Hand Gesture Recognition for the Control of an Exoskeleton

Maria Claudia F. Castro
Electrical Engineering Department
Centro Universitário da FEI
São Bernardo do Campo, Brazil
Email: mclaudia@fei.edu.br

***Abstract*—Despite the existence of many examples in multifunctional control systems there is a lack of studies that show hand gestures applied in daily life activities. Furthermore, isometric contractions, above certain thresholds, continue to be used once it is easier to deal with. However, it is a static contraction, that is not used to perform movements. Thus, a control system based on that is not intuitive, especially for subjects who have the limb with a diminished strength and that could also be benefited by rehabilitation devices, such as exoskeletons to train or regain function. In this context, the purpose of this work is to investigate the recognition of up to 4 hand gestures plus the neutral hand position, based on myoelectric signal obtained during the static phase at the end of the movement, without the use of any additional isometric contraction. Performance evaluation is done based on Linear Discriminant Analysis comparing the results of six myoelectric features and also the number of muscles necessary to achieve the best classification accuracy. The results show higher rates for the features in the frequency domain. The Spectral Magnitude Average reaches an average accuracy of 88.44% following by Spectral Moments with 85.56%. The best results achieved by each subject is variable, with a predominant use of 3 to 5 muscles depending on the feature that was used, with no standard pattern.**

***Index Terms*—Hand Gesture, Myoelectric Signal, Linear Discriminant Analysis (LDA), Pattern Recognition.**

I. Introduction

Myoelectric signals can provide information about user's motion intention and thus can be used for interconnecting nervous system to external devices. In this context, myoelectric prostheses generally use smoothed amplitude signals associated with isometric contractions from a pair of agonist-antagonist muscles to encode each movement. However, multifunctional control systems that aim to increase the number of movements, have used some kind of pattern recognition to discriminate among a set of muscular contractions during different positioning.

The literature contains many examples, and despite some methodology differences, relating to considered muscles and classifiers, usually the classification rates achieve more than 90% [1]–[4]. Multifunctional control generally considers arm flexion/extension, forearm supination/pronation, wrist flexion/extension and ulnar/radial deviation [4]–[9].

Other systems have been dedicated to finger movement control either considered independently or in combination [10]–[14], forming some grasp or pinch patterns [15]–[19]. Nevertheless, isometric contraction continues to be used as the information source since it is easier to deal with due to its higher signal amplitude, its lower sensitivity to load variation and motion artifact and due to ease of being reproduced by amputees as the level of amputation becomes higher [20]–[22].

However, it is a matter of fact that isometric contraction is not used to perform movements; in other words, it represents an static contraction. Thus, a control system based on that is not intuitive, especially for subjects who have the limb with a diminished strength and could also be benefited by rehabilitation devices such as exoskeletons to train or regain function. In those cases, the use of isometric contractions may not be an appropriate source of information due to muscle weakness [23]–[25].

In this context, the purpose of this work is to investigate the recognition of up to 4 hand gestures plus the neutral hand position, based on myoelectric signals obtained during the static phase at the end of the movement, without the use of any additional isometric contraction. The movements were performed without load and thus, the level of contractions were smaller than those usually achieved during isometric contractions, closer to the situation of muscle weakness. The performance of myoelectric signal features in time and frequency domains were evaluated using a classifier based on a Linear Discriminant Analysis. The minimum number of muscles and their configuration were also investigated in order to improve classification accuracy.

II. Materials and Methods

A. Data

Six subjects, all normally limbed with no neurological or muscular diseases, were invited to participate in this study. The protocol was approved by COEP - USJT - No.088/2011 and subjects signed the informed consent.

The experiment consisted on acquiring myoelectric signals from flexor digitorum superficialis (two different electrode positions - M1, M2), palmaris longus (M3), abductor pollicis longus (M4), extensor digiti minimi (M5) and extensor communis digitorum (M6)(figure 1), during 4 hand movements performed from neutral hand positioning (figure 2(a))to pinch with index and thumb (figure 2(b)), tripod pinch with index, middle finger and thumb (figure 2(c)), hand closed (figure 2(d))or hand opened (figure 2(e)).

Fig. 1. Electrode Positioning.

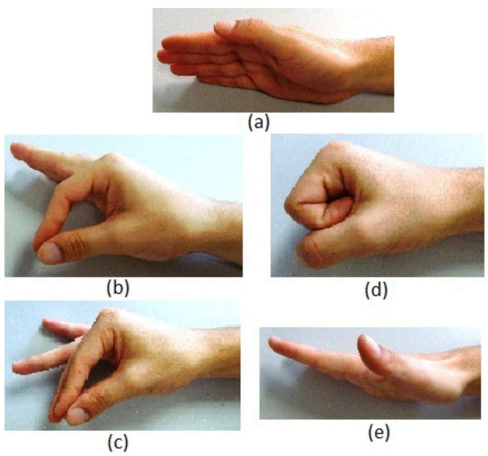

Fig. 2. Hand Positioning.

During the experiments subjects were seated on an arm chair, with their right arm supported and flexed at 90°. Each subject executed 6 series of 5 movement repetitions with a rest period among them, resulting in 30 repetitions of each movement.

Myoelectric signals were sampled at 1000 Hz and filtered within the range 20-500 Hz using the Bioamplifier plus PowerLab 16/30 configuration from AdInstruments. During the static positioning, without performing any additional force, a 1 s sample was selected from each muscle data, resulting in a 6000 x 150 data matrix (1000 data of each of 6 muscle channels x 30 repetitions for each of 4 movements plus neutral hand positioning).

B. Feature Extraction

The raw myoelectric signal is considered as a stochastic variable, and in the field of pattern recognition, feature extraction results in a dimensional reduction of original data and also provides useful information to the classifier.

In this study, a set of 6 features, either in time and frequency domains, was extracted from the selected myoelectric signals using a 100 ms windowing with 70% of overlap.

The features were Root Means Square (RMS), Mean Absolute Value (MAV), Waveform Length (WL), Average Rectified Value (ARV) also known as integral of the rectified burst or linear envelop, Spectral Magnitude Averages (PSD-Av) and Spectral Moments (PSD-Mo) [26]–[28]. Each feature was used separately and their capacity of providing sufficient and reliable information about the hand gesture to the classifier were compared through a Linear Discriminant Analysis.

The data of all muscles were originally considered and a process to find the minimum and best muscle configuration to achieve hand gesture recognition was performed by eliminating one muscle at time and checking which configuration attained the best performance.

C. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a well-known classification technique based on the data projection onto the directions that reach the best class separation. One of the methods to obtain these directions was defined by Fisher, as a solution of an eigenvectors problem based on the between-class scatter matrix S_b and the within-class scatter matrix S_w, where g is the number of classes, N_i the number of samples in class X_i, $\bar{x_i}$ the mean of class X_i and $\bar{x}$ the total mean vector [29]–[31]. The method Leave One Out was chosen to define the training and test data sets. Hence, training matrices have $(N-g)$ samples and test matrices have g samples, one of each class. Euclidean Distance was used in the classification algorithm for class assignment.

$$S_b = \sum_{k=1}^{g} N_i(\bar{x_i} - \bar{x})(\bar{x_i} - \bar{x})^T \tag{1}$$

$$S_w = \sum_{k=1}^{g} \sum_{x_k \in X_i} (\bar{x_k} - \bar{x_i})(\bar{x_k} - \bar{x_i})^T \tag{2}$$

III. Results

Figure 3 shows the average classification rates reached for each feature during the process of optimizing the number of muscles. In general, the best feature was PSD-Av followed by PSD-Mo, and the worst feature was the MAV followed by RMS, independently of the number of considered muscles. The best average classification rates were achieved for a 5-muscle configuration, with 88.44% and 85.56% for PSD-Av and PSD-Mo, respectivelly. On the other hand, the best performance among the features in the time domain occurred for a 4-muscle configuration, with 73.67% for ARV. However, when analysing individual results, for each subject, the best classification accuracies were verified when configurations from 3 to 5 muscles were used, depending on the considered feature.

There was no standard muscle configuration. For each subject, based on the considered feature, there was a different muscle configuration which improved the classification accuracy. For example, considering PSD-Av for Subject 5 the best classification rate was 94% reached using M1+M2+M5, whereas Subject 4 reached the same classification rate but

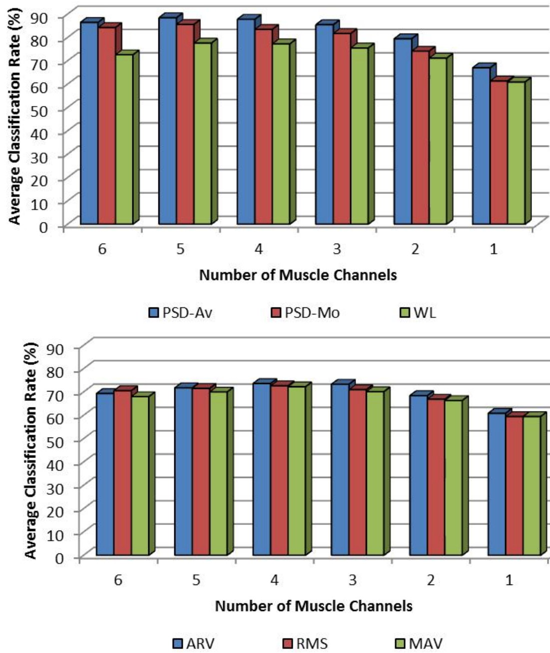

Fig. 3. Average classification rates for each feature and for each muscle number configuration.

using a 5-muscle configuration, without M3, whereas the best classification accuracy achieved by Subject 6 was 84.67% using a 4-muscle configuration (M1+M3+M5+M6). On the other hand, considering ARV, the best classification rate reached by Subject 5 was 72.67% using M1+M4+M5, Subject 4 attained 83.33% accuracy with M1+M2+M3+M6, whereas Subject 6 using other configuration with 4 muscles achieved 66.67%.

Figure 4 shows the average classification rates considering the number of muscles used to achieve the best classification rates for each subject. The performance of each feature continues the same, confirming the averaged data. However, the scores are slightly higher than those previously showed in figure 3, except for PSD-Mo and MAV that presented the same values, since the best muscle configuration are now considered.

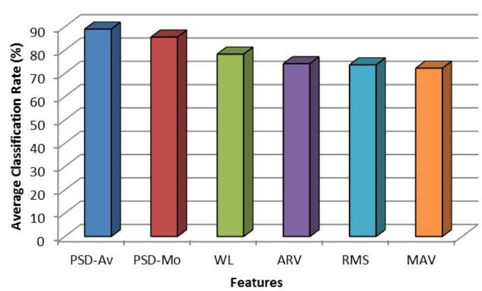

Fig. 4. Average classification rates for each feature considering the best muscle configuration for each subject.

Table I is a typical confusion matrix for PSD-Av showing that the major misclassification occurred between pinch and tripod pinch. The neutral hand position is also confused either with the tripod pinch and with hand opened.

TABLE I
CONFUSION MATRIX FOR PSD-AV.

netral positioning	27	0	2	0	1	90.00%
pinch	0	23	7	0	0	76.67%
tripod pinch	0	7	23	0	0	76.67%
hand closed	0	0	0	30	0	100.00%
hand opened	1	0	0	0	29	96.67%
average classification						88.00%

IV. DISCUSSION

Results showed that the best classification rate was achieved by each subject with different muscle configurations based on the feature considered for the classification process. Independently of the configuration, something around 3 to 5 muscles appeared to be reasonable.

Electrode positioning is a critical issue in myoelectric control systems since a slight change can contribute to provide a meaningless signal, with a weak relationship with the muscle that is monitored and with the influence of crosstalk. On the other hand, the use of pattern recognition can avoid this difficulty since it learns with the examples and experience, finding the pattern related to that situation.

Moreover, it is plausible to accept that each subject can take different control strategies to perform movements, resulting in different muscle configurations. These are some reasons that make control systems based on pattern recognition attractive, fitting control strategies to different subjects and situations. Furthermore, the contribution of each muscle during specific movement is different and also the characteristic highlighted by each feature. Thus, it was not a surprise the fact that for each feature, different muscle configurations have been used to achieve the best classification rates. Since the prosthesis control system is trained with data of a specified subject, the different strategies among them will not be a problem.

The use of a low level of contraction, close to the situation of a muscle weakness, results in lower amplitude signals compared with the condition of using isometric contraction. The better performance of the features in the frequency domain is in accordance, since these features are more robust to this situation. In the literature, there is a prevalence of using time domain features in control systems, specially MAV [1], [3], [9], [11], [20], [23], [28]. However, MAV is a feature that express amplitude variation, and for a signal with low amplitude this feature showed the worst average classification rate. The features in the frequency domain and also WL, that retain some frequency information, showed better performance than the features based on amplitude variation. The best feature was PSD-Av, which achieved an average classification accuracy of 89% with an standard deviation of 3.75. This is a good classification rate, especially considering the signal amplitude condition.

The confusion matrix also showed a misclassification between the two pinch patterns performed with two or three fingers. In a normal movement, when the index finger is flexed against to the thumb, which is in abduction, there is a slightly flexion movement of the middle finger at about $20°$. This movement can be confused with the situation which the middle finger is really flexed during the execution of the tripod pinch configuration. Since isometric contraction or force above certain threshold were not used to mark each positioning, muscle tension was low, resulting in misclassification.

These results were in accordance with [15]. This work used frequency domain features with either a neural network and statistical model classifiers to recognize among 4 hand grasp (spherical, cylindrical, lateral or key and pinch). The average classification rates ranged from 75% to 80% with no unique technique for all the subjects. The experiments in [17] were done with amputees but the intact side was used as control. Despite the 12 electrodes initially used, it was shown that a configuration specially selected with a number between 4 and 6 increased the classification error only in 2%. Moreover, the average hand-function classification errors were higher than those achieved for the wrist-movements, showing the complexity among them.

The classification rates reported in [16] were higher than those previously mentioned. Using isometric contractions in a multifunctional system control, the average classification rate to recognize up to 10 classes, including 2 grasp patterns and hand opened, was 95.70% after an optimization process based on Gaussian mixture model. The authors in [18] had also proposed a multifunctional system including hand function. The classifier based on an orthogonal fuzzy neighborhood discriminant analysis could recognize up to 8 movements of the wrist and hand with 91.5% of classification. However, despite the number of classes it is important to highlight the use of isometric contractions and the differences among the considered movement that contribute to decrease misclassification.

In a different work, using also the dynamic movement phase, [19] showed classification accuracies comparable to those obtained in static situations. This is important in applications with exoskeletons in which the beginning of the movement could be used to recognize a user's motion intention. Furthermore, at the beginning of the muscle contraction, myoelectrical signals will have amplitudes low as those used in the present work.

V. Conclusion

This work showed that there is no standard muscle configuration for all subjects that allow the studied hand movement recognition. Although, this fact could be explained by different electrode positioning, each subject used a different muscle configuration and a different number of muscles to achieve the best classification rate based on a specific feature. The features in the frequency domain were more robust to the lower amplitude signal that was used to mimic the situation of a muscle weakness, having the PSD-Av reached the best performance. The average classification rate was 89% to recognize among 4 hand gestures plus the neutral hand position. It was also shown a misclassification between the two pinch patterns due to its high similarity and the low muscle contraction performed during the movements. More studies in this field should be carried out to improve its applicability, using the normal way to perform movements as an intuitive mechanism to control systems, as well as the study of more hand gestures commonly used in daily life activities.

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