# Effects of Prosthesis Use on the Capability to Control Myoelectric Robotic Prosthetic Hands*

Manfredo Atzori, Anne-Gabrielle Mittaz Hager, Simone Elsig, Giorgio Giatsidis, Franco Bassetto, and Henning Müller

*Abstract*— **The natural control of robotic prosthetic hands with non-invasive techniques is still a challenge: myoelectric prostheses currently give some control capabilities; the application of pattern recognition techniques is promising and recently started to be applied in practice but still many questions are open in the field.**

**In particular, the effects of clinical factors on movement classification accuracy and the capability to control myoelectric prosthetic hands are analyzed in very few studies. The effect of regularly using prostheses on movement classification accuracy has been previously studied, showing differences between users of myoelectric and cosmetic prostheses.**

**In this paper we compare users of myoelectric and body-powered prostheses and intact subjects. 36 machine-learning methods are applied on 6 amputees and 40 intact subjects performing 40 movements. Then, statistical analyses are performed in order to highlight significant differences between the groups of subjects. The statistical analyses do not show significant differences between the two groups of amputees, while significant differences are obtained between amputees and intact subjects. These results constitute new information in the field and suggest new interpretations to previous hypotheses, thus adding precious information towards natural control of robotic prosthetic hands.**

## I. INTRODUCTION

The natural control of robotic prosthetic hands with non-invasive techniques is still a challenge in real life. Surface electromyography (sEMG) currently gives limited control capabilities. In most cases the movements that the prosthesis can perform are limited to opening and closing but the top-level commercial offers can perform several movements usually relying on sequential control strategies. The use of pattern recognition techniques has been described in the scientific literature (e.g. [1]–[3]) and recently started to be applied in practice (http://www.coaptengineering.com/). This approach usually relies on several sEMG electrodes and pattern recognition algorithms to classify the movement that the subject aims to perform. Targeted muscular reinnervation [4] obtained excellent results, but this technique is invasive. Non-invasive studies show classification accuracy up to 90% on approximately 10 movements [2], [3] but average results are usually below 80-90% [1].

A considerable number of publications study the engineering and computational problems involved in the field. However, very few publications study the effects of the patient characteristics, while clarifying such effects can lead to improve the control capability through an improved cooperation between surgeons, therapists and amputated subjects. One of the few studies in the field is the one by Cipriani et al. [2], in which the authors analyze the effect of regularly using prostheses on movement classification accuracy by comparing 2 myoelectric hand users, 2 cosmetic hand users and 5 intact subjects. Statistical analysis of the data revealed a difference in control accuracy based on the type of prostheses regularly used. The mentioned paper showed also significant differences between cosmetic users and able-bodied participants, while myoelectric users and intact subjects were not statistically different. The acquisition protocol included the bilateral repetition of 7 hand movements (3 repetitions training, 3-6 repetitions testing) and it was repeated three times, showing an improvement of the accuracy during the experiment. The movements were classified using as signal feature the mean of the absolute value (MAV) and as classifier the k-nearest neighbour algorithm (k-NN, with k=8 and Euclidean distance as the distance metric).

In this paper we analyze the effect of regularly using prostheses on movement classification accuracy by comparing 3 myoelectric prosthesis users (myo users), 3 body-powered prosthesis users (body-powered users) and 40 intact subjects. The used approach and the statistical analyses are very similar to what was described by Cipriani et al. in order to make the results as comparable as possible. 36 machine learning methods are applied on data from the Ninapro database[1] [5], a publicly available resource including 11 amputated subjects and 67 intact subjects performing up to 52 different hand movements. Statistical analyses do not show any significant difference between the amputated subjects, while significant differences are obtained between amputees and intact subjects. These results constitute new information in the field and suggest new interpretations to previous hypotheses, thus adding precious information towards natural control of robotic prosthetic hands.

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M. Atzori and H. Müller are with the Institute of Information Systems, University of Applied Sciences Western Switzerland, Sierre, 3960 Switzerland. (phone: +41 e-mail: {manfredo.atzori,henning.mueller}@hevs.ch).

S. Elsig and A.G. Mittaz Hager are with the School of Health Sciences, Physiotherapy, University of Applied Sciences Western Switzerland, Leukerbad, 3954, Switzerland. (e-mail: simone.elsig@gmail.com, gaby.mittaz@hevs.ch).

G.Giatsidis and F. Bassetto are with the Clinic of Plastic Surgery, Padova University Hospital, 35128, Padova, Italy. (e-mail: giorgio.giatsidis@gmail.com, franco.bassetto@unipd.it).

[1] http://ninapro.hevs.ch/

## II. Methods

### A. Subjects

Six transradially amputated subjects and forty intact subjects participated in this study. The subjects answered to a questionnaire that included generic parameters (such as age, gender, height, weight and handedness) and the assessment of clinical parameters and other factors, including type of used prosthesis (cosmetic, body-powered, myoelectric), total use of the prosthesis (years of use) and average daily use (hours) (Table I). The amputated subjects are all males with average age 44.5±12.2 years. The intact subject group includes 28 males and 12 females, 34 right handed and 6 left handed with average age of 29.9 ± 3.9 years. The experiment was conducted according to the Declaration of Helsinki and it was approved by the ethics commission of the state of Valais (Switzerland). All participants signed an informed consent form.

TABLE I. AMPUTEES CHARACTERISTICS & PROSTHESIS USE

| Subject | Handedness | Amputated Hand(s) | Performed Movements | Analyzed Movements | Used Electrodes | Prosthesis Use *(total, years)* | | | Prosthesis Use *(daily, hours)* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Cosmetic | Body-powered | Myoelectric | Cosmetic | Body-powered | Myoelectric |
| 1 | Right | Right | 39 | 29 | 12 | 0 | 0 | 13 | 0 | 0 | 8 |
| 2 | Left | Left | 50 | 40 | 12 | 0 | 0.4 | 0 | 0 | 12 | 0 |
| 3 | Right | Left | 50 | 40 | 10 | 0 | 12 | 0 | 0 | 12 | 0 |
| 4 | Right | Right | 50 | 40 | 12 | 0 | 0 | 4 | 0 | 0 | 12 |
| 5 | Right | Right | 50 | 40 | 12 | 0 | 0 | 14 | 0 | 0 | 8 |
| 6 | Right | Right | 43 | 40 | 12 | 0 | 1.66 | 0 | 0 | 14 | 0 |

### B. Acquisition Setup and Protocol

The data used in this paper come from the second and the third NinaPro database that is thoroughly described in [5]–[7]. The considered exercises are the first and the second one, including a total of 40 hand and wrist movements plus rest. Muscular activity is measured using 12 double differential sEMG electrodes (Delsys Trigno Wireless System). Myoelectric signals are sampled at a rate of 2 kHz with a baseline noise of less than 7 50 nV RMS.

The electrodes were placed combining two methods which are common in the field, i.e. a dense sampling approach [8] and a precise anatomical positioning strategy [9]. Eight electrodes are equally spaced around the forearm at the height of the radio humeral joint; two electrodes are placed on the main activity spots of the muscle flexor digitorum superficialis and of the muscle extensor digitorum superficialis; two electrodes are also placed on the main activity spots of the biceps brachii and of the triceps brachii.

During the acquisitions, subjects were seated at a desk resting their arm comfortably on the desktop. A laptop in front of the subject provided visual stimuli for each movement while at the same time recording data from the measurement devices. The intact subjects were asked to mimic movies of movement shown on the screen of the laptop with their right hand, while amputated subjects were asked to mimic the movements shown on the screen of a laptop with the missing limb as naturally as possible. The set of movements was selected from the hand taxonomy, robotics, and rehabilitation literature [10]–[13]. Each movement repetition lasted 5s, and it was alternated with a rest posture lasting 3s. The sequence of movements was not randomized in order to encourage repetitive, almost unconscious movements.

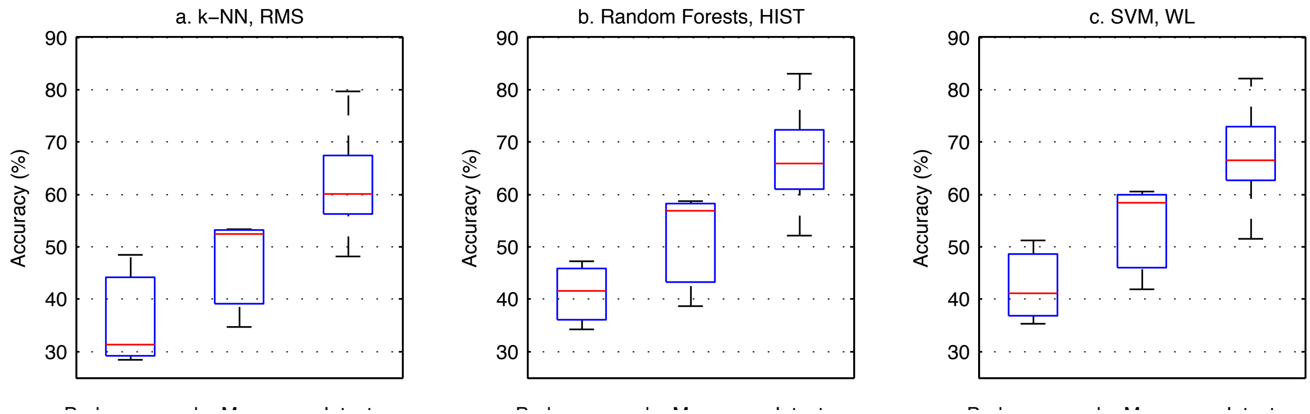
### C. Data Analysis

The classification procedure is relatively standard for the field. We followed the setting used by Gijsberts et al. [14], which is based on the popular control scheme by Englehart and Hudgins [15] consisting of preprocessing, windowing, feature extraction, and finally classification.

We considered 5 features extracted from the signals and 9 classification methods, selected upon popularity, previous application to sEMG and to ensure diversity in approaches. Root Mean Square (RMS) is commonly used for sEMG. It is easily implementable and it has a strong relationship with the force exerted by a muscle [9]. Waveform length (WL) is a robust and efficient feature to analyze sEMG [16] and it was previously applied on the Ninapro database [17]. sEMG Histogram (HIST) [18] is the histogram of the time window given a predefined number of bins (in this case twenty) and it has demonstrated excellent performance for sEMG-based movement classification [17], [18]. The feature was computed on the Ninapro database [14]. The marginal Discrete Wavelet Transform (mDWT) decomposes the signal in terms of a basis function (in this case the 7th order Daubechies wavelet) at different levels of resolution, resulting in a high-dimensional frequency-time representation, preserving only the marginals at each level of the decomposition. The feature was computed as previously on the Ninapro database [14]. The 5th feature was computed as the normalized concatenation of the others [19].

The used classifiers are well known, and they were previously applied to sEMG analysis. They include: k-Nearest Neighbors [20] ($k \in [1,15]$); Least Squares Support Vector Machines (LSSVM) [21] and Support Vector Machines (SVM) [22] (Radial Basis Function kernel; hyper-parameters tuned for each subject by grid search respectively with multiple fold cross-validation), Random Forests [23] (100 decision trees), Discriminant Analysis (Linear, Naive Bayes Linear, Quadratic, Naive Bayes Quadratic, Mahalanobis) [24]. Only low-dimensional features (RMS, WL) were used with Quadratic, Naive Bayes Quadratic and Mahalanobis Discriminant Analysis due to computational issues (i.e., singular covariance matrix). 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.

Figure 1: Examples of classification accuracies for myo-electric users, body-powered users and intact subjects with several classifiers (a. k-nearest neighbour, b.random forests and c. support vector machines) and several features (a. root mean square, b. all features, c. waveform length). The central mark in the boxes is the median; the edges of the box are the 25th and 75th percentiles; whiskers extend to approximately 2.7 times the standard deviation.




The Friedman test and the Kruskal-Wallis test with two and three groups were applied to compare body-powered users, myo users and intact subjects, similarly to what performed in previous literature (Cipriani et al. [2]). Each feature-classifier combination was tested separately. Bonferroni correction was used in comparisons involving all the three classes.

## III. Results

The average classification accuracy and standard deviation for each of the three groups are reported in Table II. The highest classification accuracy for amputees is 54.59%, which corresponds to 21.8 times the chance level.

The Friedman test (performed also by Cipriani et al. [2]) and the Kruskal-Wallis test do not show any significant difference between myo users and body-powered users with any feature-classifier combination.

The Kruskal-Wallis test with Bonferroni correction for multiple comparisons was also performed to compare myo users, body-powered users and intact subjects, highlighting significant differences ($p<0.05$) between amputated and non-amputated subjects for each of the 36 feature-classifier combination, but to no significant differences between body-powered and myo users and users.

## IV. Conclusions

This work has impact on the field of sEMG controlled dexterous hand prosthetics. In particular, it suggests that factors different from myoelectric use can also affect classification accuracy, thus obfuscating in some cases the significant effects of myoelectric prosthesis use.

The highest accuracy for amputated subjects is 54.59%. The result can seem lower than other studied analyzing fewer classes but it is definitely not considering the very low chance level (2.44%) due to the high number of classes. In particular, the ratio between the accuracy and the chance level is 22.37 in the reported case, while previous results described in literature for similar tasks are, for example, 8.5 (10 movements, accuracy 84.4% [25], 10.56 12 movements, accuracy 87.8% [8]). A more extended explanation of this, is described in Atzori et al. 2014 [5].

TABLE II. Movement Classification Accuracy (%)

| Classifier | Feature | Body-powered | Myo | Intact |
|---|---|---|---|---|
| SVM | All | 45.49±7.38 | 54.59±11.10 | 70.58±7.60 |
| | HIST | 44.30±7.20 | 53.27±11.84 | 68.94±8.57 |
| | RMS | 41.93±10.75 | 53.19±10.69 | 66.10±7.43 |
| | WL | 42.56±8.01 | 53.62±10.18 | 67.88±7.50 |
| | mDWT | 41.68±9.76 | 49.74±11.08 | 63.84±7.33 |
| LSSVM | All | 43.12±7.37 | 52.92±12.52 | 69.40±7.92 |
| | HIST | 41.50±7.97 | 51.57±12.27 | 67.34±8.60 |
| | RMS | 36.98±9.12 | 48.55±11.97 | 63.78±8.36 |
| | WL | 37.33±7.16 | 49.01±10.95 | 65.59±8.33 |
| | mDWT | 40.38±10.71 | 49.49±12.47 | 64.69±7.42 |
| Random Forests | All | 43.69±7.97 | 54.59±10.57 | 68.72±7.33 |
| | HIST | 41.09±6.53 | 51.44±11.09 | 66.50±7.77 |
| | RMS | 41.37±8.13 | 52.92±10.02 | 66.21±7.74 |
| | WL | 40.21±7.71 | 52.37±10.15 | 66.80±7.83 |
| | mDWT | 40.71±7.08 | 51.90±10.71 | 65.81±7.47 |
| k-nn | All | 36.21±6.97 | 46.36±10.70 | 63.24±9.01 |
| | HIST | 36.55±7.13 | 46.35±10.82 | 64.11±9.49 |
| | RMS | 36.08±10.82 | 46.86±10.56 | 61.19±8.23 |
| | WL | 36.39±9.04 | 46.77±10.30 | 62.81±8.43 |
| | mDWT | 26.34±4.13 | 33.92±8.63 | 48.06±6.88 |
| Linear | HIST | 38.83±10.00 | 42.54±7.95 | 55.16±8.04 |
| | RMS | 30.65±13.42 | 29.44±5.60 | 41.50±6.69 |
| | WL | 31.04±12.03 | 29.47±5.77 | 42.66±6.97 |
| | mDWT | 37.90±12.82 | 39.34±8.19 | 53.36±6.60 |
| Naive Bayes Linear | HIST | 27.64±12.38 | 23.38±8.29 | 37.73±7.35 |
| | RMS | 27.97±12.02 | 23.22±8.60 | 37.89±7.69 |
| | WL | 25.33±13.51 | 20.98±7.51 | 33.24±6.79 |
| | mDWT | 24.93±12.36 | 21.32±6.84 | 33.29±6.80 |
| Quadr. | RMS | 21.37±7.80 | 18.75±6.21 | 31.01±6.07 |
| | WL | 36.53±11.24 | 45.90±10.93 | 59.14±7.90 |
| Naive Bayes Quadr. | RMS | 36.77±9.13 | 46.66±10.24 | 61.29±7.66 |
| | WL | 25.63±10.72 | 25.38±8.31 | 39.13±7.88 |
| | mDWT | 25.36±8.21 | 25.31±8.50 | 39.39±7.81 |
| Mahal. | RMS | 21.74±6.47 | 21.93±7.56 | 34.16±7.06 |
| | WL | 33.20±10.85 | 41.09±9.21 | 52.87±8.07 |

The statistical analyses do not show significant differences between users of myoelectric prosthesis and users of body-powered prostheses, while significant differences are obtained between the groups of amputees and intact subjects. This result is particularly interesting if considered together with the results by Cipriani et al. [2], that showed significant differences between users of myoelectric prosthesis and users of cosmetic hand prostheses, as well as the statistical equality of myoelectric users and intact subjects.
Our results do not confirm the statistical equality of myoelectric users and intact subjects described by Cipriani, and they do not even show a non-significant trend. However, visual inspection of the results (e.g. Figure 1) often shows that myo users are closer to intact subjects than body-powered users. This is similar to what obtained by Cipriani if we assimilate body-powered users to cosmetic users (since both the groups are not trained to use the finger muscles located in the remaining forearm). With few subjects statistical significance can be reached easily, since one strong result can influence this, so studies with a larger group of persons would seem necessary.

The differences between the two studies can be due to differences among the subjects, the acquisition protocols and the analyses. In particular, since the Ninapro acquisition protocol lasts approximately 1.5 hours, the body-powered users could get trained during the experiment, thus reducing their difference from myo users, as described by Cipriani and confirmed by the comments of several amputated subjects who participated to the experiment. Our hypothesis (suggested also by preliminary analyses on the eleven amputated subjects included in the third Ninapro database) is that movement classification accuracy can be strongly influenced by several factors, including clinical characteristics of the amputation and training. Further studies considering the effect of clinical parameters on the entire third Ninapro database are currently under peer review.

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