Simultaneous Myoelectric Pattern Recognition using BioPatRec Platform for Hand Prosthesis

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Abstract – Currently, commercial hand prosthesis use a sequential control mesh, which makes the movement of the prosthesis counter-intuitive and clunky, often dependent on external sensors for movement execution. Pattern recognition is a method that has been developed to address these limitations. Unlike traditional strategies, pattern recognition is based on the idea that learning is done by a classification software. For that, the subject can use the natural contractions of the movement that one wishes to control. The software identifies the muscle pattern and classifies it as a target movement. Then, it will recognize the pattern the next time it is generated and create the intended prosthetic movement. In this work were proposed the combination of several methods for feature extraction together with feature selection, applying multilayer perceptron network (MLP) to recognize the motor pattern, using the BioPatRec platform [1]. **BioPatRec is an open source platform, that allows the implementation and test of several algorithms in the fields of signal processing, feature extraction and selection, pattern recognition and real-time control. The experimental results showed that the proposed features could achieve an average classification accuracy of 97.88%, which was 4.54% higher than the analysis without the features proposed in this work. The results suggest that the new features and the addition of featuring selection have the potential for the use with a myoelectric prosthesis with simultaneous control.**

Keywords: Electromyography, BioPatRec platform, Pattern recognition, Unsupervised feature selection, Multilayer perceptron network, Hand prostheses.

1 Introduction

Pattern recognition for myoelectric signal processing plays an important role on research for prosthetics [1]. In addition, the application of machine learning techniques has become widespread in the area of surface electromyography (sEMG) signals analysis, to enhance the feature extraction and selection as well the classification of the myoelectric pattern [2]–[5]. Furthermore, the use of pattern recognition brings an improvement in the degrees of freedom and movement of the prosthesis beyond the capacity of its sequential control [6].

In this study, the open source BioPatRec platform was used [1], [6], [7]. With a modular and customizable concept, researchers can compare their algorithms easily and efficiently, applying them to control a prosthesis. As advantages, users, by means of this platform, can access the sEMG signals database for both sequential and simultaneous analysis, including quantitative metrics to evaluate the performance of sequential and simultaneous control in a standardized way, as well as to apply methods that the platform provides for feature extraction, feature selection, feature reduction and myoelectric pattern classification.

The objective of this work is to analyze new algorithms for feature extraction and selection methods not provided by BioPatRec platform, four additional feature extraction methods were used: the Levinson-Durbin Recursion, the Absolute value of the Summation of the Expth Root Mean, the Mean value of the Square Root and the Absolute value of the Summation of Square Root [8]. Additionally, an unsupervised method for feature selection (UFS) was used [9].

These additions were made for the improvement of the classification of the myoelectrical signal to provide a better performance for the simultaneous movement of an upper-limb prosthesis, aiming at increasing the user comfort and giving easing for the movement.

2 Methodology

For this study, the “6mov8chUFS” (Untargeted Forearm Simultaneous) [7] database was used, which is freely available on the BioPatRec platform [1]. The sEMG signal is analyzed, and the features are extracted, following the main features are selected and finally the neural network classifies the movement.

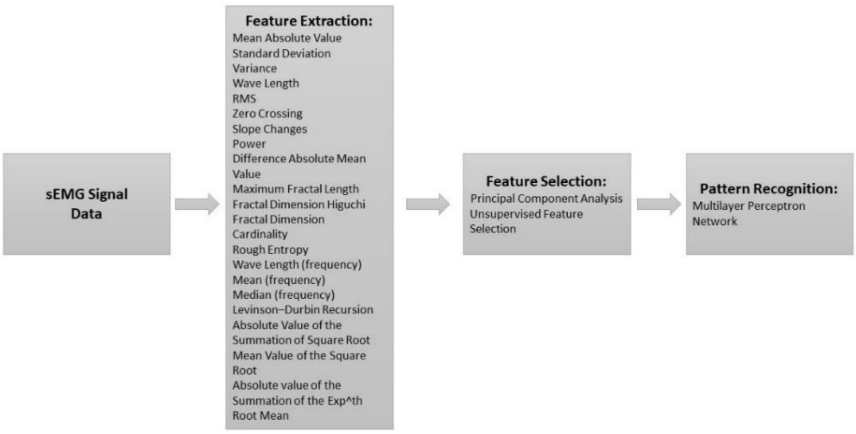

Fig. 1. Block Diagram of the proposals Myoelectric Algorithm with the use of BioPatRec Platform.

2.1 BioPatRec Platform

As previously mentioned, the biomedical signal analysis platform, BioPatRec, was used, using the Multilayer Perceptron Network with backpropagation, already configured on the platform for pattern classification.

2.2 Features Extraction

In this study were added four time-domain features described below:

a) The Absolute value of the Summation of the Square root (ASS) [8]: This is the first time-domain feature. For calculation of the ASS, the first step is to first execute a full-wave rectification on the sEMG data, this help in retaining the entire energy content of the signal. Next, the integral of the rectified EMG signal is calculated with respect to the current analysis window, as expressed mathematically in Eq. (1)

$$ASS = \left| \sum_{n=1}^{k} (x_n)^{\frac{1}{2}} \right| \quad (1)$$

where k represents the analysis window, x_n denote the data within the corresponding analysis window.

b) The Mean value of the Square Root (MSR) [8]: This is the second time-domain feature. It provides an estimated measure of the total amount of activity in the analysis window.

$$MSR = \frac{1}{k} \sum_{n=1}^{k} (x_n)^{\frac{1}{2}} \quad (2)$$

where k represents the analysis window, x_n denote the data within the corresponding analysis window.

c) The Absolute value of the Summation of the exp^th root (ASM) [8] of the data is the third time-domain feature, as shown in Eq. (3). The ASM feature provides a comprehensive insight into the amplitude of the EMG signal since it gives an approximate measure of the power of the signal which also produces a waveform that is easily analyzable. This feature contains information from which the amplitude of the rectified EMG signal could be obtained.

$$ASM = \left| \frac{\sum_{n=1}^{k} (x_n)^{exp}}{k} \right|$$
$$ex' = \begin{cases} 0.50 & , if\ (n \geq 0.25 * k\ n \leq 0.75) \\ 0.75 & , otherwise \end{cases} \quad (3)$$

The exp. variable can assume one of two possible values (0.50 or 0.75) based on the characteristic of the EMG signal segment under analysis. The ASM is therefore determined in the following three steps: first the summation of the exp^th root of all values in a given analysis window is computed; followed by the mean of the resultant values; and lastly, the absolute value of the resultant mean is evaluated.

d) The last feature added was the Levinson–Durbin Recursion [10], it is a recursive order-update method to the calculation of linear predictor coefficients, it has applications in filter design, coding, and spectral estimation. This method was used to estimate parameters of the sEMG signal.

2.3 Features Selection

A method based on the Maximal Information Compression Index (MICI), and the Entropy Representation (ER) was applied for unsupervised feature selection, in order to obtain the best feature sets for the classification [9]. Analyzing through the MICI to obtain combinations of characteristics with lower value or high redundancy. Those redundant features come together with the rejected features, in order to obtain an updated set formed by the features that provide the highest ER value during the combination with non-redundant features.

On the other hand, principal component analysis (PCA), an orthogonal linear transformation, that rearrange the components in the inverse order of variance It is used for dimensionality reduction in the BioPatRec platform as default., as it is a widely used technique.

In that study, PCA reduced the 160 features (20 for each channel) to the 64 best features for classification.

2.4 Neural Network Classifiers

Despite the existence of a wide variety of different pattern recognition algorithms, the Multi-Layer Perceptron (MLP) as a supervised Artificial Neural Network was chosen because of its inherent capacity of simultaneous classification [1], [6], [11].

An MLP can be used as a logistic regression classifier, where the input is first transformed nonlinearly by a learned transformation. This transformation projects the input data into a space in which it becomes linearly separable. This middle layer is called the hidden layer. A single hidden layer is sufficient to make MLPs a universal approximator. For this study an MLP with 3 hidden layers with eleven neurons was used, the transference function was the softmax function.

2.5 sEMG Database

As mentioned before, the 6mov8chUFS database was used, and it is available on the BioPatRec platform. This database is formed by 17 subjects, six classes of individual movements were selected, such as hand opening and closing, flexion and extension of the wrist, and prono-supination of the hand, forming 27 possible movements. The signal was measured as follows: 3 seconds contraction time with 3 seconds for relaxation between each repetition, repetitions of each motion. 8 bipolar electrodes (Disposable Ag/AgCl), 1 cm electrode diameter, 2 cm inter-electrode distance for the bipole. Electrodes were equally spaced around the most proximal third of the forearm.

The signal was extracted using overlapped time windows of 0.2 seconds and time increments of 0.05 seconds.

2.6 Statistical Evaluation

The tests were performed on seventeen subjects of the original base "6mov8chUFS". First, the BioPatRec feature selection methods were used with and without PCA. Finally, the feature selection algorithm unsupervised (UFS) was used for reducing features in place of the PCA. Thus the tests were completed they were repeated by adding the new characteristic vectors proposed in this study.

The evaluation of the classifier used a cross-validation of 48 trainings with randomized datasets were per subject and for each algorithm, 24 validation sets, and 49 test sets. For this study was used unitary range normalization.

The BioPatRec provides statistical tools to evaluate the proposed algorithms on the platform, thus, it has a wide variety of metrics [6] that were used to analyze the results, such as Accuracy (Class Specific), Sensitivity (Recall), PPV (Precision), F1, Specificity (Negative Condition), NPV (Negative Outcome) and Accuracy (Global).

a) Accuracy – Class Specific

$$AccCS = \frac{absolute\ correct\ predictions}{total\ absolute\ predictions} \tag{4}$$

b) Sensitivity

$$Sensitivity = \frac{TPs}{TPs+FNs} \tag{5}$$

c) PPV

$$PPV = \frac{TPs}{TPs+FPs} \tag{6}$$

d) F1

$$F1 = 2 * \frac{precision * sensitivity}{precision+sensitivity} \tag{7}$$

e) Specificity

$$Specificity = \frac{TNs}{TNs+FPs} \tag{8}$$

f) NPV

$$NPV = \frac{TNs}{TNs+FNs} \tag{9}$$

g) Accuracy – Global

$$AccG = \frac{TPs+ TNs}{TPs+ TNs+ FN+ FPs} \tag{10}$$

Were TP means true positive, the correct activation; TN is true negative, the correct inactivation; FP is false positive, the incorrect activation; and FN is false negative, incorrect inactivation.

3 Results and discussion

It has been shown that the individual movements can be successfully predicted offline using pattern recognition algorithms [1], [3], [12], [13] and in this study was demonstrated an increase in terms of classification accuracy was achieved when the new features were used in conjunction with a feature reduction algorithm. Table 1 shows the results obtained using the characteristics present in BioPatRec and the use of PCA or UFS to reduce characteristics.

Table 1. Quantitative indicators obtained with the comparison between old features with feature reduction algorithms.

Features Selection	Accuracy Class	Sensitivity	PPV	F1	Specificity	NPV	Accuracy Global
None	83,10	85,11	92,30	0,89	99,73	99,43	99,19
PCA	92,74	94,78	94,78	0,95	99,80	99,80	99,61
UFS	90,63	92,29	95,02	0,94	99,81	99,70	99,54

Table 2 shows the results obtained using the characteristics present in BioPatRec and those added by this study, in addition to the use of PCA or UFS to reduce the characteristics. As more characteristics are sorted, the MLP begins to diverge, but when selecting the most divergent characteristics, through the methods of selecting characteristics, rating the signal becomes easier. The performance of the proposed and the conventional methods present in the BioPatRec is shown by the gain in the accuracy and deviation shown in Tables 1 and 2.

Table 2. Quantitative indicators obtained with the comparison between the new features added to the old features sets with feature reduction algorithms.

Features Selection	Accuracy Class	Sensitivity	PPV	F1	Specificity	NPV	Accuracy Global
None	82,39	83,60	95,76	0,89	99,86	99,37	99,26
PCA	94,63	96,22	96,95	0,97	99,88	99,85	99,75
UFS	93,50	94,71	96,68	0,96	99,87	99,80	99,68

The below figure shows the distribution curves of the experiment, while the blue curve represents the old features the red one represent the experiment with the added features.

The difference between two means divided by a standard deviation for the data is represented with the "d" letter in the graphic.

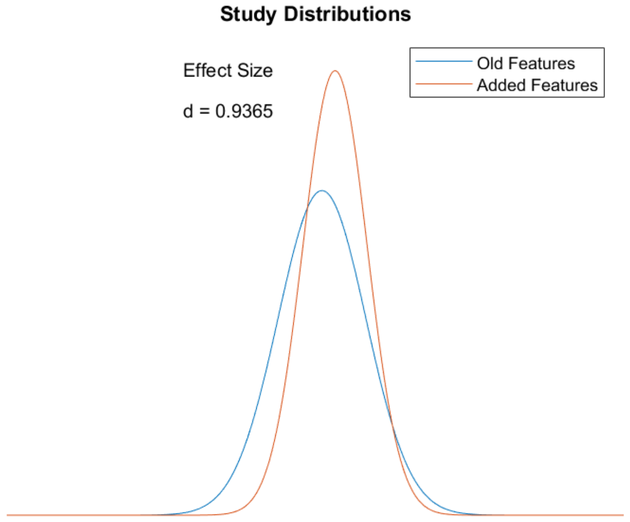

Fig. 2. Distribution of the experiment with the old features and the added features.

According to Cohen and Sawilowsky:

- d = 0.01 => very small effect size;
- d = 0.20 => small effect size;
- d = 0.50 => medium effect size;
- d = 0.80 => large effect size;
- d = 1.20 => very large effect size;
- d = 2.00 => huge effect size.

The experiment was offline, and the mean training and validation time was of 34 seconds and the mean testing time was of 0.004 seconds.

The use of BioPatRec allows a fast and accurate simulation of the pattern recognition algorithms, which streamlines the process of development and testing of theories that will be applied in the control of a myoelectric prosthesis. This platform is being used in this study and it is hoped that it can assist in the development of an adaptive learning pattern recognition system for the control of an upper limb electrical prosthesis. In addition, the fact that the BioPatRec platform is modular allows the study to be better divided into stages, such as signal processing, extraction of characteristics, classification and the decision-making system of the prosthesis, making the process agiler.

4 Conclusion

The addition of the new features in conjunction with the selection algorithms improved the characterization of the myoelectric signal, which will facilitate the decision process for the control of the myoelectric prosthesis. The help of the BioPatRec platform made the work agiler and the statistical metrics helped to evaluate the effectiveness of the algorithms applied in this study. Furthermore, this study showed that simultaneous control can be considered since it improves user comfort. In addition, simultaneous control is required for more natural control of artificial limbs, and pattern recognition has proved to be an excellent means of working with the complexity generated by simultaneous movement.

5 Acknowledgment

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