Natural Control Capabilities of Robotic Hands by Hand Amputated Subjects

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***Abstract*— People with transradial hand amputations who own a myoelectric prosthesis currently have some control capabilities via sEMG. However, the control systems are still limited and not natural. The Ninapro project is aiming at helping the scientific community to overcome these limits through the creation of publicly available electromyography data sources to develop and test machine learning algorithms. In this paper we describe the movement classification results gained from three subjects with an homogeneous level of amputation, and we compare them with the results of 40 intact subjects. The number of considered subjects can seem small at first sight, but it is not considering the literature of the field (which has to face the difficulty of recruiting trans-radial hand amputated subjects). The classification is performed with four different classifiers and the obtained balanced classification rates are up to 58.6% on 50 movements, which is an excellent result compared to the current literature. Successively, for each subject we find a subset of up to 9 highly independent movements, (defined as movements that can be distinguished with more than 90% accuracy), which is a deeply innovative step in literature. The natural control of a robotic hand in so many movements could lead to an immediate progress in robotic hand prosthetics and it could deeply change the quality of life of amputated subjects.**

I. INTRODUCTION

Hand prostheses controlled by surface electromyography (sEMG) have been used since the late 1960s [1]. However, they still have several important limits. First, usually they offer only 2 or 3 degrees of freedom and the number of movements that the subjects can perform is therefore limited (usually opening and closing of the prosthesis). The number of movements can be increased using specific control sequences but in these cases the movements are far from being natural and easy to be reproduced. Second, the control systems are not "natural", which means that the movement that the amputee would be doing with the intact hand is different from the movement performed by the prosthesis. Third, the prostheses require long and complicated training procedures. These facts contribute to the scarce diffusion of sEMG prostheses [2]. In the scientific literature, several control schemes based on classifiers have been proposed to solve these control problems [3]. However, these results are still far from the possibility of being applied in practice as any misclassification can have a negative effect.

The Non-Invasive Adaptive Prosthetics (Ninapro) project [4] has the aim to help the scientific progress in the field of sEMG movement recognition with a publicly available benchmark database [1] to develop, test and compare machine learning algorithms.

In this paper we describe the results obtained from the classification of data of three hand amputated subjects acquired within the Ninapro project and we compare the results with the Ninapro database of 40 intact subjects. Finally we find for each subject a selection of up to 9 highly independent movements that can be discriminated with high accuracy.

The application of these results to the prosthetics industry could allow the subjects to naturally control a dexterous robotic hand and can lead to strong improvements to their everyday life.

II. METHODS

A. Data Acquisition

The datasets of the amputated subjects were acquired from three subjects with a transradial amputation of the right forearm proximal to the hand. All the amputations are transradial medium and long below elbow, with a remaining percentage of 90%. The subjects are all males, with clinical characteristics described in Table I. The first subject never used a sEMG prosthesis, while the second and the third subject have been using it respectively for 14 and 5 years. The datasets of the amputated subjects are compared with the datasets from 40 healthy controls (28 males, 12 females; 34 right-handed, 6 left–handed; average age 29.9 years with standard deviation 3.9 years). The number of subjects can seem small at first sight, but (as described in Section I) it is not considering the literature of the field, which has to face the difficulty of recruiting trans-radial hand amputated subjects. Moreover, it must be noticed that the selection of subjects with homogeneous type of amputation (90% of forearm remaining in all the subjects) causes a further reduction in the number of the possible candidates.

The sEMG data were acquired according to the final version of the Ninapro acquisition protocol introduced in [4], [5], [6]. The muscular activity is gathered using 12 active double–differential wireless electrodes from a Delsys Trigno Wireless EMG system, positioned as shown in Figure 1. The protocol includes 6 repetitions of 50 movements represented in Figure 2 and described in detail in [5], [6]. During the

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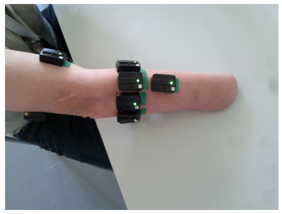
TABLE I

CLINICAL DATA OF HAND AMPUTATED SUBJECTS.

Subject	Age	Missing Hand	Years from Amputation	Remaining Forearm Percentage	Handedness
1	67	Left	1	90	Left
2	44	Right	14	90	Right
3	55	Right	5	90	Right

(a)



(b)

Fig. 1. Forearm of two of the transradial amputated subjects: (a) subject 2; (b) subject 3.

acquisition, the amputated subjects were asked to think to repeat the movements shown on the screen of a laptop according to a bilateral imitation procedure [7], while the intact subjects were asked to repeat the movements with the right hand. Each movement repetition lasted 5 seconds and was followed by 3 seconds of rest.

B. Data Analysis

1) Feature Extraction and Classification: We applied a classification procedure based on [6], [8] consisting of pre-processing, windowing (at 400 ms), feature extraction and classification. Four movement repetitions (1, 3, 4, 6) were used to generate the training features, while the remaining two (2, 5) were used to create the test set. We considered four features and four classification methods, selected upon popularity, previous application to sEMG and to ensure a diversity in approaches. The selected features (Table II) have previously been applied successfully to myoelectric signals [9], [6], [10]. Each feature $\hat{x}$ is computed from signal x of length T and subindexed by t. In Histogram (HIST) [11], B denotes number of HIST bins, and is equal to 20 along a 3σ threshold. For marginal Discrete Wavelet Transform (mDWT), we use $\psi_{l,\tau}$ to denote the mother wavelet with translation l and dilation τ, while the total number of considered translations is referred to as L. In this case we used a db7 wavelet and 3 levels [12].

The four well-known classifiers considered have all been used previously in the related literature. Linear Discriminant Analysis (LDA) [13] has been used extensively for myoelectric control [8] and is representative of classic pattern recognition approaches. Least Squares Support Vector Machine (LSSVM), is the least squares version for support vector machine Support Vector Machine (SVM) classifiers [14], and incorporate kernel machinery and regularization to address non-linearity, noise, and the curse of dimensionality. In this case it was applied with a Radial Basis Function (RBF)

TABLE II

DEFINITION OF THE USED FEATURE TYPES.

Feature	Definition (per channel)
Root Mean Square (RMS)	$\hat{x} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x_t^2}$
Waveform Length (WL)	$\hat{x} = \sum_{t=1}^{T-1} \lvert x_t - x_{t+1} \rvert$
Histogram (HIST)	$\hat{x}_{1:B} = \mathrm{hist}\left(x_{1:t}, B\right)$
marginal Discrete Wavelet Transform (mDWT)	$\hat{x}_l = \sum_{\tau=0}^{T/2^l-1} \left\lvert \sum_{t=1}^{T} x_t \psi_{l,\tau}(t) \right\rvert$
	$\psi_{l,\tau}(t) = 2^{-\frac{m}{2}} \psi(2^{-l}t - \tau)$

kernel. Random forests [15] are a combination of tree predictors which showed excellent performances on sEMG in terms of both accuracy and speed [16]. *k*-Nearest Neighbors (*k*-NN) is a non-parametric technique that classifies samples based on a majority vote among the k closest training samples [13]. In this case, we select the number of neighbors $k \in \{1, 3, 4, 5, 6, 7, 9, 11, 15\}$.

2) Highly Independent Movements: The last step of the analysis consists in the computation of the maximum number of highly independent movements. We define as highly independent movements a subset of movements that can be classified with an accuracy of above 90%. In this way, we reduce the complexity of the task but also show that for fewer movements a very high classification accuracy is possible without training the subject to perform them [17]. Moreover we also get an intuitive idea of the possible practical consequences that the described analysis could have if it was applied to the control of robotic hand prostheses. First, a one-way Multivariate Analysis of Variance (MANOVA) was performed (on the training set of each subject) for comparing the multivariate means of the movements with Mahalanobis distances. Second, a hierarchical cluster tree was created, considering the further distance between clusters (Figure 2). Third, subsets with increasing number of movements from different leaf nodes of the cluster tree were created. Fourth, each subset was classified as described in Section II-B.1. In this phase we only used the Random Forests and the *k*-NN algorithm with Root Mean Square (RMS) and Waveform Length (WL) features because these combinations showed the best balance between accuracy and computational efficiency. Last, we select the largest subset of movements with accuracy greater than 90%.

III. RESULTS

The average classification results for intact and hand amputated subjects (balanced by movement repetitions number) are shown in Figure 3. For amputated subjects, the highest average classification accuracy is 51.60%, which is obtained with Random Forests and HIST features. For intact subjects, the highest average classification accuracy is 69.16%, which is obtained with LSSVM and, again, HIST features. In any case, Random Forests and LSSVM performed very similarly for both groups with all the features. Instead, LDA and *k*-NN seem more sensitive to the feature choice. In particular, LDA

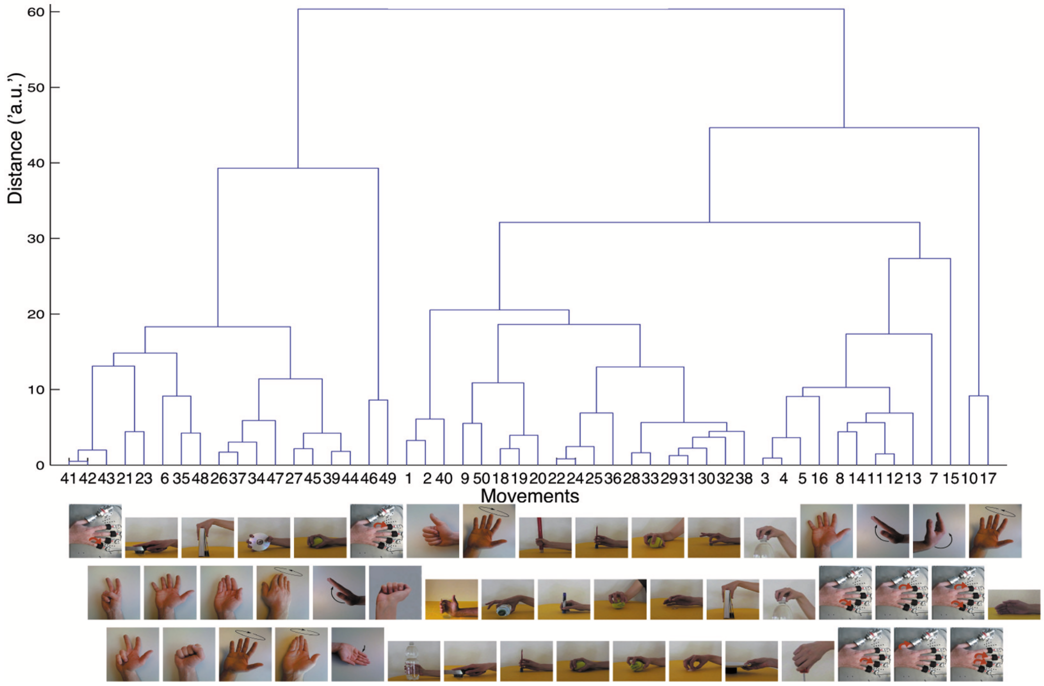


Fig. 2. Example of movement clustering dendrogram used to perform the selection of highly independent movements. Each movement number tick corresponds to the beginning of its picture below it.

shows the lowest average accuracy, while *k*-NN is often comparable to LSSVM and Random Forests for most of the features except mDWT. The highest classification accuracy for amputated subjects is 58.68%, which is obtained for subject 2 with Random Forests and HIST features.

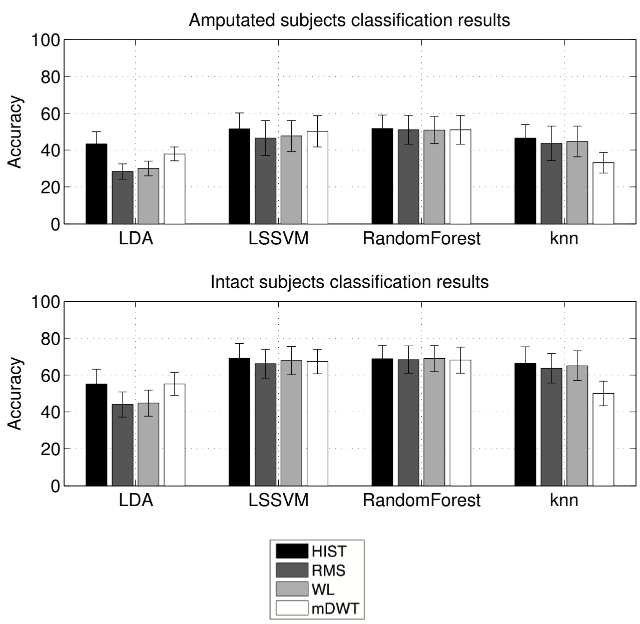


Fig. 3. Average classification results for intact and amputated subjects with standard deviations for the considered classifiers. The results are balanced by movement repetitions number.

Finally, in Figure 4 the average number of highly independent movements is presented with standard deviations for intact and amputated subjects. The average number of independent movements for amputated subjects is approximately 4.58, i.e. 6 movements less than the intact subjects. The highest number of highly independent movements for amputated subjects is 9, which is obtained for subject 2 with both Random Forests and *k*-NN with WL feature. The number of movements decreases to 7 with both classifiers considering RMS.

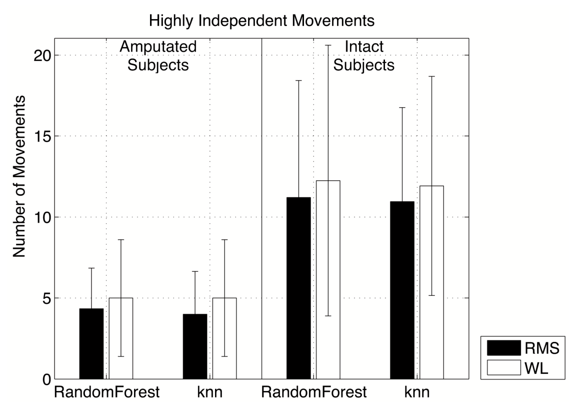


Fig. 4. Average number of highly independent movements with standard deviations for intact and amputated subjects.

IV. CONCLUSION

The sEMG movement classification results that we present in this paper enhance the high control capabilities of dexterous robotic hands by hand amputated subjects. Currently, myoelectric prostheses allow hand amputated subjects to perform a few movements. However, the control possibilities are still limited and not natural. The publicly available Ninapro database has been developed in order to overcome this limit through the evaluation of machine learning algorithms from the worldwide scientific community on a common database. We analyzed the Ninapro sEMG data of three hand amputated subjects with a transradial amputation proximal to the hand and we compare the results to 40 intact subjects.

First, we analyzed the datasets with an average classification perspective per subject. It can be seen in Figure 3 that the highest average balanced classification accuracy for the amputated subjects is 51.60%. This result is more than 25 times the chance level for 50 movements (i.e. 2%) and 20% less than the result obtained for the 40 intact subjects. It has to be noticed that the ratio between the accuracy and the chance level is much higher in this case than in previous results described in the literature for similar tasks, e.g. 8.5 (10 movements, accuracy 84.4%, [18]), 10.56 (12 movements, accuracy 87.8%, [19]). It must be noticed that often the results described in the literature are not balanced among the number of repetitions of each movement. Therefore, they can be strongly influenced by the high number of rest repetitions (which are easier to be classified). Moreover other factors can influence the classification accuracy in different amputated subjects. However, in this specific case these factors do not involve the presence of intrinsic hand muscles (which are not recorded due to anatomical and acquisition setup reasons).

Finally, the highly independent movement selection (Figure 4) highlights the concrete possibility for amputated subjects to control a robotic prosthetic hand with up to 9 different movements with low error. The natural control of so many movements for daily activities could strongly improve the quality of life of hand amputated subjects. It has to be noted that different subsets of movements could also be selected on the basis of other parameters such as the functional usefulness of the movements. This step is deeply innovative in literature, and future studies will be aimed to delineate the subsets of movements that are particularly useful for amputated subjects.

In conclusion, the results show an important step towards the natural control of dexterous prosthetic hands in real life and they strongly enhance immediate development possibilities in this field.

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