Recognition of Hand Movements in a Trans–Radial Amputated Subject by sEMG

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***Abstract*—Trans–radially amputated persons who own a myolectric prosthesis have currently some control via surface electromyography (sEMG). However, the control systems are still limited (as they include very few movements) and not always natural (as the subject has to learn to associate movements of the muscles with the movements of the prosthesis). The Ninapro project tries helping the scientific community to overcome these limits through the creation of electromyography data sources to test machine learning algorithms. In this paper the results gained from first tests made on an amputated subject with the Ninapro acquisition protocol are detailed. In agreement with neurological studies on cortical plasticity and on the anatomy of the forearm, the amputee produced stable signals for each movement in the test. Using a k–NN classification algorithm, we obtain an average classification rate of 61.5% on all 53 movements. Successively, we simplify the task reducing the number of movements to 13, resulting in no misclassified movements. This shows that for fewer movements a very high classification accuracy is possible without the subject having to learn the movements specifically.**

I. Introduction

Daily life of hand amputees can be hard in comparison to their situation before the amputation. Prostheses controlled by surface electromyography (sEMG) have been used since the late sixties [1] and contribute to remarkably improve their quality of life. However, prostheses are still far from giving to the subjects the same abilities as intact persons due to several reasons. First, the prosthesis usually offer only 2 or 3 degrees of freedom, and therefore the number of movements that can be performed is limited (usually opening and closing of the prosthesis). Second, the control systems are not "natural", meaning that the movement that is performed by the prosthesis does not reflect the movement that the amputee would be doing with the intact hand if it was still present. In some cases, the number of movements can be increased using specific control sequences. However, in most of these cases the movements are far from being natural and easy to be reproduced. Third, the training procedures are complicated and often require long and difficult learning processes that can easily discourage the amputee.

These facts contribute to the scarce use of sEMG prostheses by amputated subjects [2]. This is in contrast to recent advances in mechatronics that enhance the possibility to build and control mechanical hands with many degrees of freedom. The research community has been working hard to improve the control in hand prosthetics. The most common approach consists of control schemes based on classifiers that are used to understand which movement is desired. The approaches presented so far in the literature use various techniques for preprocessing the data [3], [4] and classifying the movements [4], [5], [6].

A review of the methods and of the results obtained till now is described in [7]. All of the considered papers analyze up to 12 movements, and most of them (except [8]) do not make parallel acquisitions of intact and amputated subjects. Results of particular interest for amputated subjects are described in [8], in [9], and in [10], where the authors obtain respectively 95.74% accuracy in the classification of 6 movements, 84.4% on 10 movements and 87.8% on 12 movements. Despite the differences between the procedures, most of the studies of the field share a common validation procedure that is based on private databases of sEMG recordings.

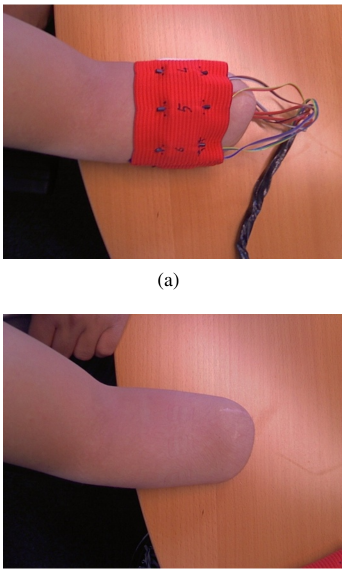
The NinaPro (Non–Invasive Adaptive Hand Prosthetics) project [11] started in January 2011, and has the aim to help the scientific progress in the field with a benchmark database to test and develop machine leaning algorithms for hand movement sEMG data. Currently, a database with 27 subjects for 53 movements is available for download on request.

In this paper we describe the results obtained from the classification of the first preliminary dataset acquired from an amputated subject during the setup and the first tests of the Ninapro database. We show that the considered amputee can produce distinct, stable signals for several movements, in agreement with neurological studies on cortical plasticity and on the anatomy of the forearm. Moreover, we compare the classification results with the average results of 27 intact subjects. Finally, we simplify the task reducing the number of movements to 13, resulting in no misclassified movements. Obviously in this way we reduce the complexity of the task, but we want to reach a different objective, i.e. showing that for fewer movements a very high classification accuracy is possible, without the subject having to learn the movements specifically. The application of the results described in this paper to the industry of hand prosthetics could lead to important changes in the life of hand amputees since (with almost standard sEMG setup) the subject could naturally control a dexterous prosthesis and could be able to do most of the movements needed for daily activities.

II. Methods

A. Data Acquisition

The dataset of the amputated subject was acquired from a subject with a transradial amputation of the right forearm. The subject is a right handed 31 year old male and was amputated 13 years before the data acquisition after an accident. The amputation is transradial shortly below the elbow, with approximately 10 cm (40%) of the forearm remaining. Since the amputation, the subject has always used myoelectric prosthesis. The dataset of the amputated subject is compared with 27 datasets from healthy controls (20 males, 7 females; 25 right-handed, 2 left-handed; average age 28 years with standard deviation 3.4 years).
The sEMG data were acquired according to the Ninapro acquisition protocol [11]. The muscular activity is gathered using eight active double–differential OttoBock MyoBock 13E200 sEMG electrodes[1]. The electrode amplification is set to 5 (which corresponds to an amplification of 14'000) according to the results of several preliminary tests. The signal is filtered and rectified by the hardware included in the electrode. The electrodes are placed around the stump of the forearm using an elastic band as shown in Figure 1.



(a)

(b)

Fig. 1. Forearm of the trans–radial amputated subject with (a) and without (b) the acquisition setup on.

A specific electrode is placed on the radio–humeral joint and the remaining electrodes are placed at approximately equal distances from it. No electrodes were placed on the main activity spots of the finger muscles as described in [11] due to the fact that there was not enough space on the stump. However, as described in the literature, pattern recognition can compensate for suboptimal placement [12], [13] and may even take advantage of muscle cross-talk, especially in amputated subjects [9]. Moreover, the described setup gives the opportunity to improve classification results applying spatial registration algorithms, as described by [14]. The signal of the electrodes was acquired at a constant interval of 100 Hz using a National Instruments DAQ card (NI–DAQ PCMCIA 6024E, 12–bit resolution).
The protocol includes 10 repetitions of 53 movements represented in Figure 2. These movements were selected from the hand taxonomy and robotics literature, (e.g., [15], [16], [17], [18], [19]), as well as from the *Disabilities of the Arm, Shoulder and Hand protocol* for functional movements [19]. During the acquisition, the subject repeated bilaterally the movements shown on the screen of a laptop according to a bilateral imitation procedure [9]. Each movement repetition lasted 5 seconds and was followed by 3 seconds of rest.

B. Analysis

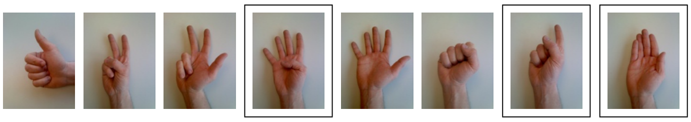
All data were synchronized by linearly interpolating them to the highest recording frequency (i.e., 100 hertz). Then, the signal of the electrodes was low–pass filtered at 1Hz using a zero–phase second order Butterworth filter. The signal from each repetition of each movement was then segmented with a relabeling algorithm that constrains movement labels to those samples in which there is increased sEMG activity [20]. Then, the data of all the movement repetitions are normalized to the same time length, and the signal is divided by the standard deviation and normalized to its maximum.
A k–NN classification algorithm [21] based on the normalized Euclidean distance [22] is applied to the repetitions of the movements with a leave one out approach.
Finally, the same classification procedure is applied to subsets of movements in order to find selections without any misclassification. Obviously in this way we reduce the complexity of the task. However with this analysis we want to reach a different objective that consists in showing that for fewer movements a very high classification accuracy is possible without training the subject to perform specific movements.

III. Results

The number of repetitions assigned to each movement by the classification procedure and the average classification results are represented in Figure 3. It can be noticed that the average classification accuracy is 61.51%, so well above the chance level (1/(number of classes ≈ 2%). Moreover, we see that in several cases (e.g. in movements 2, 10, 21, 39, 40) the percentage of repetitions classified as wrong movements is dominated by a few commonly misclassified movements, meaning that the correct movement is mistaken for a specific other one in most cases.
The average classification results for the amputated subject and for the 27 intact subjects are summarized in Table I and in Figure 4. It can be seen that the average accuracy for intact subjects is 80.16%, i.e. approximately 20% more than the accuracy obtained for the amputated subject. Moreover the intact subjects' average accuracy is included in the amputated subject accuracy plus the standard deviation, while the accuracy obtained for the amputated subject is included in the average accuracy for intact subjects minus 3 sigma.
Finally, we simplify the task removing several ambiguous movements and reducing therefore the number of movements to 13 of the 53 original ones. This subset of movements does not contain any misclassification and shows that for fewer

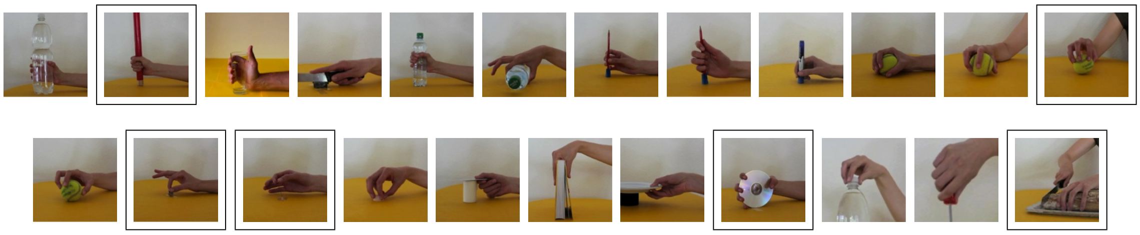
[1]Otto Bock HealthCare GmbH, http://www.ottobock.com

(a) Basic movements of the fingers.



(b) Isometric, isotonic hand configurations.

(c) Basic movements of the wrist.



(e) Grasps and functional movements.

(f) Rest position.

Fig. 2. The 53 movements acquired within the Ninapro acquisition protocol. In the boxes the simplified task of 13 movements without any misclassification.

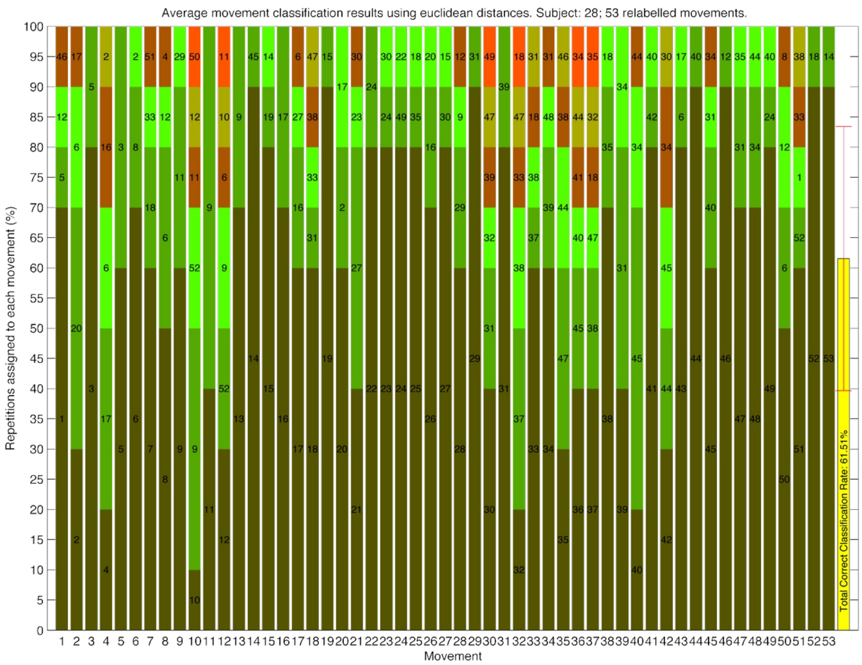


Fig. 3. Classification and misclassification results for each movement for the amputated subject. Yellow bar: average classification rate; bars of other colors: repetitions of the movement indicated on the x-axis classified as the movement indicated in the number in the middle of the bar.

TABLE I. AVERAGE CLASSIFICATION RESULTS FOR BOTH INTACT AND AMPUTATED SUBJECTS.

Subject	Mean	Standard Deviation
Amputated	61.51	22.50
Intact subjects	80.16	6.49

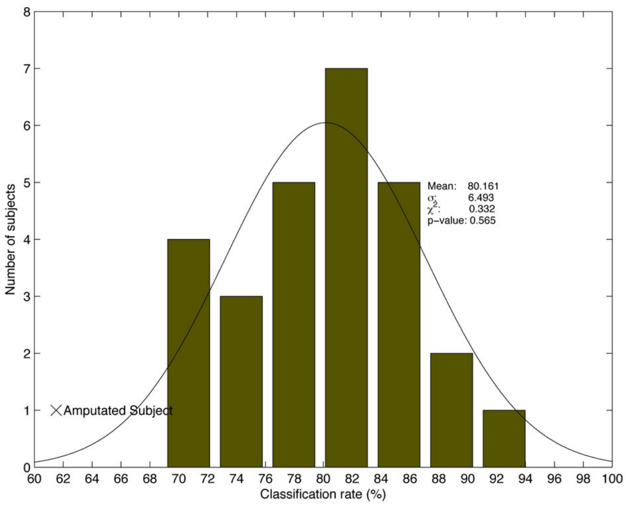


Fig. 4. Distribution (green bars) and Gaussian fit (black curve) of the classification results of all the movements in intact subjects and comparison with the amputated subject (black X).

movements a very high classification accuracy is possible without training the subject to learn the movements specifically. Smaller subsets of different movements could also be selected depending on other parameters such as the functional usefulness of the movements.

IV. CONCLUSION

In this paper we describe the classification results of the sEMG signals emitted by the remnants of the hand muscles of a hand amputated subject. The acquisition setup and procedure are defined in the Ninapro project [11]. The data was acquired as a first test for the Ninapro protocol on an amputated subject. Before considering the results, we shall note two important aspects: first, to our knowledge no sEMG database with so many movements has been described in literature for an amputated subject: the Ninapro acquisition protocol contains 53 different movements, vs. a maximum of 12 movements in other databases [7] (i.e. 4 times less); second, in very few articles till now sEMG signals from intact and amputated subjects have been acquired and analyzed in parallel [7], and in no paper it is described a statistical comparison of the two kinds of subjects.

The results highlight several interesting aspects. First, the average classification rate over all the 53 movements included in the protocol is 61.51%, so much above the chance level of 1.8%. This fact shows that the amputee still produces distinct signals for several movements, in agreement with neurological studies on cortical plasticity and on the anatomy of the forearm.

Second, the avarege of the results from the 27 intact subjects is 80.16%, therefore the classification performance of the amputated subject is just 25% less than the performance of intact subjects, despite the absence of the limb and of most of the forearm.

Third, it is shown that it is possible to simplify the task reducing the number of movements to 13 in order to avoid any misclassification. Obviously in this way we reduce the complexity of the task, however this result shows that for fewer movements a very high classification accuracy is possible without training the subject to perform specific movements. These results were only performed on a single person, which is a limitation, but most other studies also only have very small numbers of subjects. Both the number of movements and the level of accuracy are higher than the ones described in literature for similar tasks (e.g. 6 movements, accuracy 95% [9]; 10 movements, accuracy 84.4% [10]; 12 movements, accuracy 87.8% [8]). It should be noticed that the results in the literature are obtained from "long below elbow" trans–radial amputations, in which most (55%–90%) of the forearm is still present; instead, the classification results decrease strongly if less of the forearm remains, as in the case analyzed in this paper.

It is important to notice that the used dataset is preliminary as it was created to test the Ninapro protocol on an amputated subject. In the next months, final datasets from a larger number of amputated subjects will be acquired within the Ninapro project. Therefore, a better evaluation can then be performed with more subjects allowing to gain statistical validity.

It is also important to notice that the hand movements were performed with the forearm placed on a table in laboratory conditions, and therefore little shoulder and elbow reaching movements were involved. Greater reaching movements could involve additional EMG components that could reduce the success rate of hand movement classification. This fact should be deeply analyzed if the results are confirmed on larger data sets.

However, the confirmation of the described results with larger data sets, could be an important step toward the natural control of dexterous prostheses. The natural control of 13 movements for daily activities with a standard sEMG setup can improve the quality of life of hand amputated subjects in an important way.

Finally, the results highlight the usefulness of the Ninapro acquisition protocol, as the high number of movements acquired by the protocol permits to choose subsets of movements that can be used with high accuracy.

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