Repeatability of grasp recognition for robotic hand prosthesis control based on sEMG data

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***Abstract*— Control methods based on sEMG obtained promising results for hand prosthetics. Control system robustness is still often inadequate and does not allow the amputees to perform a large number of movements useful for everyday life. Only few studies analyzed the repeatability of sEMG classification of hand grasps. The main goals of this paper are to explore repeatability in sEMG data and to release a repeatability database with the recorded experiments. The data are recorded from 10 intact subjects repeating 7 grasps 12 times, twice a day for 5 days. The data are publicly available on the Ninapro web page. The analysis for the repeatability is based on the comparison of movement classification accuracy in several data acquisitions and for different subjects. The analysis is performed using mean absolute value and waveform length features and a Random Forest classifier. The accuracy obtained by training and testing on acquisitions at different times is on average 27.03% lower than training and testing on the same acquisition. The results obtained by training and testing on different acquisitions suggest that previous acquisitions can be used to train the classification algorithms. The inter-subject variability is remarkable, suggesting that specific characteristics of the subjects can affect repeatability and sEMG classification accuracy. In conclusion, the results of this paper can contribute to develop more robust control systems for hand prostheses, while the presented data allows researchers to test repeatability in further analyses.**

I. INTRODUCTION

A wide variety of mechanically advanced myoeletric prosthetic hands are now available on the market. Despite the mechanical advancements made over the years, the built-in sEMG control is often limited to opening and closing. Recently, several improvements on sEMG control have been made applying modern machine learning techniques. However, pattern recognition techniques are often not robust enough for a scenario in daily life [22], [21]. The position of the sensors is one of the main factors influencing the sEMG signals and, as a consequence, control robustness. Thus, the analysis of repeatability in sEMG hand grasp classification can help to improve the robustness of robotic prosthetic hands when external factors (such as electrode repositioning) can affect the sEMG signal.

Both the market and science are complex and changing quickly. The first commercial products exploiting pattern recognition to recognize the hand grasps have been released (e.g. CoAptEngineering [1] and TouchBionics [2]). However, the most common control systems still require long training times [22].

One of the main goals of the research community working on surface electromyography controlled hand prostheses is to improve the everyday life of the amputees. Non-invasive methods have been developed, that use sEMG electrodes to record muscular activity and pattern recognition algorithms to classify hand movements. The algorithms usually show average classification accuracies of up to 80-90% [3], while results over 90% can be reached in some cases on very few movements (e.g [1], [2]).

Healthy subjects are often chosen to acquire data in scientific experiments since performing and repeating complex movements can be strenuous for the amputees. Scientific literature showed that intact subjects can be used as a proxy measure for amputees [24]. However, parts of the muscles can be missing in amputated subjects, thus the results of amputees are often lower.

Despite the good results described in the literature on sEMG hand prosthetics, there are still several obstacles to overcome. The movement accuracy is never high enough to avoid misclassification on large sets of movements. Castellini et al. [8] show that nine postures can be classified with remarkable accuracy. In the studies for the NinaPro database the number of gestures was extended to 52 movements (including grasping), showing that using machine learning it is possible to classify a large number of tasks with an accuracy of over 80% [19], [16].

As highlighted by several papers (e.g. [22], [21]), achieving a robust control is one of the main obstacles to bring sEMG pattern recognition to real life use. sEMG signals can be influenced by several external factors that can affect control robustness, such as muscle fatigue or movements of the electrodes on the skin [9]. Thus, intersubject variability, muscle fatigue and electrode displacement should always be considered when working with sEMG [8].

Recent papers have stated that the classification accuracy of the proposed classifiers is high enough to effectively

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[1]`http://www.coaptengineering.com/`
[2]`http://www.touchbionics.com/`

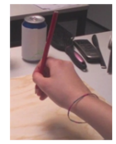
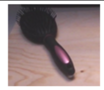
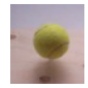
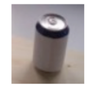
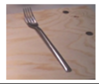
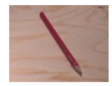
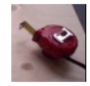
Description	Large Diameter	Adducted Thumb	Index Finger Extension	Medium Wrap	Writing Tripod	Power Sphere	Precision Sphere
Grasp							
Objects							
							

TABLE I

LIST OF GRASPS (AND RELATIVE OBJECTS) ANALYZED IN THE PROJECT.

perform EMG pattern recognition with accuracy of around 90% [3]. As Shin et al. [5] suggest, the accuracy of a classifier is not the only factor to fully estimate the performance of a classifier for prosthesis control applications. Other parameters also exist. This paper deals with repeatability of grasp recognition for robotic hand prosthesis. Repeatability is defined as the variation in repeated measurements made of the same subject, under identical conditions and in a short period of time. As reported by Taylor and Kuyatt [10], the following conditions must be fulfilled to successfully complete repeatability experiments: the same experimental tools, same observer, same measuring instrument (used under the same conditions), same location, repetition over a short period of time and the same objectives. Studies on repeatability of sEMG classification of hand grasps could improve the knowledge on the effect of external factors on robustness. Radmand et al. [6] suggest that when the arm is moved to a position different from the one in which the classifier is trained the repeatability of the data decreases. However, training in multiple positions is stressful for the amputees. Repeatability studies may help the producers of prosthesis to define sets of gestures that can be controlled robustly, while also being helpful in activities of daily life. For instance, Xiang et al. [4] suggest that hand gesture tasks with low repeatability should be avoided in myoelectric control systems. He et al. [12] investigated the variation in EMG classification over 11 consecutive days. They observed that, when they trained the classifier on data from one day and they used the following day as testing set, the classification error decreased stronlgy but it stabilized after four days for healthy subjects. These results show that, when the set of days during which the subjects perform the defined motions is enlarged, changes in EMG signal features over time become gradually smaller. Amsüss et al. [13] were able to obtain an accuracy within days per subject of $97.9\% \pm 0.8$ through five days and five subjects. They found that the classification accuracy decreased monotonically. It dropped by 4.17% per day between training- and test days. Unlike in this paper, in both articles the exact locations of the electrodes were marked through a pen and renewed every day for accurate repositioning of the electrodes.

This article deals with the repeatability of data acquisitions through sEMG sensors and it has two main goals. First, the release of a publicly available database to study repeatability in hand movement sEMG. Second, the analysis of repeatibility in sEMG, which is based on the comparison of movement classification accuracy in several data acquisitions and in several subjects.

II. ACQUISITION SETUP

The acquisition setup is based on the setup used for previous Ninapro datasets [16] The setup can be split into hardware and software.

A. Hardware

The hardware acquisition setup consists of:

- DELL Latitude E5520: the laptop used to perform the data acquisitions and to record the data.
- Tobii Pro Glasses II: a wearable eye tracking system used to record the eye movements and field of view;
- 14 Delsys Trigno double differential sEMG Wireless electrodes: used to record the muscular activity of the forearm.

The Tobii Pro Glasses II (Figure 1) are composed of the head unit (having an eyeglass design) and a recording unit (that is used to record and store the videos on an SD card). Using four infrared cameras embedded in the frame of the glasses, the device can estimate where the subject is looking within his field of view, which is recorded via a full HD camera. During data acquisition, the device is connected to the laptop through a wireless network. The muscular activity is measured with 14 Delsys Trigno sEMG Wireless electrodes. The electrodes are connected through a wireless protocol to their base station (Figure 2). The base station is connected to the laptop via a USB cable. The sEMG signals are sampled at 2 KHz while the 3-axes accelerometer in the device is sampled at 148.148 Hz. The electrodes are equally spaced in two rows around the forearm. The first row is composed of eight electrodes that are arranged

Fig. 1. Tobii Pro Glasses II.

Fig. 2. Trigno Wireless EMG.

in correspondence to the radio-humeral joint as described in [16]. The second row is composed of six electrodes that are placed just below the first row, in correspondance to the empty spaces of the first row and positioned in order to avoid positioning over the ulna. Finally, an elastic latex-free band is placed around the electrodes to avoid falls and to reduce their movement (Figure 3).

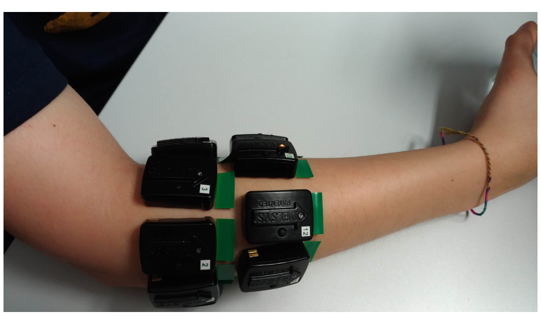


Fig. 3. Example of the final position of the electrodes.

B. Software

The software acquisition is made up of two parts that work together:

1) the software used to simultaneously record the data from all the sensors;
2) the software that guides the subjects during the data acquisitions.

The first part of the software is a custom-made multithreaded application based on a producer-consumer pattern software written in C++ by Stefano Pizzolato [20] (Figure 4). When the data are recorded, a time stamp is assigned to them, in this way it is possible to synchronize the data acquired from the devices. The second part of the software was developed

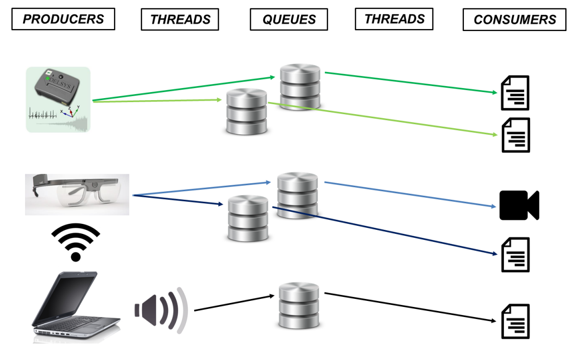


Fig. 4. Acquisition Software: CORE.

to guide the user during the data acquisition via visual and audio commands. The language of the audio commands can be chosen among four options (Italian, English, French and German) at the beginning of the acquisition.

III. Acquisition Protocol

The acquisition protocol is an evolution of the acquisition protocol used to record the previous Ninapro datasets [16]. The researcher explains the experiment to the subject, asks him to respond to a few questions (including age, gender, height, weight and laterality) and measures the length (wrist to elbow) and circumference of the subject's forearm. Then, the researcher explains the experiment to the subject. The subject sits in front of a table with the forearm leaning on it. The experiment consists of 12 repetitions of 7 grasps performed on a set of 14 objects (Table I). The set of hand grasps was chosen from the robotics and rehabilitation literature [19] [14] [15] with the goal of covering several hand movements exploited in activities of daily living (ADL). The grasp to be performed is shown to the subject with two videos (in first and third person perspective). Afterwards, a set of audio commands explains the subject the task to be performed (i.e. grasping the object, releasing the object and returning to the rest position).

While performing the experiment, a fixed image representing the grasp is shown on the screen of the laptop. The number of repetitions is equally distributed among two objects I. Each repetition lasts for 4 seconds and is followed by 4 seconds of rest. The data recorded from each subject are uploaded to Ninaweb and publicly available as the 6^{th} Ninapro dataset [3].

IV. Data Analysis

The analysis of repeatability is based on the comparison of movement classification accuracy in several data acquisitions and for several subjects.

The data are recorded from 10 subjects (3 females, 7 males, average age 27 ± 6 years). The movement classification follows the procedure suggested by Englehart et al. [23].

[3] url: http://ninapro.hevs.ch/

It includes preprocessing, relabeling, feature extraction, and classification.

First, the data are preprocessed. This step is composed of synchronization and filtering. The signals representing the movement stimuli, the accelerometers and the sEMG are synchronized to the highest frequency (2 kHz) by interpolating the timestamps with piecewise linear models. Then, the EMG signals are filtered from interferences with a Hampel filter at 50 Hz.

Data relabeling is required because the subjects do not always react promptly to the voice commands. Often, the real duration of the movement is not the same as the video. The relabeling is performed following the procedure exploited in previous work [19]. Feature extraction is performed on 200 ms time windows, with an increment of 10 ms. The features chosen are the Mean Absolute Value (MAV) and Waveform Length (WL), which previously obtained good results on sEMG [17] [18]. The feature extraction algorithms are based on the work of Chan et al. [11]. Random Forests with 100 trees are adopted as classifier. For each day, a training set is made of repetitions 1, 3, 5, 7, 9, 11 of the morning data. The test set of the same day is made of repetitions 2, 4, 6, 8, 10, 12 of the afternoon data. Afterwards, the Friedman test is used to evaluate the differences between the groups. The test was performed to compare the classification results obtained on the training and test sets coming from the same acquisitions (morning) with training and test sets coming from different acquisitions (training from the morning acquisitions, testing on the afternoon data). Then, the Kruskal-Wallis test was performed on the morning acquisitions to compare the accuracies obtained on several subjects. The Kruskal-Wallis test is a non-parametric method for examining if the samples originate from the same distribution [25].

V. Results

Figures 5 and 7 show the accuracy of the morning acquisitions with feature MAV and WL, respectively.

Whereas Figure 6 and 8 illustrate the results of the afternoon acquisitions, with features MAV and WL, respectively. Better accuracies are obtained with training and test sets coming from the same acquisitions (morning). The classification accuracies decrease by an average of 27.03% with training and test sets of different acquisitions (training from the morning acquisitions, testing on the afternoon data). The comparison of the classification accuracies obtained with training and test sets of the same acquisitions with those obtained from different acquisitions show a significant difference (Friedman test, p¡0.001). This is likely due to the positioning of the electrodes, which changes between acquisitions. Nevertheless, the accuracies with training and testing from different acquisitions is higher than the chance level for the considered number of movements (12.5%), thus suggesting that different acquisitions can be useful to train the control systems of the prosthesis. A median test on the overall accuracies per day obtained with the two features shows that the results retrieved with the WL feature are slightly higher compared to MAV. The best accuracy is reached on the same dataset (Subject 5, Day 1, Morning) with both features: $81,94\%$ for WL and $81,80\%$ for MAV. Tables II and III show the overall accuracies and standard deviations for each subject and for each day.

TABLE II

Overall Accuracy Par Subject. WL Feature.

Subject	Average	Standard Deviation
1	51,15 %	2,85
2	54,73 %	7,38
3	54,21 %	3,31
4	52,32 %	2,49
5	62,63 %	3,99
6	51,90 %	2,84
7	51,47 %	5,9
8	55,40 %	4,27
9	45,82 %	4,27
10	44,62 %	4,05
Total	52,43 %	4,68

TABLE III

Overall Accuracy Par Day. WL Feature.

Day	Average	Standard Deviation
1	52,58 %	20,12
2	51,79 %	21,12
3	52,66 %	20,79
4	53,26 %	17,32
5	51,83 %	17,69
Total	52,42 %	19,41

The Kruskal-Wallis test was performed on the morning acquisitions and the value obtained ($p < 0.001$) indicates that the null hypothesis of having all data samples from the same distribution is rejected. Thus, there are significant differences between subjects. The variability within each subject is in general low, suggesting that external factors (e.g. size of the arm, muscle fatigue, ecc.) may contribute to determine the results.

During the acquisition of subject 2 day 2 afternoon, the Trigno base disconnected from the laptop, thus reducing the accuracy for the session and increasing the standard deviation of the overall accuracy for the subject.

VI. Conclusions

In this work, we analyze the repeatability of grasp recognition for robotic hand prosthesis control based on sEMG data. The article has two main goals: first, to release a repeatability database with the data recorded during the experiments; second, to explore repeatability in sEMG data through movement classification accuracy.

The repeatability database about sEMG hand movement recognition is publicly released on the NinaPro website [4]. The data were recorded from 10 subjects (3 females, 7 males, average age 27 ± 6 years). The acquisitions are performed on 5 days, twice on each day (morning and afternoon).

The movement classification accuracies obtained when training and test sets are from the same acquisitions are 27.03% higher than those obtained when training and test

[4]url: http://ninapro.hevs.ch/

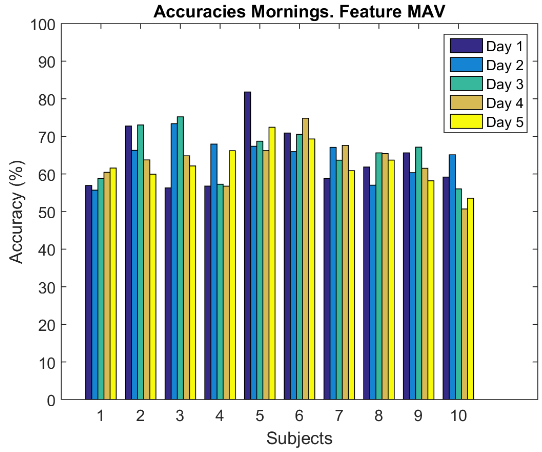


Fig. 5. Classification accuracies for the mornings of each subject using the MAV feature.

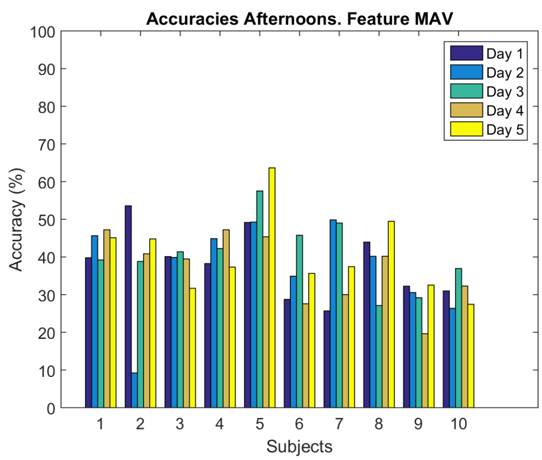


Fig. 6. Classification accuracies for the afternoons of each subject using the MAV feature.

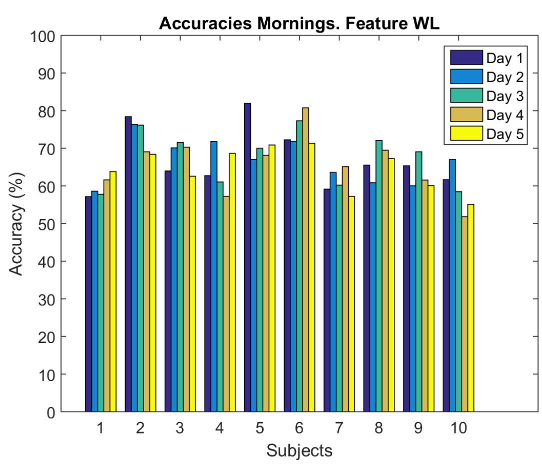


Fig. 7. Classification accuracies for the mornings of each subject using the WL feature.

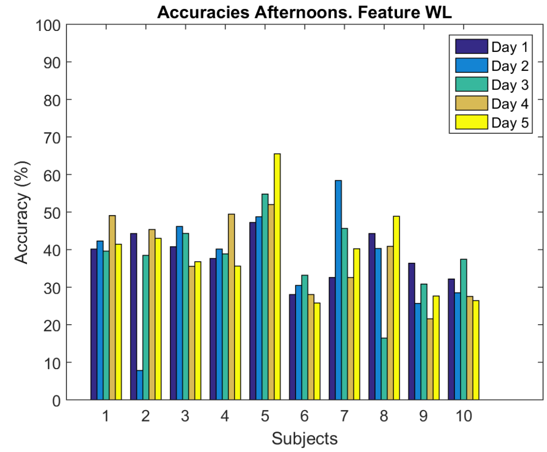


Fig. 8. Classification accuracies for the afternoons of each subject using the WL feature.

sets are from different acquisitions. The Friedman test results indicate that the difference between the two groups is significant ($p<0.001$). The Kruskal-Wallis test shows that there are significant differences between the subjects ($p<0.001$). The variability within each subject is quite low, suggesting that outside factors (e.g. size of the arm, muscle fatigue, ecc.) may contribute to determine the results.

The results of this paper provide additional information to develop more robust control systems for robotic prosthesis. At the same time, the acquired data can support researchers to analyze repeatability in future work and to better comprehend effects of outside factors on the resulting data. Future applications could make use of a bigger set of hand movements [19] and use the data recorded with the Tobii glasses in order to improve the classification of the hand grasps.

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