Classification of hand movements in amputated subjects by sEMG and accelerometers

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Abstract— **Numerous recent studies have aimed to improve myoelectric control of prostheses. However, the majority of these studies is characterized by two problems that could be easily fulfilled with recent resources supplied by the scientific literature. First, the majority of these studies use only intact subjects, with the unproved assumption that the results apply equally to amputees. Second, usually only electromyography data are used, despite other sensors (e.g., accelerometers) being easy to include into a real life prosthesis control system. In this paper we analyze the mentioned problems by the classification of 40 hand movements in 5 amputated and 40 intact subjects, using both sEMG and accelerometry data and applying several different state of the art methods. The datasets come from the NinaPro database, which supplies publicly available sEMG data to develop and test machine learning algorithms for prosthetics. The number of 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). Our results indicate that the maximum average classification accuracy for amputated subjects is 61.14%, which is just 15.86% less than intact subjects, and they show that intact subjects results can be used as proxy measure for amputated subjects. Finally, our comparison shows that accelerometry as a modality is less affected by amputation than electromyography, suggesting that real life prosthetics performance may easily be improved by inclusion of accelerometers.**

I. INTRODUCTION

Hand prostheses controlled by surface electromyography (sEMG) are normally used in clinical practice but most often 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. The recent introduction of mechatronically advanced prostheses has led to increased research on how electromyography can be used to control highly articulated robotic hands. Especially the advent of modern signal processing and machine learning techniques has resulted in a drastic boost in performance in the research setting. However, the majority of these studies is characterized by two problems that can easily be fulfilled with recent resources supplied by the scientific literature.

First, (due to the difficulty of recruiting amputated subjects) most of previous studies rely on the unproved assumption that the results obtained on intact subjects apply equally to amputees, which is not trivial because the amputation causes changes to the muscular anatomy and physiology (that may affect also myoelectric control performance). An extensive literature review by Peerdeman et al. [1] reveals that most of the studies aimed to the control of robotic hands concentrate almost exclusively on intact subjects performing less then 10 movements (with a maximum of 12 intact subjects performing 6 different movements [2]). Some other studies analyzed the combination of the two modalities in the recognition of sign language in intact subjects [3, 4], but this aim is far from the functional needs of hand amputated subjects. The few studies that include also amputated subjects usually consider less then 5 of them and (according to our knowledge) the maximum number of amputated subjects in a journal paper is 6 (performing only 10 different movements) [5]. Few studies compared the myoelectric performance of the intact arm with the one of amputated arm in unilateral amputees [6, 7], while other studies compared performance of transradial amputees with intact subjects [8, 9, 10] without assessing the possibility to use intact subjects results as a proxy measure for amputated subjects. Only Scheme et al. [11] compare performance of multiple classification methods, noting the consistency of the relative performance between intact and amputated subjects. However, the authors do not provide statistical tests to establish this consistency, nor do they compare performance of different feature extraction methods. So even though their observation reinforces the acceptability of comparing algorithms using data from intact subjects, it does not provide conclusive evidence.

Second, the majority of these studies use only electromyography data, despite other sensors (e.g., accelerometry (ACC)) being easy to include into a real life prosthesis control system. The use of ACC in the classification of hand movements was recently proposed on intact subjects [12, 13, 14], and it poses the question if accelerometry as a modality is less affected by amputation than electromyography (EMG). The potential use of accelerometers on amputated subjects is particularly interesting from a practical point of view, since their small size and low cost means that they could easily be integrated in prosthetic sockets.

In this paper we analyze the two mentioned problems by the classification of 40 hand movements in 5 amputated and 40 intact subjects, using both sEMG and accelerometry data and applying several different state of the art methods. The datasets come from the Non-Invasive Adaptive Prosthetics (NinaPro) Project [15], which has the aim to help the sci-

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TABLE I

CLINICAL DATA OF HAND AMPUTATED SUBJECTS.

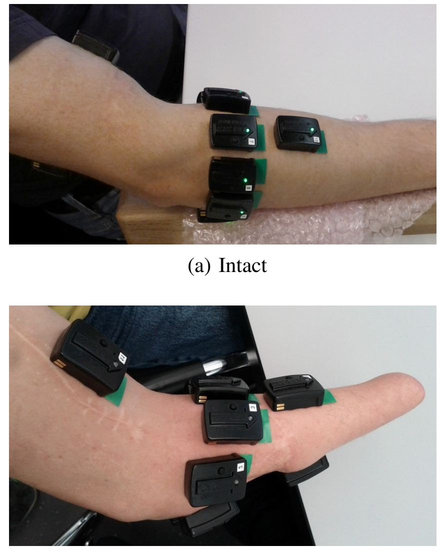
Subject	Age	Missing Hand	Years by Amputation	Remaining Forearm (%)	Handedness
1	50	Right	5	30	Right
2	67	Left	1	90	Leftt
3	35	Right	7	0	Right
4	44	Right	14	90	Right
5	45	Right	15	90	Right

entific progress in the field of sEMG movement recognition with a publicly available benchmark database. The number of amputated subjects can seem small at first sight, but it is not considering the literature of the field (described at the beginning of this section), which has to face the difficulty of recruiting trans-radial hand amputated subjects. Our results indicate that the maximum average classification accuracy for amputated subjects is just 15% less than intact subjects and that intact subjects results can be used as proxy measure for amputated subjects under some assumptions. Moreover, our comparison shows that accelerometry as a modality is less affected by amputation than electromyography, suggesting that prosthetic performance may easily be improved by inclusion of accelerometers.

II. EXPERIMENTAL SETUP

The amputated subjects group is composed by five trans-radial amputated male subjects with clinical characteristics described in Table I. The control group is composed by intact subjects (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 hand amputated subjects. The sEMG data were acquired according to the final version of the NinaPro acquisition protocol, which includes 6 repetitions of 50 movements. While subjects performed the sequence of movements as instructed by a video stimulus, their myoelectric signals were continuously recorded using 12 Delsys^{TM} Trigno wireless electrodes (see Figure 1a). Each of these electrodes also integrates a 3-axis accelerometer that measures a combination of mechanomyography (MMG) and overall arm dynamics. Details about the acquisition protocol and the movements can be found in the dedicated papers [15, 16]. In particular, the movements are exactly the same ones described in the journal paper by Gijsberts et al. [17].

We followed the classification setting used by Gijsberts and Caputo [12], which is based on the popular control scheme by Englehart and Hudgins [18] consisting of preprocessing, windowing, feature extraction, and finally classification. Since our goal is to investigate whether classification performance behaves similarly for intact and amputated subjects, we intentionally introduce variation by considering a diverse set of feature extraction and classification methods.



(a) Intact

(b) Amputee

Fig. 1. Example of electrode placement (a) on an intact subject and (b) on an amputee. Note specifically the difference in limb volume.

TABLE II

FEATURE CONFIGURATIONS.

Name	Modality	Window	Configuration
RMS	sEMG	400 ms	
WL	sEMG	400 ms	
mDWT	sEMG	400 ms	db7 wavelet, 3 levels
HIST	sEMG	400 ms	20 bins, 3σ threshold
MEAN	ACC	400 ms	

These methods were selected both based on popularity and to ensure a diversity in approaches.

The selected feature extraction methods are Root Mean Square (RMS), Waveform Length (WL), sEMG Histogram (HIST) [19], and marginal Discrete Wavelet Transform (mDWT) [20]. All these feature representations were applied successfully to myoelectric signals in general and on the NinaPro dataset in particular [21, 12, 17]. Furthermore, they represent a rather diverse set of approaches, covering traditional and low-dimensional (RMS), popular (WL), advanced (mDWT), and high-dimensional (HIST) representations. Table II summarizes the configuration for each of the feature types.

While Gijsberts et al. [17] only considered a non-linear Kernel Regularized Least Squares (KRLS) classifier, here we diversify the classification step by also including Linear Discriminant Analysis (LDA) and k-Nearest Neighbors (k-NN). LDA is a well-known statistical method to find a linear discriminant that maximizes the ratio of between-class scatter to within-class scatter [22]. It has been extensively used for myoelectric control [18] and is representative of classic pattern recognition approaches. This is in contrast to the more recent machine learning techniques such as KRLS or Support Vector Machines, which incorporate kernel machinery and regularization to address non-linearity, noise, and the curse of dimensionality. Finally, k-NN is a non-parametric technique

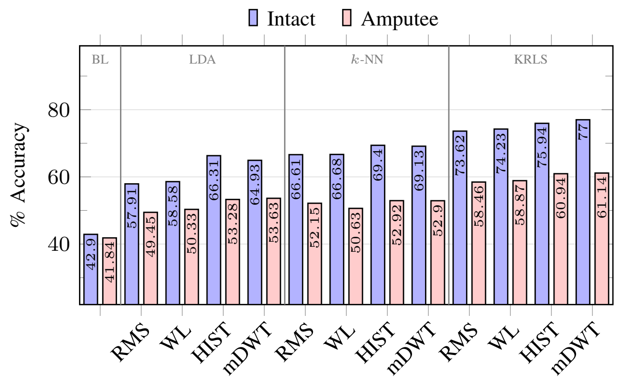


Fig. 2. Average classification accuracy for intact and amputated subjects for the baseline (BL) and the twelve combinations of features and classifiers.

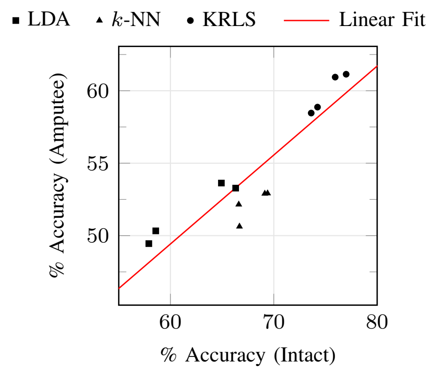


Fig. 3. Average classification accuracy for intact subjects versus that of amputated subjects for the nine combinations of features and classifiers. The linear regression with an intercept of 12.59% and a slope of 0.61 obtains a reasonably good fit of $R^2 = 0.83$.

that classifies samples based on a majority vote among the k closest training samples [22]. Unlike KRLS and LDA, it directly transduces label information from the training samples to the test samples without first inducing a model. Despite its conceptual and computational simplicity, it can achieve excellent performance provided that sufficient training data is available. Based on prior experience [12], the KRLS classifier has been used with the exp-χ^2 kernel for all considered feature representations. The kernel parameter γ and the regularization parameter λ are optimized using grid search, where $\gamma \in \{2^{-20}, 2^{-19}, \ldots, 2^3\}$ and $\lambda \in \{2^{-16}, 2^{-15}, \ldots, 2^3\}$. For k-NN, we instead select the number of neighbors $k \in \{1, 3, 4, 5, 6, 7, 9, 11, 15\}$. Furthermore, integration of sEMG and ACC is implemented for the KRLS classifier by a linear combination of cue-specific kernels [17], where the kernel weights $w \in \{0.0, 0.1, \ldots, 1.0\}$ were chosen such that $w_{\text{sEMG}} + w_{\text{ACC}} = 1$.

III. RESULTS

The average classification accuracy for the twelve combinations of feature extraction and classification methods are shown in Figure 2. The figure also contains a baseline result, which is defined as the accuracy obtained when predicting exclusively the most frequent class (i.e., the rest posture). The performance for amputees is always less than 20% inferior to the performance for intact subjects. The decrease in performance is relatively constant over all considered methods. This implies that the ranking among methods should be largely similar for both groups of subjects. Figure 3 demonstrates that large performance differences are indeed preserved when moving from intact subjects to amputees. For instance, the best and worst performing methods are identical for both groups (i.e., KRLS/mDWT and LDA/RMS). We observe some disagreements, however, in the central cluster in Figure 3, where performance differences are less pronounced (cf. k-NN and LDA with HIST and mDWT features in Figure 2). In particular, the performance penalty is larger for k-NN than for the other two methods. The small performance differences within this central cluster are however not statistically significant for the group of amputated subjects (sign test, $p \geq 30\%$) and may therefore be an artefact caused by the small sample size. Furthermore, even when considering these accuracies "as-is", we find a positive rank correlation[1] between both groups of subjects of $\tau = 0.70$. This rank correlation is in fact found to be significant (τ-test, $p = 1.6‰$), meaning that results obtained on intact subjects are indeed statistically correlated with those of amputees. A similar result can be obtained using regression analysis (see Figure 3), which estimates a positive and statistically significant regression coefficient of 0.61 between both groups (Student's t-test, $p \leq 1‰$). Figure 4 provides additional insight on how performance is distributed within the subject groups. We observe that the extrems are much further apart among amputees than among intact subjects. While performance for one amputee did not significantly exceed the baseline, the best case performance for another amputated subject was actually higher than the median result among intact subjects, regardless of the employed feature extraction and classification method. It is obvious that the heterogeneity of amputations (and medical causes that require amputation) introduces additional variability as compared to the anatomically more homogeneous intact control group. For instance, the amputated subject whose performance did not improve over the baseline was reported to have 0% remaining forearm length. Medical aspects of the amputation (e.g., remaining forearm length, trauma or not, etc.) will therefore have to be considered on an individual basis, as these are decisive factors that influence classification performance (see also [9]).

Figure 5 compares the accuracy distribution when using either sEMG, accelerometry, or a combination of both modalities (i.e., multi-modal). We observe that performance for the ACC-only and multi-modal methods is considerably higher than the sEMG-only counterparts and also more consistent among amputated subjects. Both observations suggest that accelerometry is indeed less affected by amputation

[1] Kendall's τ is a rank correlation coefficient that ranges between 1 (perfect agreement) and -1 (perfect disagreement). The corresponding τ-test tests the null hypothesis that the quantities are statistically independent.

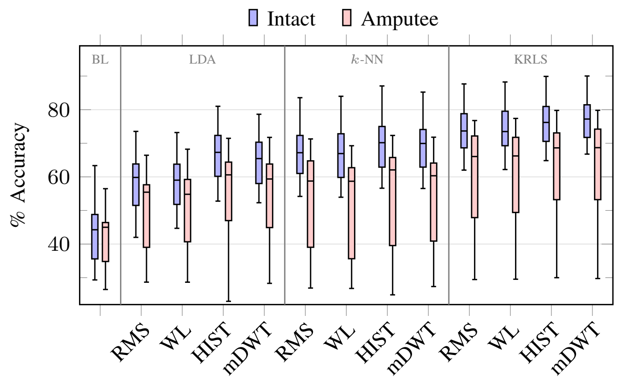


Fig. 4. Boxplots of the classification accuracy for intact and amputated subjects for the baseline (BL) and the nine combinations of features and classifiers. For the group of intact subjects, each boxplot reports the median, the first and third quartiles, and the extrema.

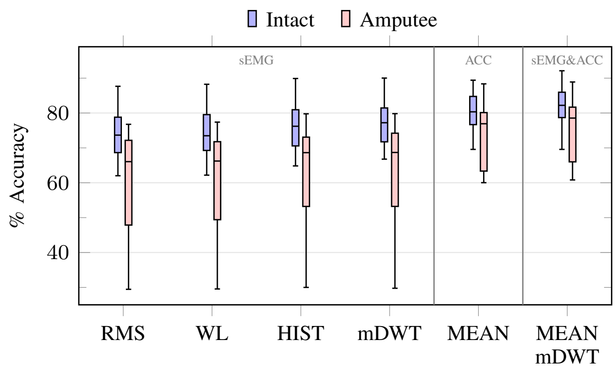


Fig. 5. Boxplots of the classification accuracy for intact and amputated subjects for the KRLS classifier. Results are reported for the three sEMG feature types, for the MEAN feature type when using accelerometry, and finally for the combination of mDWT and MEAN features extracted respectively from the sEMG and ACC modalities. For the group of intact subjects, each boxplot reports the median, the first and third quartiles, and the extrema.

than surface electromyography. The maximum performance of the multi-modal classifier is nearly identical for intact and amputated subjects (i.e., 92.1% and 88.9%), which compares favorably to the sEMG-only case (i.e., 90.0% and 79.8%). However, the most relevant advantage of including accelerometry is that it increases minimum performance among amputees from approximately 30% in the sEMG-only case (i.e., similar to baseline performance) to more than 60%.

IV. CONCLUSIONS

A large number of studies have compared different approaches to myoelectric control of robotic hands. However, the majority of these studies is characterized by two problems that we addressed in this paper. First, most of studies have compared different approaches to myoelectric control using solely intact subjects, relying on the unproved assumption that the performance on intact subjects is representative for amputees as well. This assumption is not trivial, since amputation causes changes to the muscular anatomy and physiology that may affect myoelectric control performance. Second, usually only electromyography data are used, despite other sensors (e.g. accelerometers) could be easily included into a real life prosthesis control system. In this paper we analyze the mentioned problems by the classification of 40 hand movements in 5 amputated and 40 intact subjects, using both sEMG and accelerometry data and applying several different state of the art methods. The number of subjects can seem small at first sight, but it is not considering the literature of the field (described in Section I).

Our results indicate that the maximum average classification accuracy for 5 amputated subjects is 61.14%, which is just 15.86% less than intact subjects. This result is obtained with a KRLS classifier and mDWT features, and it is very important especially considering the number of classes, which is very high compared to the literature of the field. Only one previous study by Atzori et al. [23] addressed the classification of more than 12 movements in amputated subjects, but it considered only one amputated subject and needed therefore a confirmation on more data. It must be noted also that theoretically the accuracy can be increased strongly reducing the number of movements.

The comparison of three classification methods combined with four feature extraction methods reveals a statistically significant rank correlation between accuracy obtained with intact subjects and amputated subjects ($p = 1.6‰$). Although this implies that intact subjects can indeed be used as proxy measure, one should be aware that (1) the rank correlation is not necessarily perfect, (2) performance for amputees is considerably worse than for intact subjects, and (3) the variability among amputated subjects is higher. It must be noticed that the classification results are not balanced according to the movement repetition number.

Accelerometer data are included into the NinaPro database, and in this work we evaluate also the benefit of using accelerometry as an additional control modality. Our results show that accelerometry is less affected by amputation than surface electromyography, as suggested by a recent study on intact subjects by Gijsberts and Caputo [12]. Including accelerometry yields drastic increases in performance for intact as well as amputated subjects, while also the variability among amputated subjects is found to be much smaller. This indicates that accelerometry prosthetic performance may easily be improved by inclusion of accelerometers.

In conclusion, the results represent an important step towards the natural control of dexterous prosthetic hands. First, they contribute to improve the comprehension of past and future studies based only on intact subjects, justifying their use as a proxy measure for amputees in preliminary analyses. Second, they show that improving the accuracy by combining sEMG and accelerometry into a standard setup would bring the results closer to real life natural control needs, which could strongly improve the quality of life of hand amputated subjects.

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