Abstract— This work reports results of a pattern recognition system based on superficial electromyography (sEMG), with possibilities of operating in online mode of control. Features based on time domain, time frequency and fractal analyses were considered, as well as two classifiers were compared through error of misclassification. The system was tested on one non-amputee volunteer in online mode with possibility of biofeedback of performance. Also, the system was validated on one forearm amputee by a pseudo-online scheme to identify the needs towards a real time system. Advantages of using visual feedback for the user were demonstrated in this study.

Keywords— Electromyography, trans-femoral amputee, upper-limb prosthesis, pattern recognition.

1 Introduction

In the last 20 years several researches have been focused on hand prostheses development, being one of the most advanced areas in rehabilitation robotic field. These works range from actuators and mechanic systems to the development of techniques to improve the control, providing more functionality to the prostheses, similar to a sound limb. Ideal upper-limb prosthesis must be recognized as a natural part of the amputee body, supplying motors and sensorial limb abilities. One of the major problems is the acceptance by amputees, taking into account the facilities and comfort, exterior appearance, but, most of all, its functionality. There are a variety of prostheses, from purely aesthetics to actives hand prosthesis. The myoelectric prostheses use MES (Myoelectric Signal) to generate commands for the control system of the device. Commonly, pattern recognition systems are used to classify sEMG acquired from a set of hand gestures.

In an upper-limb prosthesis design, one of the major problems for acceptance by amputees is the functionality. A satisfactory and useful dexterous prosthesis should provide the amputee with an intuitive and close-to-natural way of controlling the artificial limb by decoding the efferent motor commands dispatched by the amputee's brain with accuracy and acceptable cognitive effort (Matrone et al. 2012). Offline studies have decoded successfully up to six gestures from the forearm, but an online control with high accuracy and usability is still an open study (Shenoy et al. 2008).

The most common method employed for prostheses control is based on MES processing. Contraction from different muscles can be mapped using systems with arrays of electrodes, but the complexity and the processing time are increased. In fact, low density sEMG with a few number of electrodes reduces problems during fixation and computational cost for real time applications, but requires more efficient features extraction methods (Arjunan & Kumar 2010). However, at low-level muscle contraction in processes with similar energy, statistical features are not reliable [4]. Furthermore, there is a non-linear relationship between force and electric activity on the muscles with low levels of contraction. Low-level sEMG signals can be defined as the response of a muscle contraction during a movement realized by its own muscular group with less force as possible. Detrended Fluctuation Analysis (DFA) is a fractal technique which combines advantages from time and frequency domains. Phinyomark uses DFA to classify low level sEMG signals (Phinyomark et al. 2012). Eight gestures were classified with the wrist, hand and forearm using weak upper-limb sEMG signals for five channels. The individual finger movements were not taken into account in their work.

The functions to be controlled and the methods in pattern recognition to process the MES have been the focus on research about myoelectric prostheses. Despite many works have successfully identified different hand gestures with high precision, few of them have reported results identifying dexterous movements with individual fingers and grasp functions to handle different types of objects (Matrone et al. 2012),(Arjunan & Kumar 2010). Moreover, few
of them conducted a study with forearm amputees (Hudgins et al. 1993), (Ito et al. 1991), (Daley et al. 2012), (Zhang & Zhou 2013), (Tommasi et al. 2013).

In previous works, we presented the classification of individual finger movements and grasp gestures on healthy subjects (Villarejo et al. 2013) and amputees (Villarejo et al. 2014) in offline mode. These offline results provide the basis for the development of an accurate online control for amputees. Thus, this work was aimed at validating the pattern recognition system developed in online mode with able-bodied and amputee voluntaries. A variant mode called pseudo-online was tested for the results with the amputee. In this mode, new data from a different capturing session are used for validation, without any visual feedback with the system response. In the following pages the pattern recognition system for upper-limb myoelectric control is described. Two aspects were taken into account: the first, sEMG low density, is the collection of less information as possible, using four sEMG channels, while the other one are the low-level sEMG contractions. Finally, the methods for the performed experiments are provided and the collected results are presented and discussed.

2 Methods

2.1 Subjects

One able-bodied subject (AB) performed the experiments described in this section, using his dominant hand. In addition, an amputee subject (AM), female aged 35, volunteered to participate in this study. The amputee subject has trans-radial two-third proximal amputation of the right forearm. The volunteers knew the objectives and methodology of this study and signed the free consent form according to the ethical principles of the Federal University of Espirito Santo (UFES). All procedures were approved by the UFES ethical committee.

2.2 EMG recording

The signals were acquired using bipolar electrodes, manufactured by Touch Bionics. These active electrodes have embedded a pre-amplification and electronic conditioning, with a 60Hz notch filter and a variable gain. The skin was previously cleaned with 70% alcohol, and conductive gel was used before attaching the electrodes. Four electrodes were placed on muscles described in Table 1. The subject was seated in a chair with both hands on a table and trained before performing the tasks.

2.3 Experimental protocol

The gestures were performed following a same sequence, and each task was maintained for 5-6 seconds, followed of a background activity (rest state) of 4-5 seconds to avoid fatigue. Visual and oral cues were presented to perform each repetition for data synchronization. Experiments were repeated with the volunteer in three evaluation sessions on different days for enhanced generalization capability for performing tasks. The sEMG signals were recorded for six different gestures related to perform individual finger flexion and rest state. The rest state was included being recorded as the first class. The muscle activity was identified for each repetition extracting the segments corresponding to the isometric contraction on the motor task. It was done by taking two seconds after started the motor tasks, until one second before starting the return to the rest state. An examiner was ensuring that the gesture was started with no more than 1 second after the cue, in order to avoid potential errors. The background activity among each repetition was discarded for the analysis. This protocol was repeated for both offline and online modes.

2.2 Signal processing

The sEMG data were pre-processed subtracting the DC level from each signal. In the offline experiments, the trials were reorganized by concatenating all the same movements. A windowing function was used to compute the features according to the criteria in (Hudgins et al. 1993), where the response expected by the subject would be ready in no more than 300 ms. A sliding window with 250 samples of length (250 ms) and an increment of 125 samples (125 ms) for overlapping was applied for each channel. The duration of the analysis window was chosen for target real-time classification, by minimizing the delay between performed and decoded action.

Previous works have shown that an optimal set features configuration for offline classification on both group of voluntaries, able-bodied and amputee, was based on Wave Length (WL), Mean Absolute Value (MAV) on time domain; Total Power (TP) on frequency domain; and DFA on fractal analysis (Villarejo et al. 2014). Principal Components Analysis (PCA) was used as a projection method before classification. In this study, first six components were used for all cases. Finally, two classifiers methods based on K-Nearest Neighbor- hood (KNN) and Artificial Neural Networks (ANN) were implemented to compare the accuracy of pattern recognition. In
KNN method, a $k$ value of 5 was used. In ANN, a Multilayer Perceptron (MLP) was configured with 16 nodes in the input layer, a hidden layer with 32 nodes and an output layer size of six related to each class. In order to evaluate the classifiers from different tests, the error of misclassification was taken into account. Confusion matrix are used to describe the distribution of classification gestures, and Kappa coefficient proposed by Cohen (Japkowicz & Shah, Mohak (McGill University 2014), which represents the concordance between the targets and the prediction values, was also computed.

2.2 Offline / online study methods

Firstly, offline experiments were performed to analyze and define the pattern recognition system with both voluntaries, AB and AM. Secondly, online experiments with AB voluntary were performed using the previous trained system, following the same protocol. Finally, as an intermediate stage between offline and online experiments, a pseudo-online mode with the AM voluntary was studied. Futures works will include new experiments with amputees on real time.

For offline study, a five-fold cross-validation on all data sessions, repeated three times and averaged, was used for training and validation of classifiers. For online study, all previous sessions were used for training and new data were collected while AB voluntary performed the gestures. This study initially was performed without any feedback during experiments. Later a biofeedback of the current response about gesture recognition through a visual representation on the PC was included. In pseudo-online mode, data sessions were used independently for training and validation of classifiers and no random methods were used. Tests of ability of classifiers were conducted to generalize the capacity of maintaining repeated gestures by the amputees. Each experiment was performed for each subject individually.

3 Results and Discussion

The results are divided on the three experimental stages described before for each voluntary. For AB subject, the system off-line had a success rate of 98.56% with KNN, with a confusion matrix shown in Figure 2, and the kappa constant was 0.98, which corresponds to a high concordance between outputs and targets in the classifier. The lowest rates in the confusion matrix were above 93.88%.

On the other hand, the online tests showed 81.00% of success rate achieved by subject AB for KNN without biofeedback, according to the confusion matrix shown in Figure 2a. The kappa was 0.77 with a low concordance in the results. In this case, the success rate was lower in relation to the off-line results, and middle finger classes had the worst success rate, below 28%, mainly confused with the little finger class. With the inclusion of biofeedback, the results were improved significantly. The success rate was 95.16% and the kappa had a very high concordance of 0.94. These results are illustrated in Figure 2b. It is evident the improvement in performance when using visual feedback for online results. Similar results were obtained with ANN classifier, according to Table 2.

For amputee subject, results show high accuracy for offline tests of 96.86% with KNN, and kappa of 0.96, resulting in very good performance (Figure 2c). For ANN, results were 93.27% of recognizing and 0.92 for kappa. The opposite occurred with the pseudo-online test results, where the success decreased to 35.94% with KNN (Figure 2d) and 45.16% for ANN. Also, kappa coefficient denotes a very low concordance on both cases, below 0.6. Nevertheless, an analysis of matrix confusion gives a better understanding about this poor results, as it is possible to observe that the first three classes had a high accuracy, but the others are very confused. This may be due to the process of muscles after amputation and the difficulty of keeping natural patterns learned before.

Table 2 shows the performed experiments for offline (OFF-L) and online (ON-L) modes for AB subject (with biofeedback), and Pseudo-Online (PON-L) mode used for AM subject. Comparison between both classifiers show a close resemblance on results, being KNN the technique with the best performance.

Table 2. Results for classification for AB subject and AM subject for KNN and ANN.

<table>
<thead>
<tr>
<th>Sub</th>
<th>Classifier</th>
<th>KNN</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OFF-L</td>
<td>ON-L</td>
<td></td>
</tr>
<tr>
<td>AB</td>
<td>Error [%]</td>
<td>1.44</td>
<td>4.84</td>
</tr>
<tr>
<td></td>
<td>Kappa</td>
<td>0.98</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>OFF-L</td>
<td>PON-L</td>
<td>OFF-L</td>
</tr>
<tr>
<td>AM</td>
<td>Error [%]</td>
<td>3.14</td>
<td>35.94</td>
</tr>
<tr>
<td></td>
<td>Kappa</td>
<td>0.96</td>
<td>0.57</td>
</tr>
</tbody>
</table>
5 Conclusion

This study presents results on decoding individual finger flexion for able-bodied and amputee volatunaries. We analyzed weak sEMG signals during the experiments in order to achieve a suitable and natural control system for amputees. A study to determine a pattern recognition system was developed and tested in offline and online modes for one non amputee. Also, the system was tested in offline mode for an amputee with high accuracy on the stiffness recognition. A pseudo-online mode was tested on the amputee, as an intermediate stage toward a real time system. This method shows a low rate of recognizing, especially on the last three fingers. The closeness of muscles related to the gestures proposed in this work makes a growing challenge for amputees over time, as low usage of muscles makes them prone to atrophy in daily routine. On the other hand, it was shown the needed to provide a feedback to the user in order to improve the myoelectric control. Online experiments with amputees will be considered on future works. Nevertheless, the results presented in this work are an important step to obtain a real time functionality system for amputees.

References


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