International Journal of Bioelectromagnetism
Vol. 14, No. 4, pp. 185 - 189, 2012
www.ijbem.org

Hand Prostheses Control by Using natural Electromyographic Pattern Obtained in Grasping Tasks

KH Somerlik-Fuchs[abcd], TB Krueger [d], J Carpaneto [e], T Stieglitz [bc], S Micera [ef]

[a] *Neurocentre University Clinics of the Albert-Ludwigs-University Freiburg, Freiburg, Germany*
[b] *Laboratory for Biomedical Microtechnology, Department of Microsystems, Albert-Ludwigs-University Freiburg, Freiburg, Germany*
[c] *Bernstein Center Freiburg, Albert-Ludwigs-University Freiburg, Freiburg, Germany*
[d] *inomed Medizintechnik GmbH, Emmendingen, Germany*
[e] *Neural Engineering Area, The BioRobotics Institute, Scuola Superiore Sant'Anna Pisa, Pisa, Italy*
[f] *Translational Neural Engineering Laboratory, Center for Neuroprosthetics & School of Engineering, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland*

Correspondence: KH Somerlik-Fuchs, Neurocentre, University Clinics Freiburg, Breisacherstr. 64, 79106 Freiburg, Germany.
E-mail: karin.somerlik@uniklinik-freiburg.de, phone +49 761 270 52400, fax +49 761 270 50030

Abstract. In order to restore lost hand functions in amputees, voluntarily controllable hand prostheses are being developed. Control based on recording and analyzing electromyographic (EMG) signals is a common approach due to non-invasive methods and typically good signal quality. However, extracting the desired information in an effective and natural way is difficult. After amputation the 'homologous' muscles that controlled finger movements may no longer be available in their original state. This causes the need to use either specially trained control movements that require willful interaction of the user or more invasive methods using signals from the central nervous system, peripheral nerves or target reinnervated muscles together with complex pattern recognition algorithms. Therefore acceptance of functional hand prostheses is low. This pilot study with four able-bodied subjects reveals that prediction of the intended grip type is possible by analyzing the activation pattern of upper arm and shoulder muscles during the 'natural' reaching phase. Classification is performed with a support vector machine (SVM) algorithm resulting in a high robustness.

Keywords: hand prostheses; physiologic grasping; support vector machine; surface electromyography; upper limb prostheses

1. Introduction

Developing human-machine interfaces (HMIs) is one of the big research topics in biomedical engineering in the last decades. Hand prostheses are only one example of these devices; however, the big challenge in all imaginable applications is the signal analysis to detect the user's intention. Therefore Reischl defined the quality of a signal used for HMIs to be dependent on its (1) voluntary generateability, (2) physiologic resemblance, (3) signal-to-noise-ratio, (4) required degree of invasiveness and (5) computational effort influencing the system response time [Reischl, 2006]. According to this rating, electromyographic signals, recorded by means of surface electrode (sEMG), represent such a high quality signal, as they reflect the voluntary muscle activation and are obtainable in an easy and non-invasive way [Merletti et al.,2009; Oskoei and Hu, 2007]. Therefore this method is often used in research [Micera et al., 2010] and in commercially available prostheses.

However the EMG based control of artificial prostheses is difficult due to the lack of 'homologous' muscles (i.e. those muscles controlling e.g. finger movement in an able-bodied subject are impaired or completely lost in an amputee). Therefore commercially available control systems for hand prostheses use trained control commands like contracting one muscle for finger closing and another for opening. Physiologic resemblance is so poor that acceptance of using such a prostheses is low, even though good results can be obtained after a quite long training phase. Controlling a multi-degree of freedom (DoFs) hand prostheses with this method would be even more difficult.

Alternative methods have been focused by different research groups to successfully control dexterous hand prostheses [Micera et al., 2010]. Intraneural electrodes [Micera et al., 2010b] have been used as well as replantation of residual nerves to remaining muscles (targeted muscle reinnervation) [Miller et al., 2008] with the aim to obtain a physiologic control for a multi-DoFs hand prostheses. Though results are encouraging, these methods suffer from their high invasiveness.

The rational for the idea of this paper to use the residual muscles of the upper arm and shoulder region bases on a study from Lemon and colleagues who showed different EMG pattern during grasping tasks in monkeys [Brochier et al., 2004] and a study in able-bodied subjects [Martelloni et al., 2009].

This pilot study shows the possibility to discriminate three different grip types during grasping tasks in four able-bodied subjects by means of a support vector machine (SVM) classifier that can be used for a non-invasive physiologic control of a dexterous hand prosthesis.

2. Material and Methods

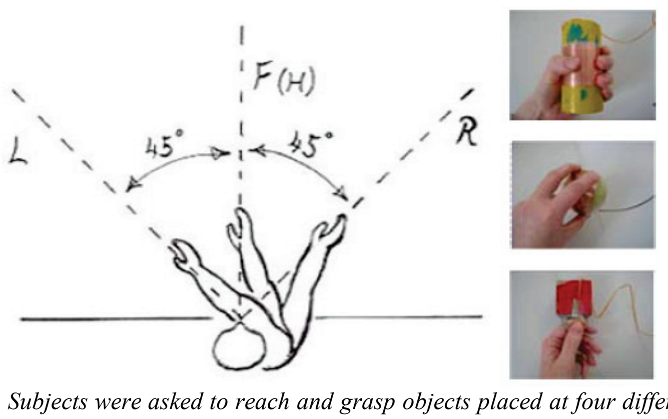
2.1. Subjects

Four able-bodied subjects (2 female and 2 male, mean age (27.48 years, SD 1.28 years, mean size 169 cm, SD 4 cm, all right-handed) participated in the study. They provided their written consent after being informed about the experimental procedures. All subjects were healthy without any known history of neurological abnormalities or musculo-skeletical disorders.

2.2. Experimental Setup

Subjects sat comfortably in front of a table with their dominant arm in an assigned resting position (muscles relaxed with the hand lying on the table plate). The chair was adjusted in its height correspondingly. They were asked to reach and grasp for six different objects placed randomly at four different positions in a mixed order. Front (F), Right (R), Left (L) were lying in the table plane while for Height (H) a platform was placed at position F to add an upwards directed movement (see Fig. 1) The six objects were grasped using three different grip types: the cylindrical grip for the beaker (diameter 6.6 cm) and the cylinder (diameter 4.8 cm), the tripod grip for the tennis ball (diameter 6 cm) and the Christmas bowl (diameter 3.8 cm) and the lateral pinch for the key (thickness 0.5 cm) and the videotape (thickness 2 cm). The distance of the positions was chosen dependent on the arm length of the subjects in order to allow comfortable reaching of the objects while completely extending the elbow.

Each subject was asked to grasp for each object at each position for a total of 10 times (finally 10x6x4 grasping trials). To avoid muscle fatigue a break was included after the half of the grasps. The time for the movement was not predefined. So subjects could choose themselves whether to go fast or slow as well as when to start. Contact sensors gave information about movement start (contact loss of finger tips and table plate) and completed grasping (contact between finger tips and object).



(left) Experimental setup: Subjects were asked to reach and grasp objects placed at four different positions along the specified lines (F, L, R, H). Distances were adjusted to the anthropometric data of the subjects. (right) Examples of the objects and resulting grip types.

Subjects were requested only to move their dominant arm and to keep their remaining body fixed. An upright position and a correct posture at the beginning of the experiment were controlled. However subjects were not restrained in any way.

Disposable pre-gelled Ag/AgCl surface electrodes (50 mm diameter, Pirrone & Co, Milano, Italy) were used. Recordings were done by means of a wireless commercial system (Telemyo 2400R and Telemyo 2400T, Noraxon, Scottsdale, AZ, USA). Raw data were acquired in bipolar configuration (interelectrode distance 10 mm), 1.5 kHz sampling frequency, using 1st order 10 Hz hardware high pass filter and 8th order 500 Hz hardware Butterworth low pass anti-aliases filter. The signals were amplified with a gain of 500 and stored with a resolution of 12 bit for further analysis in Matlab (The MathWorks, Natick, MA, USA). An additional 6th order 20 Hz Butterworth was applied digitally to remove residual offset.

Exact positioning of the electrodes on the muscles was tested according to [Kendall et al., 2005]. Fourteen different muscles were recorded, namely the M. pectoralis major, M. latissimus dorsi, M. trapezius (pars descendens), M. deltoideus posterior (pars spinalis), M. deltoideus medius (pars acromialis) and M. deltoideus (pars clavicularis) in the region of the shoulder, the M. triceps brachii (caput laterale), the M. triceps brachii (caput longum) and the M. biceps brachii in the upper arm as well as the M. extensor digitorum, M. flexor carpi radialis, M. brachioradialis, M. extensor carpi ulnaris and M. flexor digitorum superficialis in the forearm.

2.3. Data Analysis

EMG recordings were cut into intervals containing 1000 samples before and after movement start and labeled according to the object and position. Although many different feature sets were proposed in literature for the classification of sEMGs [Huang et al., 2005; Oskoei and Hu, 2007; Zardoshti-Kermani et al., 1995] only the integrated absolute value (IAV) was used (see Eq.1). This feature gives an impression about the overall activation of the muscle as it increases for stronger or longer activation in a defined time interval. It is supposed to be sufficient to obtain fast and robust classification results [Oskoei and Hu, 2008]. The IAV is defined as the sum of the absolute value of all EMG samples x in a defined time interval i from t_1 to t_2:

$$IAV_i = \sum_{k=t_1}^{t_2} |x_k| \tag{1}$$

where

IAV = Integrated Absolute Value
i = time interval
t1, t2 = start and end time of the interval
x = value of the sample
k = number of the sample.

The IAV was extracted for each muscle and each grip for time intervals corresponding to 25%, 50%, 75% and 100% of the movement as well as of 100 ms, 200 ms, 300 ms or 400 ms starting with the onset of the movement. The grasping movement always took longer than 400 ms.

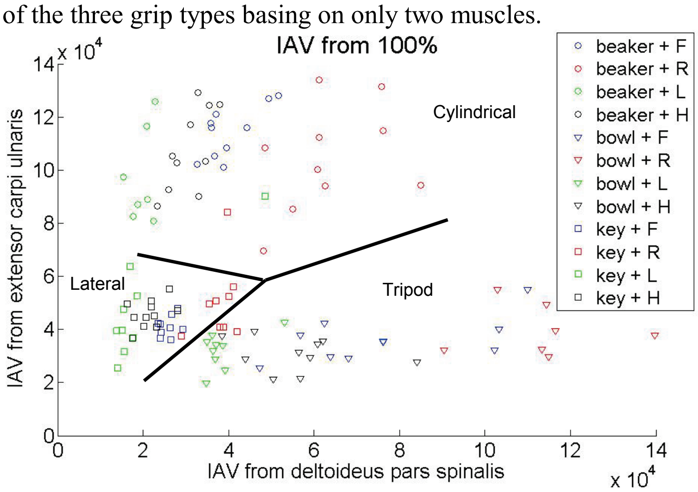
Feature values were scaled to be in the interval [0, 1] and a principal component analysis was performed to detect channels that obtain the main information. Classification was done by means of C-SVM with a radial basis function kernel. (C and γ selected after a grid optimization using four-fold cross-validation using LIBSVM toolbox [Hsu et al., 2008].

The classifier was trained by 50% of the recorded data (training data) and tested on the other half (test data). The performance of the classifier was expressed with the recognition ratio (RR), i.e. the ratio between the number of correctly identified grips and the size of the test data.

Different (reduced) muscle sets in order to simulate different amputation levels and to evaluate the usability of more proximal muscles only in regard to classification performances were used. A transomeral amputation for example was simulated by reducing the muscles to those located in the upper arm and shoulder region, while even higher amputation levels were simulated by applying the classification to the pectoralis major, the trapezius descendens, the latissimus dorsi and the deltoid posterior and anterior only.

3. Results

Overall activation level of a single muscle seems to be dependent on the intended grip type. Fig. 2 shows a 2D plot for one of the test subjects of the IAV computed from 100% of the movement with an exemplary separation of the three grip types basing on only two muscles.



(left) Experimental setup: Subjects were asked to reach and grasp objects placed at four different positions along the specified lines (F, L, R, H). Distances were adjusted to the anthropometric data of the subjects. (right) Examples of the objects and resulting grip types.

Discrimination between the two different sized objects provoking the same grip type was not investigated. The aim of using two sizes was to show more flexibility of the method, which should clearly be dependent on the grip type rather than on the object itself. In the following the datasets of the two objects are therefore combined to one representing a grip type.

Given the position of the object RRs of discrimination of the three different grip types depend on the time window used for the feature extraction. The shorter the time window the lower the performance of the classification, see Table 1. For three of the subjects 300 ms windows result in an accuracy of about 80% that can be further increased by taking 400 ms into account or by combining the windows 100 ms, 200 ms and 300 ms in the feature set. The letter results in RRs of more than 80% for all four subjects.

RRs for different time windows for classification among the three different grip types.

Subject	*100 ms*	*200 ms*	*300 ms*	*400 ms*
A	75.1±3.6%	79.4±4%	81.8±4.1%	88.5±4.2%
B	68.1±3.5%	75.8±3.8%	79.1±4%	79.9±4%
C	71.7±3.6%	77.2±3.8%	82.7±4%	86.4±4.1%
D	68.5±3.5%	70.7±3.5%	71.9±3.6%	72.9±3.6%
average	70.9±1.4%	75.8±1.6%	78.9±2.1%	81.9±3.0%

These results are even better if the IAV is computed from 25-100% of the movement, i.e. if the time windows are adapted to the overall duration of the grasping movement individually to each grasp. In this case RRs above 75% are obtained for all subjects, in one even 95%, see Table 2.

RRs for different percentages of the reaching movement for classification among the three different grip types.

Subject	25%	50%	75%	100 %
A	76.1±3.7%	81.9±4%	87.3±4.2%	86.6±4.2%
B	73.9±3.7%	80.8±3.9%	85.2±4.1%	85.5±4.1%
C	78.6±3.8%	89.8±4.2%	92±4.3%	94.3±4.4%
D	72.7±3.6%	71.7±3.5%	77±3.7%	77.2±3.8%
average	75.3±1.1%	81±3.2%	85.4±2.7%	85.9±3.0%

RRs above 85% are achieved on average if all the muscles can be used for classification. According to the different amputation levels described before, fewer muscles are used for classification in Table 3. In the simulated transhumeral amputation it seems to be better to use only 75% of the movement for feature extraction instead of 100% that resulted in the best RRs so far. An average RR of 73% is reached in this case. Assuming only the five shoulder muscles are left, the classification goes down to an average RR of 48%. Nevertheless there seem to be still some different activation patterns depending on the grip since we get performance above chance.

RRs for different percentages depending on the level of amputation – no position information of the object are used in this classification.

Muscle Set	25%	50%	75%	100 %
all	75.3%	81.0%	85.4%	85.9%
transomeral	51.9%	62.3%	81.8%	78.8%
shoulder	40.3%	41.2%	47.7%	43.4%

4. Discussion and Conclusions

Several research groups are currently work to improve the control of hand prostheses by means of sEMG or more invasive techniques [Huang et al., 2005; Micera et al., 2010; Micera et al., 2010b; Miller et al., 2008; Oskoei and Hu, 2007; Reischl, 2006]. However most of them require long training sessions with the users to achieve stable and reliable results. This decreases the acceptance of potential users. A physiologic and therefore intuitive control with non-invasive techniques might strongly enhance the benefit of multi-DoFs hand prostheses for amputees. Experiments of analyzing muscle patterns in reaching and grasping trials [Brochier et al., 2004; Martelloni et al., 2009] encouraged the idea that the activation of shoulder and upper arm muscles during these movements can obtain enough information to decide on the targeted grip type.

The presented pilot study suggests that correct prediction of the grip type is possible for defined positions if more than 300 ms intervals are used, as well as that there might be a chance to predict the grip type even if the position of the object is known but only the upper arm and shoulder muscles can be used. As the results differ strongly among subjects, there might also be a chance to improve results by slightly adapting the performed grasping movement. In the presented study the subjects were asked to perform the movement as normal for them as possible. It would be interesting whether they would improve RRs by getting a feedback of successful classifications in the course of the experiment; this effect would further enhance usability for a prostheses control. Therefore further experiments have to be carried out in order to obtain more significant results and also to test possible improvement by including learning algorithms to the classifier. Finally, the possibility of recording high-density EMG signals will be also investigated [Daley et al., 2012].

References

Brochier T, Spinks RL, Umilta MA, Lemon RN. Patterns of Muscle Activity Underlying Object-Specific Grasp by the Macaque Monkey. *Journal of Neurophysiology*, 92:1770–1782, 2004.

Daley H, Englehart K, Hargrove L, Kuruganti U. High density electromyography data of normally limbed and transradial amputee subjects for multifunction prosthetic control. *Journal of Electromyography and Kinesiology*, 22(3): 478-484, 2012.

Huang Y, Englehart KB, Hudgins B. A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses. *IEEE Transactions on Biomedical Engineering*, 52:1801-1811, 2005.

Hsu CW, Chang CC, Lin CJ. A Practical Guide to Support Vector Classification. *www.csie.ntu.edu.tw*, 2008.

Kendall FP, Kendall McCreary E, Provance PG. Muscles; Testing and Function with Posture and Pain, Lippincott Williams & Wilkins, Philadelphia, 2005.

Martelloni C, Carpaneto J, Micera S. Characterization of EMG patterns from proximal arm muscles during object- and orientation-specific grasps. *IEEE Transactions on Biomedical Engineering*, 56: 2529-36, 2009.

Merletti R, Botter A, Troiano A, Merlo E, Minetto MA. Technology and instrumentation for detection and conditioning of the surface electromyographic signal: state of the art. *Clinical Biomechanics*, 24: 122-134, 2009.

Micera S, Carpaneto J, Raspopovic S. Control of hand prostheses using peripheral information, *IEEE Reviews in Biomedical Engineering*, 3: 48-68, 2010.

Micera S, Citi L, Rigosa J, Carpaneto J, Raspopovic S, Di Pino G, Rossini L, Yoshida K, Denaro L, Dario P, Rossini PM. Decoding information from neural signals recorded using intraneural electrodes: toward the development of a neurocontrolled hand prosthesis. *Proceedings of the IEEE*, 98: 407-417, 2010b.

Miller LA, Stubblefield KA, Lipschutz RD, Lock BA, Kuiken TA. Improved Myoelectric Prosthesis Control Using Targeted Reinnervation Surgery: A Case Series. *IEEE Transactions on Neural Systems Rehabilitation Engineering*, 16:46-50, 2008.

Oskoei MA, Hu H. Myoelectric control systems – A survey. *Biomedical Signal Processing and Control Journal*, 2:275-294, 2007.

Oskoei MA, Hu H. Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb. *IEEE Transactions on Biomedical Engineering*, 55:1956-1965, 2008.

Reischl M. Ein Verfahren zum automatischen Entwurf von Mensch-Maschine-Schnittstellen am Beispiel myo-elektrischer Handprothesen. Universitätsverlag Karlsruhe, Universität Karlsruhe, 2006.

Zardoshti-Kermani M, Wheeler BC, Badie K, Hashemi RM. EMG Feature Evaluation for Movement Control of Upper Extremity Prostheses. *IEEE Transactions on Rehabilitation Engineering*, 3:324-333, 1995.