ROBUST TRAINING AND CONTROL STRATEGIES FOR THE GRASP TYPE SELECTION OF HAND PROSTHESES

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Abstract: Man/machine interfaces are often designed on patient training data (e.g. electromyographic or electroencephalographic time series) from one session. The design process adapts parameters for signal processing and classification. The automatically adapted classification routine delivers good results on this data set but the man/machine interface might show a lack of classification accuracy (robustness) at following sessions and at activities of daily living. This article discusses the underlying effects and presents a method for robust design. A comparison with a common design delivers conclusions about the accuracy of validation techniques. The new methods are applied to electromyographic patient data for the control of a hand prosthesis.

Keywords: Classification, Medical applications, Robust performance, Signal analysis, Discriminant analysis, Man/machine interfaces, Finite state machines, Implementation

1. INTRODUCTION

Most hand prostheses or virtual keyboards use electromyographic (EMG, myoelectric) or electroencephalographic (EEG) signals as input for their man/machine interface (MMI) (Birbaumer *et al.*, 2000; Hudgins *et al.*, 1993; Reischl *et al.*, 2004*b*). In case of hand prostheses, the MMI interprets myoelectric signals which originate from muscle contractions of the residual limb (Herberts *et al.*, 1978; Nishikawa, 2001; Englehart *et al.*, 2003). As a result, the subject's intended grasp type is executed by the prosthesis. To adapt an MMI individually to a subject, several examples of these input signals have to be gathered within a training session. As the subject possibly does not generate these signals as in daily life, the MMI has to be evaluated in another independent validation session. The design of the MMI can then be done automatically by feature extraction and classification algorithms. Therefore, the authors proposed a new control concept in (Reischl *et al.*, 2004*a*; Reischl *et al.*, 2004*b*). Here, the patient chooses a grasp type by generating distinct muscle contraction patterns called "switch signals". A description is given in Section 2. As the most common grasp types are spherical grasp, cylindrical grasp, pincer grasp, lateral grasp and the use of a single finger at least five different switch signals have to be implemented. To cope with patient differences in anatomy, training, etc. switch signals are individually taught to the system. An algorithm is presented in (Reischl *et al.*, 2004*a*; Reischl *et al.*, 2004*b*). However, as signals generated in training sessions differ from signals generated in daily living, estimated parameters are often not adequate and deliver non-robust classifiers (Reischl *et al.*, 2005). Similar problems exist for all types of man/machine interfaces e.g. virtual keyboards.

Section 3 discusses robustness aspects regarding classification algorithms for MMIs, proposes methods to increase robustness and proves the functionality of the concept with data from a limbed subject controlling a hand prosthesis by EMG signals. Section 4 gives conclusions and gives a glimpse of ongoing work.

2. CONTROL

The proportional control of multiple degrees of freedom (DOF, finger joint angles) with only a few myoelectric signals is a difficult problem. A sequential solution is to choose a grasp type, to combine DOFs for the chosen grasp types and to control the speed of the finger movement afterwards. To decouple grasp type selection and movement control a universal state machine for implementation of MMIs based on biometric signals is introduced (Fig. 1). A state $i, 1 \leq i \leq K$, is activated by a transition $T_{N,i}$. To get back to the neutral state, a universal transition T_N has to be given. Within a state, various actions may be executed by transitions $T_{i,i}$.

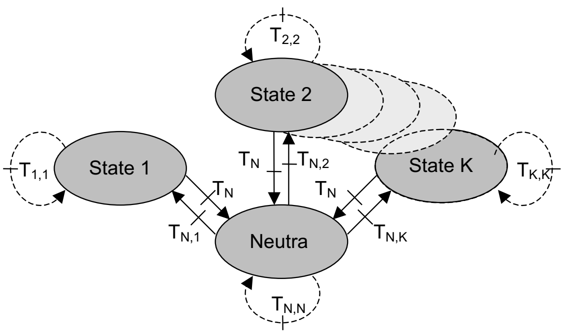

Fig. 1. State machine for the implementation of state-discrete MMIs

Thus, the user either *chooses a grasp type* by a transition $T_{N,i}$ or *operates a chosen grasp type* by a transition $T_{i,i}$. For a hand prosthesis, the states $1, \ldots, K$ of the state machine from Fig. 1 are modified according to Fig. 2. The system works with two myoelectric electrodes with integrated signal processing providing activity signals of muscles (rectification and low-pass filter). In this way, the system can be seen as a multifunctional upgrade of a commercial prosthesis control. As an example, the opening and closing of a chosen grasp type is equivalent to the Otto-Bock system. Transitions $T_{N,i}$ are distinct muscle contraction sequences, transition T_N is a cocontraction of both muscles. Working only with two muscle groups the user is able to switch between a neutral state, a preshape state and movement states.

To choose a grasp type the muscle contraction sequence has to be given either with one or with both

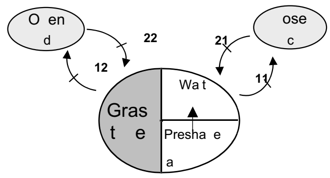

Fig. 2. State i from Fig. 1 for execution of a grasp type. E_{11}: contraction of muscle 1, E_{12}: contraction of muscle 2, E_{21}: relaxation of muscle 1, E_{22}: relaxation of muscle 2

recorded muscles. This sequence is called switch signal and each switch signal is related to a certain grasp type. Switch signals may be designed arbitrary or chosen by the patient, as long as the patient is able to reproduce the corresponding muscle contraction without major variations. A set of generated switch signals has to be recorded in order to teach the system reliably. Possible switch signal patterns are given in (Reischl *et al.*, 2004*a*) [1]. The detection of a known switch signal leads to a preshape state of the prosthesis, which gives a visual feedback of the identified grasp type. The preshape state is a position of finger angles which is optimal to execute the following closing of the grasp type. For example, the preshape of a cylindrical grasp is a hand with a thumb in hinged position.

To operate the chosen grasp type the user generates control signals by activating one muscle group to close the grasp type or the other to open it. The amplitude of the signal determines the movement speed. A cocontraction [2] switches back to the neutral state. A sequence of EMG signals and resulting states is shown in Fig. 3. A switch signal is only given when the grasp type is changed - otherwise only opening and closing commands are given and no time delay exists (Reischl *et al.*, 2004*b*).

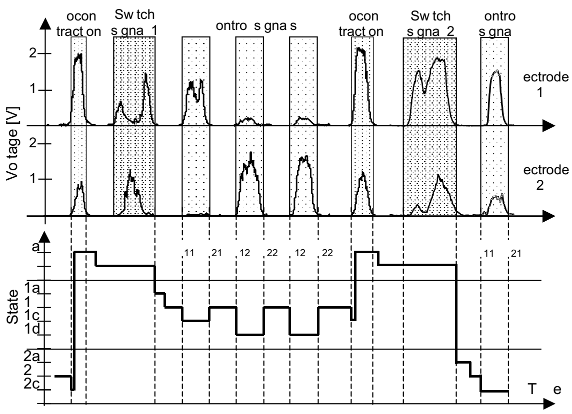

Fig. 3. Typical sequence of EMG signals for prosthesis operation using two rectified and bandpass-filtered electrode signals, see also Fig. 2

[1] Approaches on functional electrical stimulation resemble the presented approach, however the great variety of possible switch signals is not given - often only one switch signal can be reproduced reliably (Saxena *et al.*, 1995).

[2] simultaneous contraction of both muscles: $E_{11} \wedge E_{12}$

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