Spatial Registration of Hand Muscle Electromyography Signals

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Abstract

Currently, surface electromyography (sEMG) prostheses are characterized by low control capabilities and long training times. This is in contrast with recent advances in mechatronics, thanks to which mechanical hands have often many degrees-of-freedom and force control. Therefore, there is a need of techniques able to increase control capabilities with sEMG signals.
Several reasons determine differences in the signal patterns, and make the classification of sEMG signals a challenging task. One of the reasons is the positioning of the electrodes on the subjects. In this paper we evaluate the positioning effect on the Ninapro database using automatic classification of the data for its evaluation.

Keywords *prosthetics, surface electromyography, sEMG, signal processing*

1 Introduction

Subjects with hand amputations often interface with prosthesis via surface electromyography (sEMG) but learning to control the device is frequently a long and difficult process.

Currently, hand prosthetics usually does not offer more than 2-3 degrees of freedom (usually, open/close is the only movement possible) and a very coarse control of the force. This is in contrast with recent advances in mechatronics, thanks to which mechanical hands with many degrees of freedom and fine-grained force control are being built. The NinaPro (Non-Invasive Adaptive Hand Prosthetics, http://www.idiap.ch/project/ninapro/) project started in January 2011 with the aim of fulfilling the need of easy and natural controls for the dexterous prostheses, and the need to provide the scientific community with a large dataset of sEMG signals to test and evaluate the classification procedures. The main goal of this project is to develop a family of algorithms able to significantly augment the dexterity control of EMG prostheses and to reduce the required training time.

The current NinaPro data set is stored in a database with a web interface: it consists of data from 27 healthy human subjects. Besides basic data on the subjects such as age, gender, etc. it also contains signal data in the form of 10 repetitions of 52 different hand/wrist movements.

For each subject, the sEMG signal is acquired using ten electrodes. Two electrodes are placed according to anatomical guidelines [1,2]. The remaining eight electrodes are placed uniformly around the forearm following the main trend in pattern matching research [3,4,5]. In order to maintain a constant positioning among subjects, the electrodes are placed at a constant distance from the radio-humeral joint.

The inter-subject difference in the positioning of the electrodes is probably an important reason that contributes to making the classification of sEMG signals a challenging task. The sEMG signal classification has been treated in several publications [6,7,8]. However less papers analyse the effect of positioning differences and the use of spatial co-registration methods for sEMG signals [9,10], also if the effect of positioning can have a very strong impact on classification results [9].

In this paper we evaluate the effect of inter-subject differences in the positioning of the electrodes on the Ninapro database and on machine learning classification of the sEMG data, and the possibility to compensate it through spatial registration of the signal.

2 Methods

The acquisition setup of the Ninapro data is shown in Fig. 1. It is composed of: a laptop with a PCMCIA Slot (DELL Latitude E5520); a digital acquisition card (National Instruments DAQCard-6024E, PCMCIA); ten sEMG electrodes (Otto Bock 13E200); a Cyberglove II (CyberGlove Systems LLC) with 22 sensors; a 2-axes inclinometer (Kübler 8.IS40.23411); custom-made acquisition software implemented to acquire the data of all the peripherals in a synchronized way; a password protected web-based interface to the database to store the data.

Intact subjects wear the sEMG electrodes, the dataglove and the inclinometer on the right hand, while amputated subjects wear the sEMG electrodes on the stump and the dataglove and the inclinometer on the intact limb.

The current NinaPro database includes 10 repetitions of 52 different movements for 27 intact subjects. The movements are based on the robotics and taxonomy literature such as the DASH (Disabilities of the Arm, Shoulder and Hand) protocol for functional movements [11]. Each movement lasts 5 seconds, is followed by 3 seconds of rest and is repeated 10 times.

To evaluate the effect of changes in the positioning of the electrodes among subjects (Fig. 2), we considered the eight electrodes that are equally spaced on the elastic armband and two sets of movements selected from the Ninapro database: 1) three grasp movements considered in [12] and the resting position (Tab. 1); 2) eleven of the twelve movements considered in [14] and the resting position (Tab. 2).

We assumed the distance between each electrode and the axial coordinate of the armband on the forearm to be constant while we considered the armband liable to rotation.

First, we simulated the rotation of the armband on the arm through the linear interpolation of the signals from the subsequent electrodes. The simulated rotation is performed both in clockwise and anticlockwise direction at steps of 1/10 of the distance between each of the electrodes (that, depending on the subject, corresponds approximately to 2-5 mm). The rotation simulation ends when the simulated position of the electrodes meets the position of the non-rotated previous or following one.

In order to evaluate the similarity between the signals across subjects and the effect of the rotation simulation, first we measured the distance between the sEMG signals obtained from of each subject both in the original configuration and in the twenty different forms obtained by the rotation simulation. The mentioned evaluation was performed on the first 29 movements included in the Ninapro database. The distance between the sEMG signals was computed as the average along the timeline of the Euclidean distance between the synchronized electrode components.

Then, for each pair of subjects, we identified the signals (simulated or not) that minimized the distance between the sEMG signals and we used them to evaluate possible classification improvements.

We wanted to evaluate the effect of spatial registration on the quantitative estimate of the classification performance. To this extent, we employed a Least-Squares support vector machine (LS-SVM, [16]) classifier to predict the movement class in the previously described settings. LS-SVM is a kernel-based classifier that attempts to maximize the margin between two classes. It has been demonstrated experimentally that the classification performance of LS-SVM is typically comparable with the performance of Support Vector Machines (SVM) [17], however LS-SVM have advantages over SVM [18].

In our experiments, a multi-class LS-SVM with RBF kernel is trained for each distinct subject using ten repetitions of each movement. The model is then tested on all remaining subjects, considering ten repetitions of each movement.

Before performing the classification, the signal was pre-processed. All data were synchronized by linearly interpolating all data to the highest recording frequency (i.e., 100Hz). Both sEMG and Cyberglove signals were subsequently low-pass filtered at 1Hz using a zero-phase second order Butterworth filter. Samples with an ambiguous label (as those recorded during transition between rest and the actual movement) were removed by dividing each movement (including the resting position) into three equally sized segments and only retaining data from the center segment. We then averaged the data contained in this segment to obtain a single sample per movement. In order to consider the resting position as the other movements, 10 samples were randomly chosen from the set corresponding to the rest. Finally, the signal from individual subjects was normalized such that each sEMG signals had zero mean and unit standard deviation.

We evaluated the effect of rotation simulation on LS-SVM classification in two cases: first considering only the electrodes involved in the process (i.e. the 8 electrodes equally spaced on the elastic armband), then considering all 10 electrodes included in the Ninapro database. The statistical significance of the results was evaluated with a Kolmogorov-Smirnov Test.

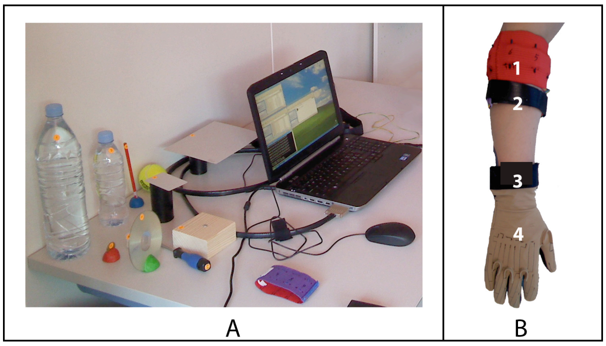

Figure 1. Acquisition setup: A) grasp and functional objects, laptop with the acquisition software; B.1) equally spaced electrodes; B.2) electrodes placed anatomically; B.3) inclinometer; B.4) cyberglove.

#	Description	Reference
1	Large diameter grasp	[13]
2	Tripod grasp	[13]
3	Tip pinch grasp	[13]
4	Resting position	

Table 1: First set of movements.

#	Description	Reference
1	Index flexion	[14]
2	Index extension	[14]
3	Middle flexion	[14]
4	Middle extension	[14]
5	Ring flexion	[14]
6	Ring extension	[14]
7	Little finger flexion	[14]
8	Little finger extension	[14]
9	Thumb adduction	[14]
10	Thumb abduction	[14]
11	Flexion of ring and little finger	[15]
12	Resting position	

Table 2: Second set of analysed movements.

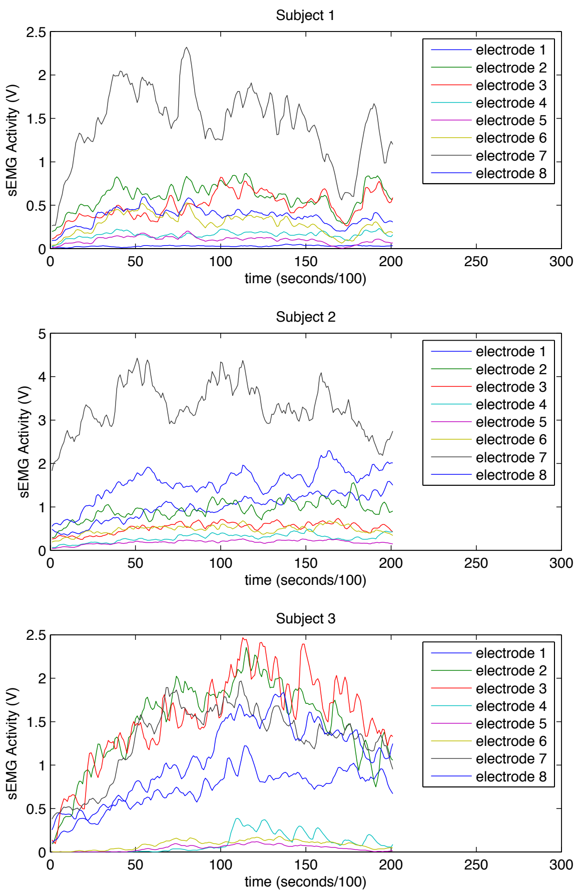

Figure 2. Inter-individual variability of sEMG signal patterns. Example of sEMG signal patterns from three different subjects doing the same movement.

3 Results

The evaluation of the similarity between the signals of different subjects and the effect of the rotation simulation showed that rotation simulation can increase the similarity of signals across subjects up to 33% compared to the original value, with mean value and standard deviation on all the subjects equal to (8.12 ± 7.02) %.
The maximum of the inter-subject signal similarity improvement due to rotation simulation (i.e. the reduction of the distance), computed in percentage with respect to the original signal is shown in Fig. 3, together with a representation of the rotation matrix that corresponds to the maximum inter-subject similarity improvements.
Spatial registration obtained through rotation simulation affects the quantitative estimate of the LS-SVM classification performance improving the classification results.
Considering only the 8 electrodes placed on the elastic armband, the classification error decreased from 57.94% to 53.26% in the case of three movements, while it decreased from 84.48% to 83.27% in the case of eleven movements.

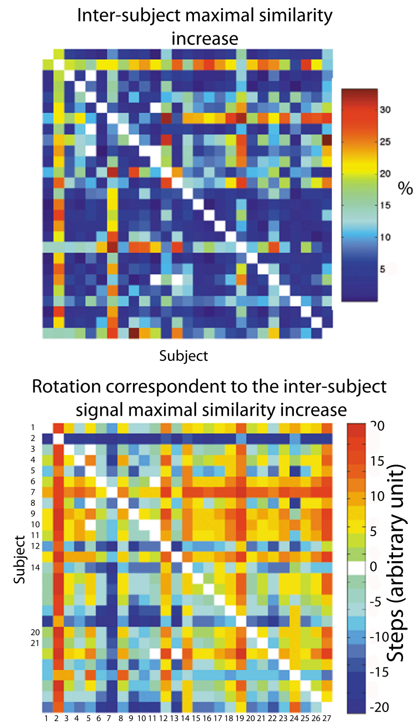

Figure 3. Maximum inter-subject signal similarity improvement due to rotation simulation, computed in percentage with respect to the original signal *(top)*. Rotations correspond to the maximum of the inter-subject similarity improvements *(bottom)*.

Considering only the 8 electrodes placed on the elastic armband, the classification error decreased from 57.94% to 53.26% in the case of three movements, while it decreased from 84.48% to 83.27% in the case of eleven movements (Fig. 4). The classification improvement was therefore respectively of 4.69 and 1.21 percentage points, with an improvement of 8.09% (p=0.01) and 2.09% (p=0.04) of the original values.

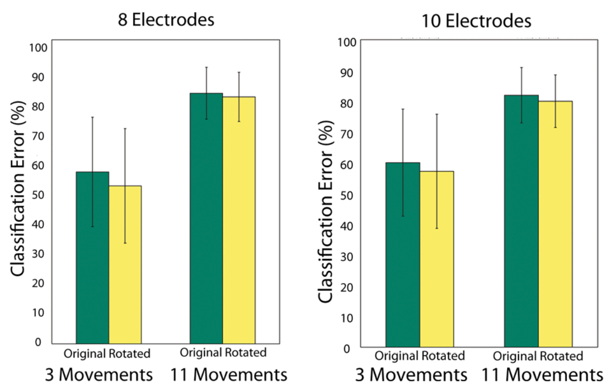

Figure 4. Means and standard deviations of the LS-SVM classification errors on the signal of the 8 electrodes equally spaced on the elastic armband *(left)* and from all the electrodes *(right)*.

Considering all 10 electrodes included in the Ninapro database, the classification error decreased from 60.41% to 57.54% in the case of three movements, while it decreased from 82.44% to 80.51% in the case of eleven movements. The classification improvement was therefore respectively of 2.87 and 1.94 percentage points, with an improvement of 4.74% (p=0.05) and 3.2% (p=0.02) of the original values.

4 Conclusions

The spatial registration was performed simulating the rotation of the elastic armband that is used to acquire the data in the Ninapro database.

The results show the usefulness of spatial registration on the sEMG signal from hand movements to augment inter-subject similarity. Considering only the 8 electrodes placed on the elastic armband, the average classification improvement over the original values is 8.09% in the case of three movements and 2.09% in the case of eleven movements. The obtained p-values (respectively p=0.01 and p=0.04) enhance the statistical significance of the results. Considering all the 10 electrodes included in the Ninapro database, the average classification improvement over the original values is 4.74% in the case of three movements and 3.3% in the case of eleven movements. The obtained p-values (respectively p=0.05 and p=0.02) enhance the statistical significance of the results.

The difference between the average improvement of the similarity of the signals (8.12 ± 7.02)% and the average improvement in the classification with LS-SVM (2.99 ± 1.43)% encourages us to go more into details for both the spatial registration and the features used to perform the LS-SVM classification.

Unfortunately, the inter-subject classification performance is only slightly above chance level (i.e., 1 – 1/c with c being the number of classes). In other words, the data for a given subject are still not very representative for the data of other subjects.

This fact underlines that there is still considerable inter-subject variability and that more studies are required to acquire a deeper understanding of the data to take into account factors that can help to compare several persons.

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