DEVELOPMENT OF A PATTERN RECOGNITION-BASED MYOELECTRIC TRANSHUMERAL PROSTHESIS WITH MULTIFUNCTIONAL SIMULTANEOUS CONTROL USING A MODEL-DRIVEN APPROACH FOR MECHATRONIC SYSTEMS

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INTRODUCTION

Modern components and materials in combination with recent pattern recognition methods for electromyographic (EMG) signals enable creating multi-functional arm prostheses with intelligent and user-friendly control [1]. While the usage of pattern recognition of features extracted from EMG signals has proven highly efficient in transradial prostheses [2,3], most current transhumeral prostheses utilize the amplitude of EMG signals from residual arm muscles to control open and close the hand. Co-contracting the muscles usually performs a switch to a different mode like flexion and extension of the elbow, which is cumbersome and does not allow simultaneous movements.

In this paper we describe the systematic development process of an active myoelectric transhumeral prosthesis that allows opening, closing and rotating of the hand with simultaneous extension and flexion of the elbow joint.

Numerous requirements concerning the motion- and security functions have to be considered during the system design process. Therefore we utilize the methodology of model-driven design of mechatronic systems and adapt it to the development of prosthetic systems. Mechatronic models describe both the physical- and the control-engineering model in one integrated model and enable us to design and optimize various aspects of a natural motion sequence from the early phases of the design up to the prototype phase. The result is a prosthesis prototype with an embedded Freescale -based controller. For movement recognition we rely on Support Vector Machines to classify surface EMG signals taken from residual humeral muscles. To validate our approach, a set of experiments was conducted by a transhumeral amputee.

MODEL-BASED DESIGN APPROACH OF MECHATRONIC SYSTEMS

The usage of an integrated development framework supporting the development process from the model to the prototype is crucial in modern active prosthesis development. Especially in the field of mechatronic application the integration of prototyping hardware into the design process is of great importance [4]. The usage of prototyping hardware simplifies the transition from the model to a prototype. It is common to subdivide the model-based design process into three phases: the model-, test rig-, and prototype phase.

In the model phase all system components can be designed and optimized using a virtual model before building a prototype. Different variants of components and functions can be tested by means of simulations. This phase allows the designers to develop the mechanical components in parallel with the actuators, sensor system and electronic functions. The phase results in models able to run under hard real time condition in the test rig phase.

During the test rig phase the already built system components are analysed to determine if they fulfil the performance specifications. Model parameters of the components are identified on a test rig and the dynamic behaviour can be adjusted in the model if necessary. The entire system model will be stepwise adjusted by validated component parameters.

In the prototyping phase the entire system will be analysed and tested. The main focus in this phase is on the examination of effects, which cannot be easily determined using the virtual model. These effects are for example abrasion or friction. Results of these phases form a knowledge base for further development.

APPLICATION TO PROSTHESIS DESIGN

Adapting the model-driven design paradigm to the requirements of prosthetic systems enables the developers to design and optimize all aspects of a natural motion sequence from the early phases of the design up to the prototype phase.

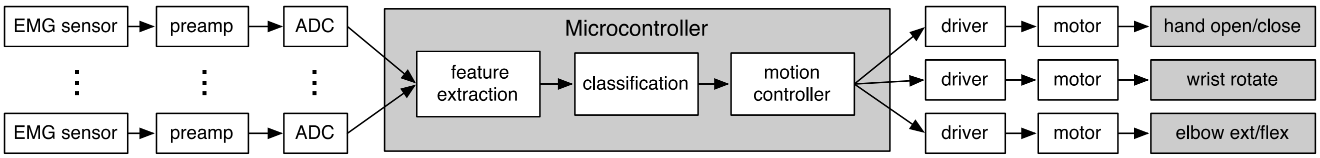

Figure 1: General function. EMG signals are acquired, amplified and digitalized. Feature extraction and classification are implemented on the microcontroller. The motion controller instructs the drivers to perform a movement.

During the development process, mechatronic models are used which combine both the physical- as well as the control engineering models in one integrated model. This model-based approach leads to a considerable reduction of necessary tests. Furthermore, feedback and dynamic system behaviour can be considered in the early design stages.

Modelling of prosthesis in CV (Modelling Phase)

Figure 1 shows the function of the prosthesis in principal. It includes all features of a typical mechatronic system consisting of actuators, sensors, a mechanical structure and information processing. All these components have to be developed in an integrative manner.

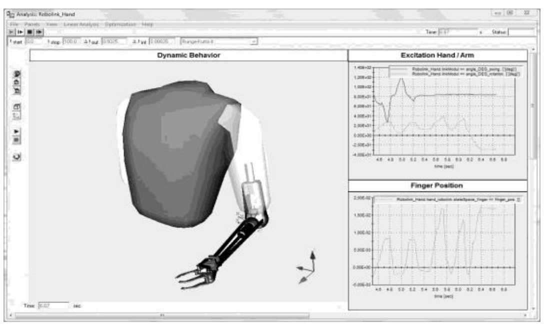

Figure 2: Simulation experiment with 3d animation

The mechanical structure of the prosthesis is modelled as a multi body system, which describes the most important parts of the dynamical behaviour. The information processing unit consists of the feature extraction module, the classifier, and the controller unit for the motion of the prosthesis. Feature extraction and classification are described in the following chapter. Figure 2 shows a simulation experiment of the prosthesis model with time plot and a 3d animation.

Test Rig Phase

The results of the model phase are used as a basis for the construction of the prosthesis. Data of mass, length, forces and torques enable the designer to test the components stepwise on a test rig.

Testing of the controller design that was optimized during the model phase was done with the prototyping system CAMeL-View TestRig [5,6]. With this rapid prototyping system the components of the prosthesis were analysed and set in operation before the prototyping hardware was available. Figure 3 shows a test setup for the controller design. The reference data for the controller can be used from EMG measurement data collected in preceding experiments with test persons.

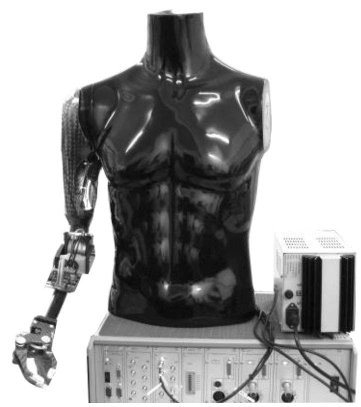

Figure 3: Prosthesis test rig setup

The results of the test rig phase were considered in the model. Identified parameters like bearing friction were compared with model parameters and adjusted accordingly.

Prototype Phase

Fig. 4(c) shows the first prototype of the prosthesis. In the current state of development the system is in an intensive test phase.

(a) (b) (c)

Figure 4: Front (a) and rear (b) view of experimental setup and prosthesis prototype (c)

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EMG DATA ACQUISITION, FEATURE EXTRACTION AND CLASSIFICATION

We developed a feature extraction and classification scheme to simultaneously control hand/wrist and elbow movements. It is used in all three phases of the development process.

EMG data acquisition

For EMG data acquisition, we use a Nexus 16 analog digital converter to monitor eight EMG sensor channels with 24-bit resolution at a sampling rate of 1024 Hz. As electrodes we use standard ARBO Ag/AgCl ECG electrodes.

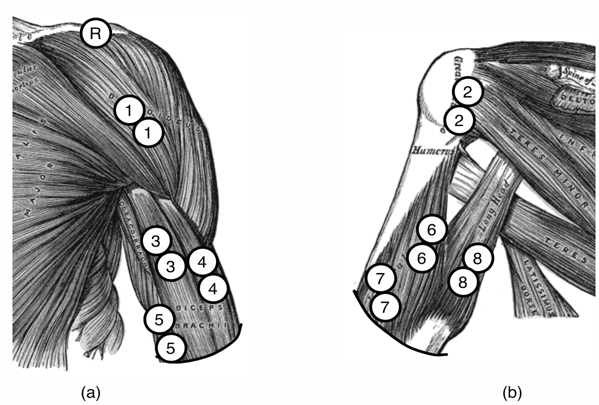

Figure 5: Electrode placing on front (a) and rear (b) arm muscles: 1, 2. M. deltoideus, 3, 4, 5. M. biceps brachii, 6, 7, 8 M. triceps brachii

We have placed the eight electrode pairs on the following arm muscles: M. deltoideus, M. biceps brachii, and M. triceps brachii. Additionally, a reference electrode was placed on the shoulder. The electrode placement scheme is presented in Fig. 5. The exact electrode positions are determined specifically for the test subject to obtain pronounced and reproducible signals.

Feature extraction

Based on the raw EMG signals d_{jkp}, where j denotes the time index, k the channel, and p the movement, we extract features in two steps following the approach presented in [8].

First, the steady state signal starting one second after the beginning of a movement is smoothed by a root mean square (RMS) method with a window size of w_s = 10 samples.

The first 100 ms (102 samples at 1024 Hz) of the rectified and smoothed signal are thus given by:

$$d'_{jkp} = [\frac{1}{w_s} \sum_{i=j}^{j+w_s-1} d^2_{ikp}]^{\frac{1}{2}} \qquad (1)$$

with j = 1...102. Then, a logarithm-transformed moving average with window size of w_f = 20 samples and shift amount of s_f = 10 samples is computed from d'_{jkp}. A feature then comprises 10 values and is defined as:

$$f_{l_m kp} = -log(\frac{1}{w_f} \sum_{j=l_m}^{l_m+w_f-1} d'_{jkp}) \qquad (2)$$

with $l_m = 1+(m-1)*s_f$, and m = 1...10. Two feature vectors are computed: feature vector 1 consisting of features extracted from channels 1 and 2 (20 values), and feature vector 2 consisting of features from channels 3-8 (60 values). This is illustrated in Fig. 6(c).

Movement classification

For EMG signal classification we rely on support vector machines (SVMs) [7]. In our experiments we employ an exhaustive search on SVM's parameters to identify good performing values for C and gamma. An extensive comparison of SVMs to other classifiers for EMG signal classification can be found in [8].

Two classifiers are created during the training phase of the system: SVM 1 from feature vector 1 and SVM 2 from feature vector 2. During the test phase, SVM 1 determines the elbow movement (flexion, extension, relax), while SVM 2 simultaneously decides the hand/wrist movement (hand open/close, pronation, supination, relax). This is illustrated in Fig. 6(d) and (e).

EXPERIMENTAL RESULTS

In this section we report on experiments we have performed to evaluate the system's movement classification performance.

Experiments

In a single experiment run, the test subject had to perform a sequence of six different movements. These movements are hand open and close, pronation and supination of the wrist and extension and flexion of the elbow. In total, 16 experiment runs have been conducted. Each movement starts with a relaxation part of about 4 seconds followed by a contraction part that lasts about 5 seconds, as shown in Fig. 6(a).

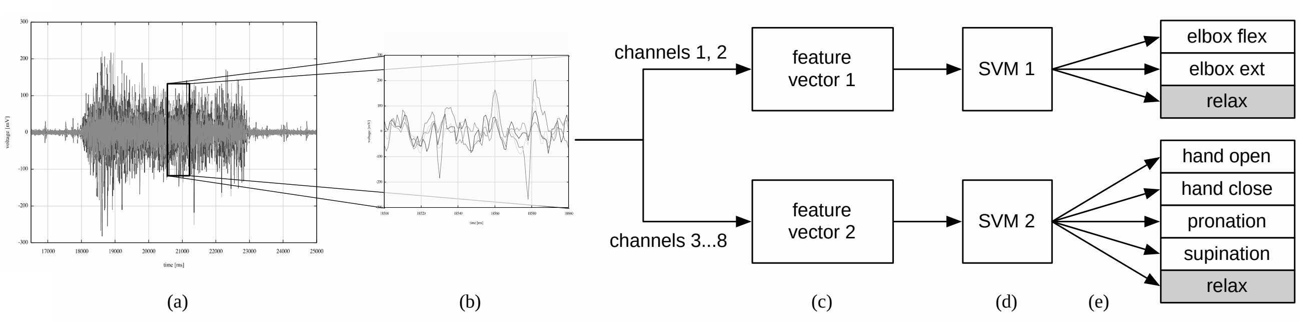

Figure 6: EMG signal processing. Raw signal for all eight channels (a) and 100 ms of the steady state phase (b). Two feature vectors are extracted: one from channels 1 and 2, and one from channels 3-8 (c) and fed into two classifiers (d). Both classifiers determine hand/wrist and elbow movements simultaneously (e).

The EMG signal for the contraction part divides into a one second phase at the onset of the contraction containing the transient components of the EMG signal, and a four seconds steady state phase, which corresponds to a constant force contraction. The steady phase has been used for classification. Features extracted from the 8 odd-numbered trials have been used as training data sets while features from the even-numbered trials were used as training data.

Results

We measure the classification performance of the trained SVM classifier by the classification accuracy, which is defined as:

$$\frac{\text{number of correct classifications}}{\text{total number of classifications}} \times 100\% \qquad (3)$$

The classifiers SVM 1 and SVM 2 were used for offline classification of features extracted from the EMG signals. We used 100 ms feature extraction windows with an overlap of 50 ms, resulting in a new prediction every 50 ms. The classification decisions were used to control the virtual prosthesis and the test rig model. Table 1 shows the classification accuracies of the 6 movements. The average accuracy is 90,85%, further investigations will be made to determine whether this accuracy will be sufficient for a satisfying prosthesis operation.

CONCLUSION

In this paper, we have presented an approach to develop an EMG-based transhumeral prosthesis with multifunctional simultaneous control using a three-phased model-driven scheme for mechatronic systems. As a result, a first prototype of the prosthesis was built that allows opening and closing the hand, rotation of the wrist and simultaneous extension and flexion of the elbow joint.

Table 1: Movement classification accuracy

classifier	SVM 1		SVM 2			
movement	ext	flex	open	close	pron	sup
accuracy (%)	96.1	95.3	88.0	90.7	87.1	87.9

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