EMG Discrete Classification Towards a Myoelectric Control of a Robotic Exoskeleton in Motor Rehabilitation

N. Irastorza-Landa, A. Sarasola-Sanz, F. Shiman, E. López-Larraz, J. Klein, D. Valencia, A. Belloso, F.O. Morin, N. Birbaumer and A. Ramos-Murguialday

Abstract Myoelectric control constitutes a promising interface for robot-aided motor rehabilitation therapies. The development of accurate classifiers and suitable training protocols for this purpose are still challenging. In this study, eight healthy participants underwent electromyography (EMG) recordings while they performed reaching movements in four directions and five different hand movements wearing an exoskeleton on their right upper-limb. We developed an offline classifier based on a back-propagation artificial neural network (ANN) trained with the waveform length as time-domain feature extracted from EMG signals to classify discrete movements. A maximum overall classification performance of 75.54 % ± 5.17 and 67.37 % ± 8.75 were achieved for reaching and hand movements, respectively. We demonstrated that similar or better classification results could be achieved using a small number of electrodes placed over the main muscles involved in the movement instead of a large set of electrodes. This work is a first step towards a discrete decoding-based myoelectric control for a motor rehabilitation exoskeleton.

This study was funded by the GRUENS, the NSFC 31450110072, the DFG-Koselleck and the BMBF MOTOR-BIC (FKZ 13GW0053). A. Sarasola-Sanz's work is supported by the DAAD and N. Irastorza-Landa's work by the Basque Government.

N. Irastorza-Landa · A. Sarasola-Sanz · F. Shiman · E. López-Larraz · N. Birbaumer · A. Ramos-Murguialday (✉)
Institute of Medical Psychology and Behavioral Neurobiology,
University of Tübingen, Tubingen, Germany
e-mail: ander.ramos@med.uni-tuebingen.de

N. Irastorza-Landa
e-mail: nerea.irastorza-landa@medizin.uni-tuebingen.de

N. Irastorza-Landa · A. Sarasola-Sanz · F. Shiman
IMPRS for Cognitive and Systems Neuroscience, Tubingen, Germany

N. Irastorza-Landa
IKERBASQUE, Basque Foundation for Science, Bilbao, Spain

J. Klein · D. Valencia · A. Belloso · F.O. Morin · A. Ramos-Murguialday
TECNALIA, San Sebastian, Spain

J. Ibáñez et al. (eds.), *Converging Clinical and Engineering Research on Neurorehabilitation II*, Biosystems & Biorobotics 15,
DOI 10.1007/978-3-319-46669-9_29

1 Introduction

Myoelectric control constitutes a natural and intuitive interface for assistive and rehabilitative technologies for patients with motor impairment such as stroke patients. The development of kinematics-decoding models from electromyography still remains a challenge, especially in patients with an altered EMG activity. A dexterous EMG-based control of individual degrees of freedom (DoF) of an exoskeleton is therefore still a challenging approach. However, recent research findings classifying residual muscle activity related to motor intention during discrete movements in paralyzed limbs of chronic stroke patients suggest that EMG signals can be a promising source for the control of rehabilitation robots in these patients [1]. EMG classification of discrete movements during robot-aided motor rehabilitation tasks can serve as a way of coupling the motor intention reflected in the patients' residual EMG with the movement performed by the paralyzed limb. In this study we use ANNs for the discrete classification of upper-arm and hand/wrist movements using a reduced set of EMG electrodes. This work serves as a first step towards the implementation of a myoelectric control strategy for motor rehabilitation robots.

2 Materials and Methods

2.1 Experimental Protocol

Eight healthy right handed subjects (5 males, age 25 $\pm$ 2.74) were recruited for this study. Participants performed two different tasks while sitting and wearing a 7-DoF exoskeleton (Tecnalia, San Sebastian, Spain) on their right upper limb. Task A consisted of reaching movements (hand relaxed) from a predefined rest position towards four different goals indicated by targets of different colors around the workspace (see Fig. 1) and returning to the rest position. In task B, participants performed five hand/wrist movements: pronation, supination, pointing (index extension), cylindrical grasp and pinch grip. Each subject performed 50 reaching trials to each target and 30 trials of each hand/wrist movement. The timing of the tasks was instructed by imperative auditory cues and an inter-trial rest period was given to avoid fatigue. Ten bipolar Ag/AgCl electrodes from Myotronics-Noromed (Tukwila, WA, USA) were placed over the: (1) the abductor pollicis longus, (2) extensor carpi ulnaris, (3) extensor digitorium, (4) flexor carpi radialis, plamaris longus and flexor carpi ulnaris, (5) pronator teres, (6) long head of biceps, (7) external head of triceps, (8) anterior portion of deltoid, (9) lateral portion of deltoid and (10) posterior portion of deltoid. The ground monopolar electrode was placed over the right clavicle. The EMG signals were acquired at 2500 Hz using a bipolar amplifier (Brainproducts, Gilching, Germany). Kinematic data were acquired from the custom made exoskeleton at 18 Hz.

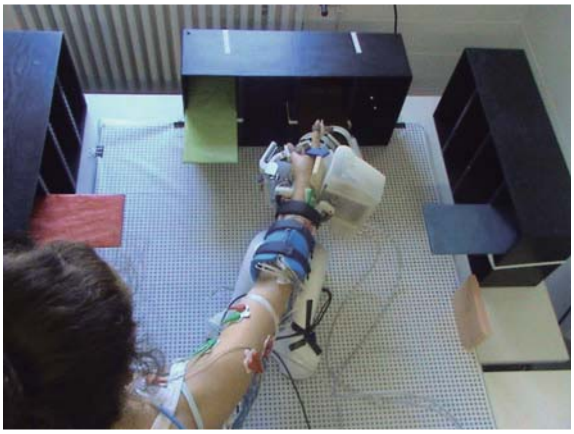

Fig. 1 A subject with EMG electrodes placed over the upper arm performing task A: starting from a predefined rest position, reaching movements towards four different directions indicated by targets of different colors (*red*, *green*, *brown*, *blue*) and return to rest position

2.2 Data Processing

The EMG signals were notch filtered, band-pass filtered between 10 Hz and 500 Hz using a 4th order butterworth filter and rectified. Kinematic data were low pass filtered at 1.5 Hz. EMG and kinematic data were synchronized offline and kinematic data were upsampled to the EMG data frequency. We epoched the EMG data recorded in task A in six classes based on the kinematic data: reaching movement towards four different directions (red, green, brown, blue targets), returning phase to rest position (returning trials from any target to the rest position were considered as a single class to simplify the future online control of the exoskeleton based on the classifier output) and resting phase (arm still at rest position). EMG data of task B were epoched into six classes: pronation, supination, pointing, grasping, pinch grip and resting phase (hand relaxed). Epoched EMG signals were baseline corrected and the waveform length (WL) feature was computed on sliding windows of 200 ms every 20 ms.

2.3 Classification Algorithm

ANNs have been broadly used for discrete decoding of upper arm, hand and individuated finger movements with high accuracies based on EMG [2], especially when using a high number of EMG electrodes [3]. Here we use an ANN classifier trained with the extracted WL feature for the pattern recognition of six movements (see Sect. 2.2). A multilayer perceptron (MLP) neural network was developed using a single hidden layer of three different numbers of nodes and the number of output neurons equal to the number of movements to be classified, six in each task type.

Two independent sets of networks were trained, validated and tested separately for the classification of movements of task A and B. Tan-sigmoid and softmax transfer functions were assigned for the hidden and output nodes, respectively, as commonly found in the literature [4]. The output neuron with the maximum probability value was selected as the classifier output. The network underwent training using the scaled conjugate gradient backpropagation algorithm. We used three different subsets of electrodes for movement classification: (i) all the electrodes (1–10), (ii) electrodes over muscles mainly involved in the movements following neurophysiology (6–10 for task A, 1-6 for task B), (iii) electrodes over muscles not involved in the movements (1–5 for task A, 7–10 for task B). For each task type and electrode set combination case, an inner fivefold cross validation (CV) was performed to find the best network parameters (i.e. number of nodes in the hidden layer) by searching the network with minimum validation mean square error results among all the networks trained for such case. The networks were trained using the best parameters and tested on a separate test dataset in an outer fivefold CV. The reported performance of the classifier was computed as the mean and standard deviation of the percentage of true positives (i.e. data points correctly classified) obtained with networks trained over the fivefolds to classify the independent test set in the outer CV.

3 Results

The mean and standard deviation of the classification success rate achieved for the 8 subjects in the classification of movements of task A and B are summarized in Table 1. The table presents the performance of the classifiers for each combination of task type and electrode set for classification and the chance level in each classification case.

Table 1 Classification success rates in %

Task	Electrodes placed over			
	All muscles	Muscles involved	Muscles not involved	Chance level
A	75.54 ± 5.17	73.63 ± 5.86	52.23 ± 5.54	16.7 %
B	66.74 ± 6.83	67.37 ± 8.75	39.42 ± 3.67	16.7 %

4 Discussion and Conclusions

In this work we show that it is possible to classify six functional arm and hand movements in healthy participants with accuracies above 67 % based on the EMG activity from six EMG bipolar electrodes only. Similar or better classification results could be achieved using only a small number of electrodes placed over the muscles mainly involved in the movement execution instead of a large set of electrodes. This finding suggests that a combination in parallel of these two classifiers could allow classifying upper-limb movements involving fore- and upper-arm muscles simultaneously. However, more data and further analysis are needed to prove this speculation since muscle activity changes depending on posture, substantially more in stroke patients [5], and online classification presents additional issues such as time delays.

Our future work will focus on the design and development of classifiers for fore- and upper-arm combined movements, the classification of residual EMG activity of stroke patients and the online implementation and testing of the classifier in a real-time scenario for the online electromyographic control of the rehabilitation exoskeleton.

References

1. A. Ramos-Murguialday, E. García-Cossio, A. Walter, W. Cho, D. Broetz, M. Bogdan, L.G. Cohen, N. Birbaumer, Detecting paretic arm motion intention through muscle activity decoding in severe chronic stroke. Ann. Clin. Transl. Neurol. **2**(1), 1–11 (2015). PMC. Web. 15 April 2016
2. M. Ison, P. Artemiadis, Beyond user-specificity for EMG decoding using multiresolution muscle synergy analysis. Conference: ASME 2013 Dynamic Systems and Control Conference, At Palo Alto, California (2013). doi:10.1115/DSCC2013-4070
3. F. Tenore, A. Ramos, A. Murguialday, A. Fahmy, R. Etienne-Cummings, N.V. Thakor, Towards real-time control of individuated finger movements using surface myoelectric signals. IEEE T Biomed. Eng. **56**(5), 1427 (2009)
4. F.H.Y. Chan, Y.-S. Yang, F.K. Lam, Y.-T. Zhang, P.A. Parker, Fuzzy EMG classification for prosthesis control. IEEE Trans. Rehab. Eng. **8**(3), 305–311 (2000)
5. E. García-Cossio, N. Birbaumer, A. Ramos-Murguialday, acilitation of completely paralyzed forearm muscle activity in chronic stroke patients, in *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*, San Diego, CA, 2013, pp. 1545–1548