An Implementation of Movement Classification for Prosthesis Control Using Custom-Made EMG System

Luka Mejić[1], Strahinja Došen[2], Vojin Ilić[1], Darko Stanišić[1], Nikola Jorgovanović[1]

Abstract: Electromyography (EMG) is a well known technique used for recording electrical activity produced by human muscles. In the last few decades, EMG signals are used as a control input for prosthetic hands. There are several multifunctional myoelectric prosthetic hands for amputees on the market, but so forth, none of these devices permits the natural control of more than two degrees of freedom. In this paper we present our implementation of the pattern classification using custom made components (electrodes and an embedded EMG amplifier). The components were evaluated in offline and online tests, in able bodied as well as amputee subjects. This type of control is based on computing the time domain features of the EMG signals recorded from the forearm and using these features as input for a Linear Discriminant Analysis (LDA) classifier estimating the intention of the prosthetic user.

Keywords: Grasping, Grips, Hand, Electromyography, Classification, LDA, Signals, Feature, Analysis, Neural prosthesis, Forearm.

1   Introduction

After a forearm upper-limb amputation, muscle functions are preserved so that an amputee can still produce isometric muscle contractions [1]. Muscle electrical activity can be recorded and used to estimate motor intention of the user (e.g., close hand), which can then be translated into the commands for the prosthetic device.

There are several commercial EMG controlled prosthetic hands that can improve the quality of amputee's life. Typically, these devices are controlled using only two muscle signals, which allow for proportional control of a single function. For example, flexor activity determines hand closing speed and force increase, while extensor activity controls hand opening and force decrease. In

the case of multiple functions, as in modern robotic hands, the user needs to switch between them by generating a discrete command, e.g., a brief coactivation of the flexor and extensor [2]. Consequently, the whole control process, known as sequential and proportional control, is not natural and intuitive. When using this method, the prosthetic hands operate as a finite state machine, where every state represents one active function (e.g., grasp type, write rotation) [2].

An alternative approach, extensively treated in the scientific literature, is to use signals from more muscles for more intuitive control. The EMG signals are recorded and processed to extract time and frequency domain features [3 – 4]. The features are used as inputs into pattern classification that estimates the user motor intention. Thus, the user can activate each function directly, without the need for tedious and slow switching commands. Many classification approaches were presented and tested for prosthesis control, including the artificial neural network (ANN), Bayesian classifier, fuzzy and neuro-fuzzy networks etc. [3 – 4]. ANN classifier that used time domain features and autoregressive coefficients was proposed in [5]. They achieved over 90% accuracy of the grip type classification. The LDA classifier is a commonly used method, due to its simplicity, ease of implementation and good control performance [6]. Inputs of LDA classifier were only time domain features of EMG signals, but Principal Component Analysis (PCA) algorithm must be used before classification to reduce dimensionality of the system.

Our implementation and tests of the pattern recognition pipeline are presented in this manuscript based on LDA classifier and time domain features. This pipeline includes a novel custom made system for recording the EMG signals comprising flexible matrix electrode and an embedded EMG amplifier.

The whole experiment had a few segments. Due to the fact, that amputees could have forgotten how to contract forearm muscles for making different hand grips, since they were unlikely to use those muscles during everyday life, we should firstly check that subject's ability. If that ability exists, we examine what EMG signal features of the forearm muscles are suitable to make grip classification on. The other task of the experiment was to design a classifier based on the features of the EMG signals, for which we ensured that are suitable to make classification on. The experiment ends with the tasks for the examinees designed to test classification accuracy and artificial hand control quality.

The whole paper represents an extension of the [7].

2   The Method

Signals were recorded using four bipolar EMG channels arranged equidistantly and circumferentially around the forearm. The subjects were asked to perform pronation, supination, lateral grasp, pinch grasp, hand open and hand

rest. The hand and wrist of healthy subjects were immobilized in order to perform isometric muscle contractions. That was done by bracing subjects forearm and palm to a static board (Fig. 1). The EMG electrodes were custom designed for differential recording by Tecnalia Research & Innovation, San Sebastian, Spain. The electrodes (Fig. 2) were flexible and could be wrapped around the forearm and they have excellent conductive characteristics (electrode-skin impedance is less than 40 kΩ with a proper skin preparation). The electrodes were placed over the palmaris longus, the flexor the carpi radialis, the brachioradialis, the flexor digitorum profundus, the supinator, the pronator teres, the extensor digitorum, the extensor carpi ulnaris and the flexor carpi ulnaris. The EMG signals were recorded using a custom-made 8-channel DC EMG amplifier. Signals were digitized by a 24-bit sigma/delta AD converter and transferred to the PC via Bluetooth communication. The sampling frequency was 2 kHz. Raw signals were filtered using a Butterworth band pass filter which passed only frequencies in signals between 10 and 500 Hz.

Fig. 1 – *Hand immobilization of healthy able bodied subjects. The novel flexible electrode for recording EMG signals is wrapped around the subject forearm.*

Two time domain features were computed from the recorded EMG data, i.e., RMS and wave length, based on their suitability for grip classification [7]. The pilot tests demonstrated that the best results were achieved when all the features were calculated in the time window of 200 ms with a 50% overlap.

L. Mejić, S. Došen, V. Ilić, D. Stanišić, N. Jorgovanović

Fig. 2 – *Flexible matrix electrode for recording EMG designed by*
Tecnalia Research & Innovation, San Sebastian, Spain.

A   Root Mean Square (RMS)

$$\text{EMG}_{\text{RMS}} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x(k)^2} \;, \tag{1}$$

where $x(k)$ represents the k-th sample of the EMG signal and N is number of samples per time window.

B.   Wavelength (WL)

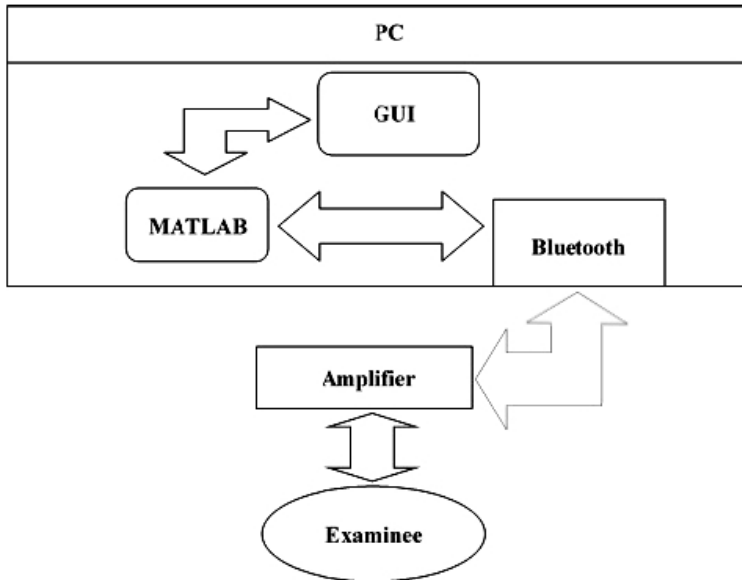$$\text{EMG}_{\text{WL}} = \sum_{k=2}^{N} \left| x(k) - x(k-1) \right|, \tag{2}$$

where $x(k)$ and $x(k-1)$ represents the k-th sample and one before it of the EMG signal, respectively. N is number of samples per time window.

As demonstrated in [7], these two features can provide good classification results.

Six subjects participated in the experiment to evaluate the system. Two subjects were amputees. Both of the amputees had amputation more than 20 years ago. All participants read and signed written informed consent form prior to the experiment.

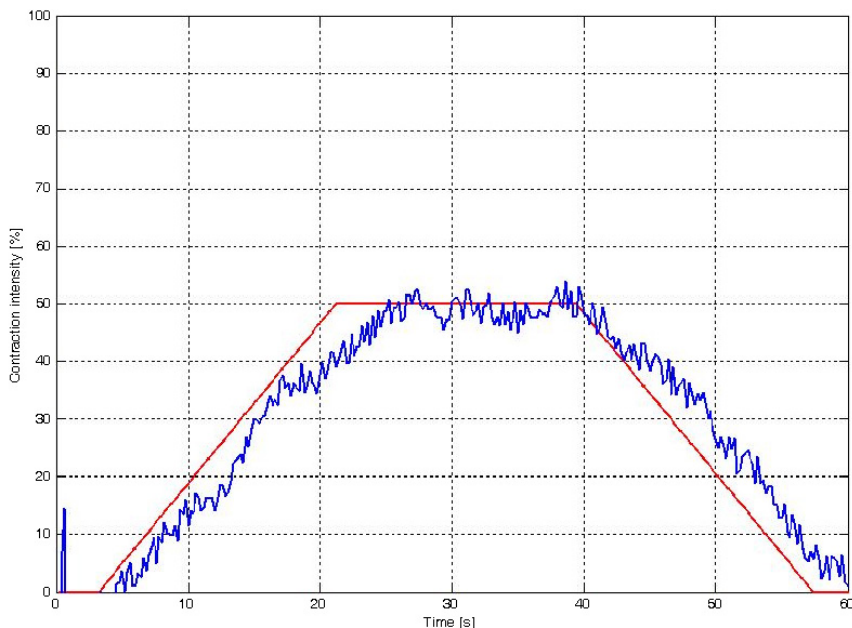The whole setup needed for the experiment is shown in Fig. 3.

The EMG signals were normalized to the maximum value produced during maximum voluntary contraction. Therefore, the muscle activity on each electrode had equal contribution to the classification [7].

Fig. 3 – *Experimental setup.*

The subjects were first asked to perform a maximum voluntary contraction in all the movement classes. After that, the subjects performed the indicated movement class using the indicated intensity of contraction. This was implemented as a tracking task, in which the desired and generated contraction intensity was displayed on a computer monitor (Fig. 4). The intensity was determined as the mean sum of RMS feature values across the four EMG signals. For every movement class, three trajectories were tracked, with plateaus at 30%, 50% and 70% of the maximum contraction.

The data processing and classification was implemented in MATLAB and Statistics Toolbox Release 2013a, The MathWorks, Inc., Natick, Massachusetts, United States. The inputs for classification were EMG signal features calculated and normalized as described before. The outputs were six movement classes. The collected data were used for training. Due to test the classification, an experiment was performed. Twenty tasks were sequentially presented to the subjects. In each task, a picture was displayed indicating the movement class that the subject should reproduce by activating the muscles. The subjects were expected to generate the desired muscle activity in the next 5 seconds. The classification quality was calculated as the percent of correctly classified movements.

Fig. 4 – *The reference (red) and generated (blue) contraction intensity at 50% of a movement class shown in real-time on a computer monitor (feedback for the subject).*

In order to test the online control which includes classification and also proportional estimation, a Fitts Law test has been implemented [8]. Two circles were shown on the screen of a PC. Full circle represented reference and the empty (controlled) circle represented the current position that the subject achieved. The task for the subject was to move the controlled circle into the boundaries set by the reference within 60 seconds. Each subject performed 20 tasks with the reference in different random positions. If the subject reached the reference boundaries and stayed within it for 3 seconds, the reference circle would change its position and diameter. The reference circle would be changed, if the subject did not reach the reference boundaries within 60 seconds.

The movement of the controlled circle was determined by a combination of LDA classifier output and normalized EMG intensity. The movement classes were mapped to movement directions of the circle: pronation to upward, supination to downwards, lateral grip and hand open to left and right movement on the screen. The speed of the circle movement is directly proportional to the intensity of the muscle contraction. Circle diameter is changed if the LDAs output is a pinch grip and it is directly proportional to the normalized contraction intensities in that grip. The GUI of this part of the experiment is shown on Fig. 5.
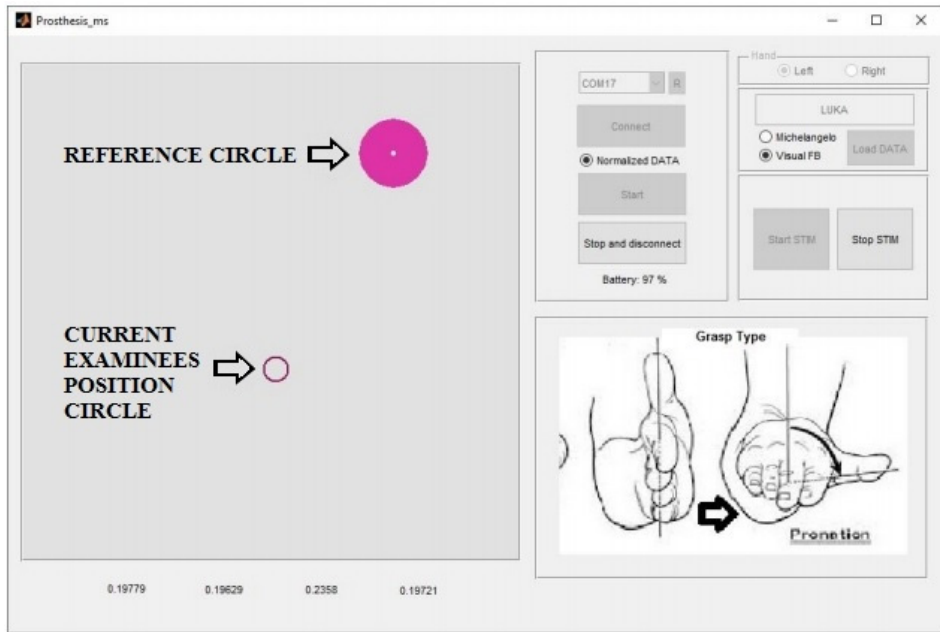
Fig. 5 – *Prosthesis control testing based on Fitts Law.*

3   Results

The classification quality results for 6 subjects are shown in Fig. 6. The median of the movement classification accuracy was 90%.
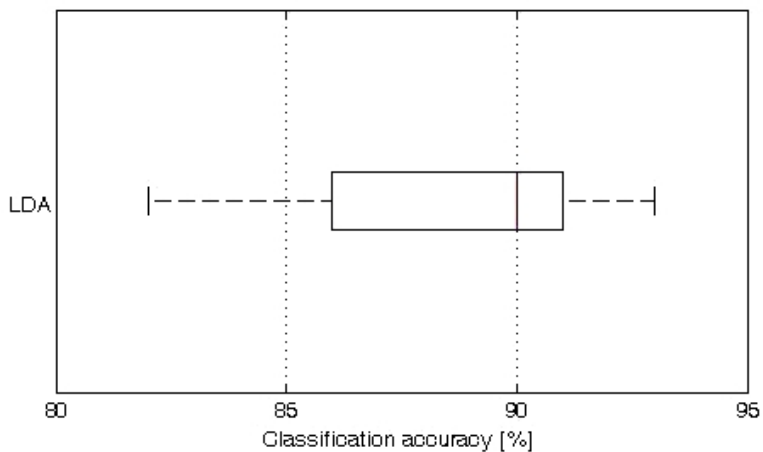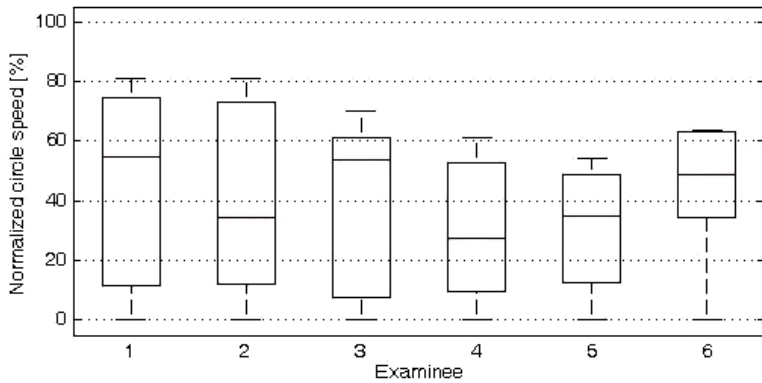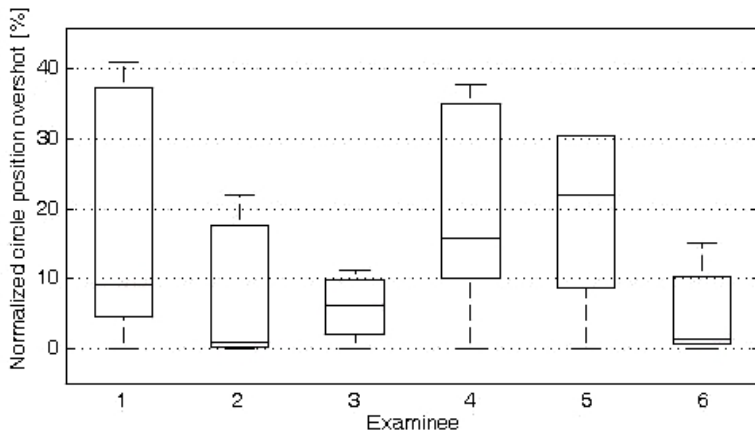

Fig. 6 – *LDA classification accuracy.*

To assess the performance, we computed the average speed of the circle, overshot of the circle position relative to the reference circle and overshot of the circle diameter also relative to the reference circle.

All performance parameters were normalized. The average circle speed was normalized by the maximum speed of circle that can be achieved. The difference of the circle position relative to the reference circle was normalized by the Euclidian distance between the reference circle and the position of the controlled circle at the moment when the reference was changed. The diameter of the controlled circle was normalized by the diameter of the reference circle. The control performance was better, when the overshot parameters were lower and the speed was higher. The summary results for the tested subjects are presented in Fig. 7, 8, and 9.
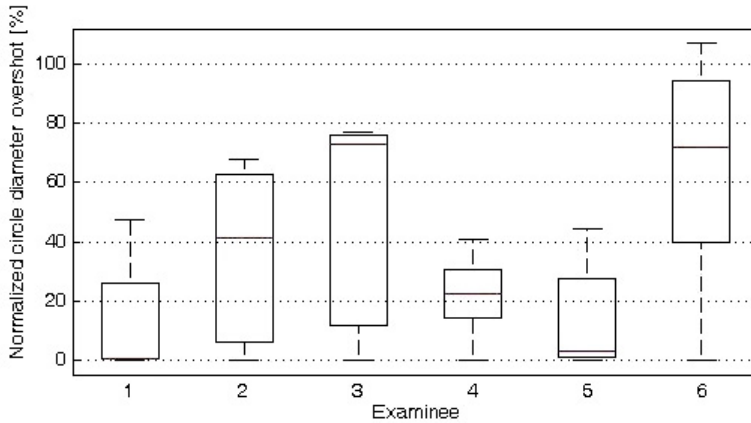

Fig. 7 – *Normalized circle speed of all examines.*

Fig. 8 – *Normalized circle position overshot of all examines.*

Fig. 9 – *Normalized circle diameter overshot of all examines.*

All subjects achieved similar circle speeds. The subjects 3 and 6 were able to reach fast circle movement and minor position overshots, but large diameter overshots. The minor diameter overshots were achieved by examinee 1, but there was wide range of position overshots and circle speed.

It is important to notice, that the quality of the prosthesis control is likely to improve through time, because of the subject training. The results presented here are without any prior training.

4 Conclusion

Our implementation of the pattern classification for prosthesis control using custom made EMG recording components has been presented in this paper. A novel flexible electrode and a miniature embedded amplifier were used to record the EMG signals. The classification was performed using a common method, LDA and time domain features. The system components were evaluated in offline as well as in online control.

The experimental results from the two transradial amputee and four able bodied subjects showed that only two time domain features of the surface EMG signals are sufficient for the proposed system to output a real time classification accuracy of approximately 90% for the six targeted hand movements.

One of the future directions of the study will be the implementation of proposed prosthesis control approach on an embedded system.

5 Acknowledgment

6 References

[1] A. Pantall, S. Durham, D. Ewins: Surface Electromyographic Activity of Five Residual Limb Muscles Recorded During Isometric Contraction in Transfemoral Amputees with Osseointegrated Prostheses, Clinical Biomechanics, Vol. 26, No. 7, Aug.2011, pp. 760 – 765.

[2] O. Bock: Living. With Michelangelo, Ottobock. Available at: http://www.ottobock.co.uk/search_results.jsp?q=Living+with+Michelangelo.

[3] M.A. Oskoei, H. Hu: Myoelectric Control Systems - A Survey, Biomedical Signal Processing and Control, Vol. 2, No. 4, Oct. 2007, pp. 275 – 294.

[4] M. Zecca, S. Micera, M.C. Carrozza, P. Dario: Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal, Critical Reviews™ in Biomedical Engineering, Vol. 30, No. 4-6, 2002, pp. 459 – 485.

[5] A.D.C. Chan, K.B. Englehart: Continuous Myoelectric Control for Powered Prostheses using Hidden Markov Models, IEEE Transactions on Biomedical Engineering, Vol. 52, No. 1, Jan. 2005, pp. 121 – 124.

[6] K. Englehart, B. Hudgins: A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control, IEEE Transactions on Biomedical Engineering, Vol. 50, No. 7, July 2003, pp. 848 – 854.

[7] L. Mejic, N. Jorgovanovic, S. Dosen, V. Ilic, Z. Tepic: Analysis of the Myoelectric Signal Features During the Grasping, 3. International Conference on Electrical, Electronic and Computing Engineering, Zlatibor, Serbia, 13-16 June 2016, pp. MEI3.2.1 – 4.

[8] E.J. Scheme, K.B. Englehart: Validation of a Selective Ensemble-based Classification Scheme for Myoelectric Control using a Three Dimensional Fitts' Law Test, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 21, No. 4, July 2013, pp. 616 – 623.

[9] A. Fougner, O. Stavdahl, P.J. Kyberd, Y.G. Losier, P.A. Parker: Control of Upper Limb Prostheses: Terminology and Proportional Myoelectric Control - A Review, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 20, No. 5, Sept. 2012, pp. 663 – 677.