# Towards Multi-movement Hand Prostheses: Combining Adaptive Classification with High Precision Sockets

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*Abstract*— **The acceptance of hand prostheses strongly depends on their user-friendliness and functionality. Current prostheses are limited to a few movements and their operation is all but intuitive. The development of practically applicable multi-movement prostheses requires the combination of modern classification methods with novel techniques for manufacturing high precision sockets.**

**In this paper, we introduce an approach for classifying EMG signals taken from forearm muscles using support vector machines. This classifier technique is used in an adaptive operation mode and customized to the amputee, which allows us to recognize eleven different hand movements with high accuracy. Then, we present a novel manufacturing technique for prosthesis sockets enabling a precise amputee-specific fitting and EMG sensor placement.**

## I. Introduction

The acceptance of hand prostheses strongly depends on their user-friendliness and functionality. Prosthesis development thus involves finding the right trade-offs between functionality, weight, power consumption and appearance. Most current prostheses [1],[2] are limited to a few movements and their operation is all but intuitive. Moreover, such prostheses are often rather heavy, lack the sufficient holding force for many tasks and develop too much noise during operation.

Recently, multi-movement prostheses have gained interest. A prominent example is Touch Bionics' iLimb, a true 5-finger hand prosthesis [3] with greatly improved functionality and cosmetic appeal. However, also the iLimb shows limited holding force and generates noise. Additionally, all available prostheses require substantial maintenance effort and are very expensive.

Increasing the degrees of freedom requires more motors and drives and makes the mechanical construction more involved, e.g., absorbing multi-modal vibrations. Technological progress, especially novel materials, allows for more compact and lighter electrical and mechanical components. At the same time, appropriate prosthesis controllers need to be developed that can recognize multiple movements and steer the prosthesis' drives to realize also more complex movements in a natural way.

Electromyographic (EMG) signals are widely-used to steer prostheses. EMG signals are typically taken from the skin, in rare cases directly from muscles which incurs the general risk of surgery and a higher maintenance effort. Recent research programs investigate electrodes that can be injected in the amputation stump [4]. To measure skin-based EMG signals, EMG electrodes are placed on a sensor carrier and fixed within the prosthesis socket. The development of practically applicable multi-movement prostheses requires the combination of modern EMG signal processing methods with novel techniques for manufacturing high precision sockets.

In Section II of this paper, we present an approach for classifying EMG signals taken from forearm muscles using support vector machines. This classifier technique is customized to the amputee and allows us to recognize eleven different hand movements with high accuracy. We compare fixed and adaptive operation modes and demonstrate the need for an adaptive classification. The corresponding experiments are described in Section III. A novel manufacturing method for high-precision sockets is outlined in Section IV. Finally, Section V concludes the paper.

## II. EMG Signal Classification

We have developed a feature extraction and classification scheme for EMG signals and conducted a series of experiments [5]. This section briefly presents the signal processing scheme.

### A. Sensor System and Feature Extraction

For EMG data acquisition, we use a MindMedia Nexus 10 Biofeedback System [6] to continuously monitor four EMG sensor channels with 24 bit resolution at a sampling rate of 2048 Hz. We have placed the four electrode pairs on the top, bottom, medial, and lateral sides of the forearm with the reference at the wrist. The exact electrode positions are determined specifically for the test subject to obtain pronounced signals. A reproducible biomechanical experiment setup is an important requirement for such a measurement system. Thus, after the initial calibration we have marked the electrode positions to be able to re-establish the experimental setup on different days.

In a single experiment run, the test subject had to perform a sequence of eleven different movements. These movements are extension, flexion, ulnar deviation, radial deviation, pronation, supination, open, close, key grip, pincer grip and extract the index finger, and are depicted in Figure 1. In total, 110 experiments have been conducted during different

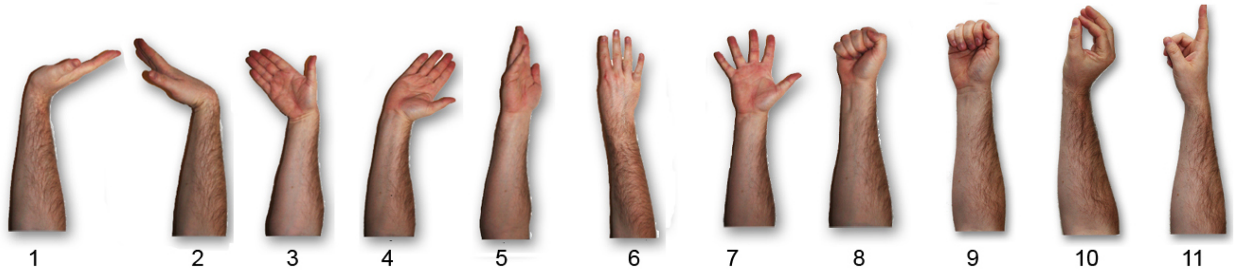


Fig. 1. Motion classes: 1) extension 2) flexion 3) ulnar deviation 4) radial deviation 5) pronation 6) supination 7) open 8) close 9) key grip 10) pincer grip and 11) extract index finger.

times of a day, over a period of three weeks. Each movement starts with a relaxation part of about 4 seconds followed by a contraction part that lasts about 5 seconds, as shown in Figure 2(a). 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.

Signal processing and feature extraction is done completely in the digital domain. Based on the raw EMG signals $d_{jkp}$, where $j$ denotes the time index, $k$ the channel ($k = 1 \ldots 4$), and $p$ the movement ($p = 1 \ldots 11$), we extract features in two steps following the approach presented in [7]:

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 $w_s = 21$ samples, shown in Figure 2(c). The first 100 ms (208 samples at 2048 Hz) of the rectified and smoothed signal are thus given by

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

with $j = 1 \ldots 208$.

Second, a logarithm-transformed moving average with window size of $w_f$ = 40 samples (20 ms) and shift amount of $s_f$ = 21 samples (10 ms) is computed from $d'_{jkp}$. A feature then comprises 10 values and is defined as

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

with $l_m = 1 + (m-1) \cdot s_f$, and $m = 1 \ldots 10$. Taking all four channels into account, the feature vector for a single movement consists of 40 values which are fed into the classifier. These 40 values are depicted in Figure 2(d). The feature vectors for all 11 movements together form one data set.

### B. Classification

For classification we rely on support vector machines (SVMs) [8] as they are state-of-the-art methods with robust behavior for a large variety of classification problems. SVMs basically use a hyperplane to separate two classes. For problems that can not be linearly separated in the input space, SVMs find a solution using a nonlinear transformation of the original input space into a higher-dimensional so-called feature space, where an optimally separating hyperplane can be determined. Those hyperplanes are called optimal that have a maximal margin, where margin means the minimal distance from the separating hyperplane to the closest data points, which are denoted as support vectors. The transformation is usually realized by nonlinear kernel functions, e.g., Gaussian kernels. nu-SVMs, which we have used in our experiments, introduce slack variables - being subject to minimization as well - to allow a certain degree of missclassification. The key advantage of SVMs is the principle of structural risk minimization which typically yields very good generalization performance compared to other classifier paradigms. An extensive comparison of SVMs to other classifiers for EMG signal classification can be found in [7].

## III. Experimental Results

In this section, we report on experiments we have performed to answer two specific questions: First, what is the recognition accuracy we can achieve with EMG signal-based classification in dependency of the number of movements to recognize? Second, to what extent does the recognition accuracy drop over time for an initially trained classifier?

To evaluate our EMG signal classification approach, we have determined the recognition accuracies using leave-one-out cross-validation on the complete data. That is, we have used all but one data set to train a classifier and then tested it on this data set. This process is repeated for all data sets.

As shown in Table I, the resulting accuracy averaged over all 11 movements is 91.3%. However, in most practical cases less than 11 movements will be required. Generally, discriminating between a smaller number of movements should yield better accuracies. For validation we have gradually reduced the number of movements by discarding the movement with the worst recognition accuracy. The resulting accuracies for 11 down to only two movements are summarized in Table I. A classification accuracy of 100% is reached for four and less movements. In practice, the prosthesis will dictate the set of movements to be classified.

In order to analyze the longer-term behavior of EMG signal classification, we have conducted another series of experiments where we look at the data sets over time. To this end, we have extracted feature vectors from the EMG signal's steady state every 10 ms, classified them, and taken a majority vote over 15 consecutive classifications. In this way we receive one final classification every 150 ms and

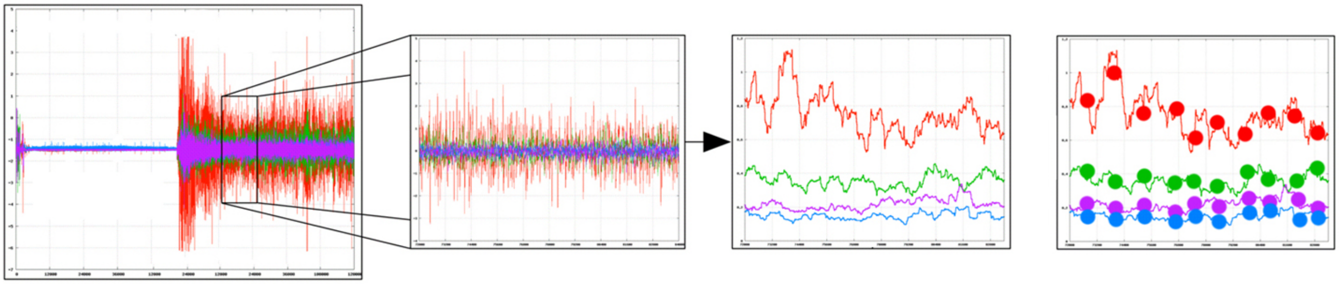


Fig. 2. EMG signal preprocessing. Raw signal for all four channels (a) consisting of a four seconds relaxation phase, a one second transient phase with intensified activity, and a four 4 seconds steady state contraction phase. (b) presents 100 ms of the steady state phase, and (c) the RMS smoothed signals from which the features are extracted (d).

suppress sporadic, short-period missclassifications. Figure 3 compares the classification accuracies of five classifiers. Four of them use a fixed model where the classifiers have been trained once with the first 5, 10, 20 and 30 data sets.

Our experiments reveal that while using more training data results in an improved recognition accuracy, about 30 data sets are sufficient to create a fixed model classifier with maximal accuracy. As Figure 3 also clearly shows, the recognition accuracies for the fixed model classifiers degrade over time. The accuracies follow roughly three distinct phases. In the first phase which took four days (20 data sets), the accuracies dropped by some 10%. The second phase of about six days (30 data sets) shows rather stable accuracies. In the third phase, which is more than 10 days after training the classifiers, the accuracies start to drop again. Generally, the accuracies vary over time and show outliers also due to the actual concentration of the test subject and effects of familiarization with the data acquisition procedure.

In comparison to the fixed model classifiers, Figure 3 shows the accuracy achieved for an adaptive model classifier that is continuously re-trained with up to 30 preceding data sets. The adaptive model leads to significantly better results, demonstrating that re-training the classifier is key to successfully discriminating between multiple movements.

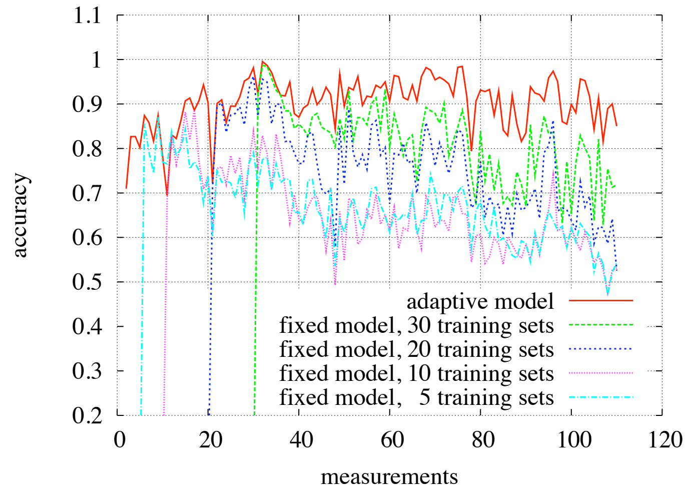


Fig. 3. Recognition accuracies for fixed and adaptive model classifiers.

## IV. High-precision Prostheses Sockets

To enable multi-movement prosthesis control based on EMG signals, a high-precision socket is required including a sensor carrier that places the sensor electrodes exactly at their optimal positions. Apparently, such as socket must be highly amputee-specific. We present a novel technique for manufacturing such a sensor carrier and a high-precision socket rather quickly and at a reasonable cost.

| number of movements | 11 | 10 | 9 | 8 |
|---|---|---|---|---|
| accuracy [%] | 91.3 | 94.5 | 96.1 | 97.5 |

| number of movements | 7 | 6 | 5 | 4-2 |
|---|---|---|---|---|
| accuracy [%] | 98.1 | 98.6 | 99.7 | 100.0 |

TABLE I

Gradually discarding movements with the worst recognition accuracy improves the over-all recognition rate. Discarded movements (from 11 to 4): radial deviation, pincer grip, open, supination, pronation, key grip, index finger.

In an initial session, a technician and a physiotherapist work with the amputee and conduct a palpation of the musculature, determine the elbow function - if applicable - and rate the activities of the different muscles by assigning scores. The subsequent socket and sensor carrier manufacturing technique comprises following steps:

1) The optimal sensor positions are determined through a series of EMG signal measurements and movement classifications using the techniques described in Section II. The sensor positions are marked on the amputation stump. An example for an amputation stump with EMG sensor electrodes is shown in Figure 4.
2) The arm with the amputation stump is scanned and a three-dimensional volume model is generated. Figure 5 shows such a model, augmented with a model of a prosthesis part. A two-dimensional projection of the 3D model, i.e., the surface, is then printed on a transparent and highly-flexible carrier foil. The foil is properly cut, curved in and fixed to form a socket dummy.

Fig. 4. Optimal sensor positions are determined through EMG signal measurements.

Fig. 5. 3D model of the stump.

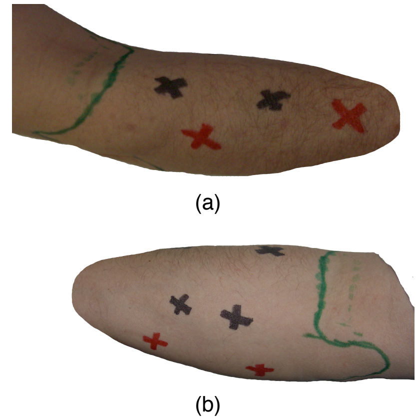

Fig. 6. Determining muscular movement areas, affected by elbow mobility. Lateral (a) and medial (b) view.

3) The socket dummy is placed on the amputation stump and the areas required for the muscular movements are marked, considering the elbow mobility. An example is shown in Figure 6.
4) The marked socket dummy is placed on a slightly compressed plaster copy of the amputation stump, and the muscular activity areas are transferred from the dummy to the plaster copy. To allow for a certain extent of free space for muscle movements in the final socket, the muscular activity areas are modulated with plaster according to the characteristics of the specific muscles.
5) A PU silicon sensor carrier with a thickness of approximately 2.5 mm is manufactured from the modulated plaster copy of the stump. Completed with EMG sensors, the sensor carrier is tested on the amputee through another series of EMG signal classifications. To ensure an optimal and permanent location of the carrier on the stump, a vacuum valve is incorporated into the silicon. Together with the carbon socket, this produces slight negative pressure and holds the sensor carrier locked.
6) The final socket is manufactured through a carbon deep-drawing process based on the modulated stump copy and the sensor carrier.

## V. Conclusion

In this paper, we have presented an EMG signal feature extraction and classification approach and demonstrated experimentally that we are able to recognize up to 11 hand movements with acceptably high accuracy. Equally important, we have seen that an adaptive classification technique is required to sustain the high recognition accuracies over time. We have further outlined a novel manufacturing technique for high-precision sockets and the corresponding sensor carriers. Future work includes the optimization of the feature extraction and classification scheme as well as the manufacturing technique, and extensive tests in orthopedic use.

We are convinced that the combination of both the EMG signal classification scheme and the high-precision sockets will enable a new breed of hand prostheses. Consequently, we are additionally working on improved motors, drives and mechanical constructions with the goal to minimize a prosthesis' weight and noise and improve its holding force up to 25 kg. Augmented with a control based on the presented EMG signal classification technique and the highly precise sockets, these developments will result in prostheses with improved wearing comfort and versatile grasping functions, at a reasonable price.

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