the implementation of adaptation mechanisms which seek to minimize the error between the user's intention and the HMI's action. The user's ability to control the electromyographic (EMG) signals can be enhanced by a training environment (TE) comprising virtual reality (VR) technology and hardware. Those TEs can be designed as adaptive systems to provide ways of efficient training. Finally, the human user self-adapts by forming a mental model as he learns how to operate the HMI [1]. Adaptive HMIs always imply co-adaptive learning of both human and machine [2, 3].

Crucial applications for HMIs are assistive devices. Abundance of work has gone into the development of HMIs based on various kinds of biosignals such as hand prostheses [4, 5, 6]. However, comparatively little work has been done within the field of adaptive TEs and HMIs [7, 8, 9]. The characteristics can be adapted offline or online by a single- or multi-objective optimization. An offline, single-objective adaptive HMI which seeks to minimize the endpoint error in a cursor pointing task was developed in [2]. This work presents the concept of a co-adaptive, closed-loop, offline, single-objective, multi-feature TE based on myoelectric control signals with multimodal feedback.

Co-Adaptive Training Environment

Fig. 1 depicts the flow chart of the proposed concept. Our goal is to enable the user to operate a HMI with high accuracy and high learning speed. The proposed concept seeks to find the optimal parameters offline. Three parameter sets, namely $\mathbf{p}_{HMI}$, $\mathbf{p}_{TE}$ and $\mathbf{p}_{H}$, can be identified representing the whole closed loop system. $\mathbf{p}_{HMI}$ characterizes the HMI, e.g. coefficients of the filters, $\mathbf{p}_{TE}$ stands for the TE, e.g. task related coefficients, and $\mathbf{p}_{H}$ represents the human user, e.g. neurophysiological parameters.
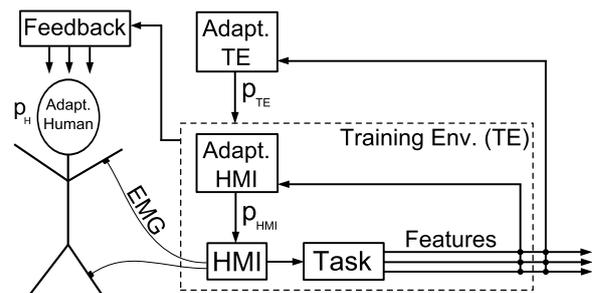

Figure 1: Flow chart of co-adaptive training environment

In order to measure the user's current performance we ask the user to fulfill a task. As [2] concluded, the adaptation only based on one feature is limited and does not lead to better performance. Therefore, we propose a multi-feature approach to measure the performance in a closed loop. The TE extracts the following features:

- task completion time t (offline, shown after the task),
- endpoint error δ_E (offline),
- path error δ_P (online),
- number of collisions with obstacles γ_{coll} (online),
- number of changes in direction γ_{dir} (online),
- number of changes in speed γ_{speed} (online) and
- distance traveled ξ (offline).

The endpoint error denotes the Euclidean distance between the actual and the desired endpoint. The area between the actual and the desired path serves as a measurement for the path error. If the paradigm contains obstacles, γ_{coll} is incremented each time a collision is detected. γ_{dir} is incremented as soon as the movement direction changes significantly, i.e. above angle threshold α. Furthermore, the moment that

the movement speed changes significantly, i.e. above upper acceleration threshold a_{high} or below lower acceleration threshold a_{low}, γ_{speed} is incremented. Lastly, the traveled distance is the length of the actual path.

Based on the above described features the parameter sets $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$ are adapted. The features can be handled by a multi-objective optimization (Pareto) or integrated into a single-objective Q leading to the optimization problem

$$\mathbf{p}_{\text{opt}_{\text{HMI,TE}}} = \underset{\mathbf{p}_{\text{HMI}}, \mathbf{p}_{\text{TE}}}{\arg\max} \, Q(\mathbf{p}_{\text{HMI}}, \mathbf{p}_{\text{TE}}, \mathbf{p}_{\text{H}}), \qquad (1)$$

which can not be solved directly. Yet, candidates for optimal parameter sets $\mathbf{p}_{\text{opt}_{\text{HMI,TE}}}$ can be found by varying $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$ between trials. Q can be seen as the user's weighted performance, which depends on the three parameter sets. Note, that we only can vary the parameter sets $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$. The parameter set $\mathbf{p}_{\text{H}}$ represents the mental model of the HMI in the human's brain [9]. It cannot be affected directly by our adaptation.

Parts of the proposed concept were already implemented in a graphical user interface (GUI) with standard C++ and the Qt-Framework. Fig. 2 depicts a screen shot of the GUI showing the driving task as an example test paradigm. The cursor (top right corner) in that test paradigm is controlled by two independent EMG signals.
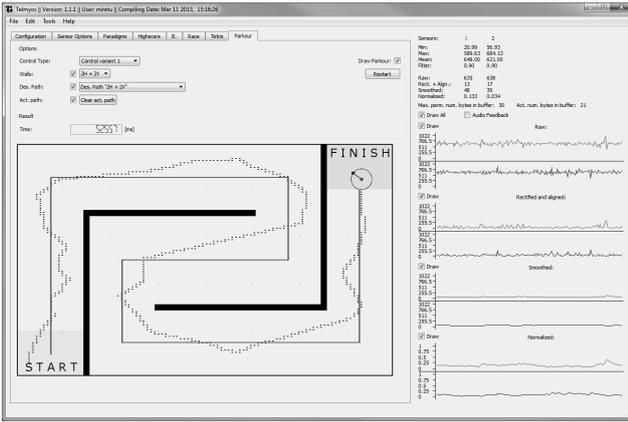

Figure 2: GUI showing a test paradigm

As the meaningfulness of the extracted features highly depends on the given task we weight the features. That leads to the function

$$Q(\mathbf{p}_{\text{HMI}}, \mathbf{p}_{\text{TE}}, \mathbf{p}_{\text{H}}) = \mathbf{w}^T \mathbf{g} \qquad (2)$$
$$\mathbf{g}^T = (t, \delta_{\text{E}}, \delta_{\text{P}}, \gamma_{\text{coll}}, \gamma_{\text{dir}}, \gamma_{\text{speed}}, \xi) \qquad (3)$$
$$\mathbf{w}^T = (w_t, w_{\delta_{\text{E}}}, w_{\delta_{\text{P}}}, w_{\gamma_{\text{coll}}}, w_{\gamma_{\text{dir}}}, w_{\gamma_{\text{speed}}}, w_\xi) \qquad (4)$$

where the predefined vector $\mathbf{w}$ contains the weights associated with the feature vector $\mathbf{g}$. Features which do not convey any meaningful information for that task will be associated with weights close to zero, e.g. path error in a reaching task.

The adaptation routines change the parameter sets $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$ according to Eq. 1. The user is asked to complete the task again with adapted HMI and TE, but the user is not told that the HMI and TE were modified between trials. The features are extracted once more. After some iterations, i.e. after a termination criterion was fulfilled or manual termination was performed, the TE has found optimal parameters sets $\mathbf{p}_{\text{opt}_{\text{HMI,TE}}}$ which enables the user to complete the given task with high accuracy and high learning speed.

Results and Outlook

The proposed concept allows to quantify the performance of humans using an EMG-based HMI to fulfill a given task. Moreover, it is capable to adapt the parameter sets $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$. As the next important steps we plan to identify the most relevant parameters of $\mathbf{p}_{\text{HMI}}$ and $\mathbf{p}_{\text{TE}}$, implement the full concept and evaluate its feasibility in a pilot study with volunteers.

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