A Comparison of Myoelectric Pattern Recognition Methods to Control an Upper Limb Active Exoskeleton

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Abstract. Physically impaired people may use Surface Electromyography (sEMG) signals to control assistive devices in an automatic way. sEMG signals directly reflect the human motion intention, they can be used as input information for active exoskeleton control. This paper proposes a set of myoelectric algorithms based on machine learning for detecting movement intention aimed at controlling an upper limb active exoskeleton. The algorithms use a feature extraction stage based on a combination of time and frequency domain features (mean absolute value – waveform length, and auto-regressive model, respectively). The pattern recognition stage uses Linear Discriminant Analysis, K-Nearest Neighbor, Support Vector Machine and Bayesian classifiers. Additionally, two post-processing techniques are incorporated: majority vote and transition removal. The performance of the algorithms is evaluated with parameters of sensitivity, specificity, positive predictive value, error rate and active error rate, under typical conditions. These evaluations allow identifying pattern recognition algorithms for real-time control of an active exoskeleton.

Keywords: Movement intention detection, myoelectric patterns recognition, machine learning, majority vote, surface electromyography, transition removal.

1 Introduction

Passive prostheses and orthoses are devices for functional compensation and physical rehabilitation of the human motor system. These are used on people suffering amputations and muscular disorders, but do not provide an intuitive reaction in its control to restore motor functions. On the other hand, active exoskeletons and myoelectric prostheses execute these functions in a natural way according to its learning process [1]. Surface Electromyography signal is the electrical manifestation of the neuromuscular activation associated with a contracting muscle [1]. sEMG pattern recognition based on control has emerged as a promising alternative in rehabilitation robotic devices [1]. Many studies have evaluated sEMG features in

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classification algorithms aiming to control active prostheses and robotic exoskeletons [2]. Different features extraction methods have been used in pattern recognition involving both time domain and time-frequency domain features. Some of these include mean absolute value [3], zero crossings (ZC) [3], slope sign changes (SSC) [3], auto-regressive (AR) model coefficients [3], cepstrum coefficients [3], waveform length (WL) [3] and wavelet packet transform [3]. Numerous studies have been proposed to classify the features extracted from the sEMG like Bayesian classifier (BYN) [4], linear discriminant analysis (LDA) [5], hidden Markov model [6], multi-layer perceptron (MLP) [4], fuzzy classifier [7], gaussian mixture model [8] and support vector machines (SVM) [9]. Most of the studies have been accomplished in health people to verify the feasibility of implemented algorithms for sEMG-based pattern recognition in human upper limbs.

This work is motivated by the ongoing development of a 4-Degree of Freedom (DoF) upper limb active exoskeleton for muscular rehabilitation therapies. The first stage of this work is related to the performance evaluation in off-line mode of myoelectric algorithms to control external devices. Next section describes the methodology utilized in the feature extraction methods, the myoelectric pattern classification process and the post-processing algorithms, supported on an experimental protocol. Also, the quantitative parameters used in the performance evaluation are here described. Later, the results and discussions are presented, based on the qualitative and quantitative parameters set. Finally, the conclusion about of this work is presented.

2 Methods

Figure 1 shows the blocks diagram of the different myoelectric algorithms. First, the sEMG data are segmented in windows of 256 ms, overlapped of 32 ms, taking into account that delays in myoelectric control must be inferior to 300 ms [1]. Later, each data segment is processed through a feature extraction method conformed from a combination of parameters in temporal and spectral domains aimed at extracting information from sEMG. Linear Discriminant Analysis, Support Vector Machine, K-Nearest Neighbor (KNN) and Bayesian classifier are employed for pattern recognition of seven classes, associated to upper limb movement. Finally, majority vote and transition removal algorithms are used to improve the pattern classification results.

2.1 Experimental Protocol Description

The stages of training and validation of the proposed algorithms were implemented using a set of signals from a sEMG database provided by the University of Carleton, Canada [8] from thirty healthy subjects. From this database, six sEMG recordings were taken for each subject, in four trials. Acquired recordings on eight channels with a sampling frequency of 3 kHz were provided through Ag-AgCl electrodes arranged at locations of the upper limb as shown in figure 2. Previous to the classification process, data were undersampled to 1 kHz. In each trial, subjects repeated four times, and in a random way, the following seven movements: hand open, hand close, wrist flexion, wrist extension, forearm pronation, forearm supination and resting. Each movement repetition lasted 3 s. A rest period of 5 s was introduced at beginning and ending of each trial, then the whole trial lasted 94 s [7]. The class identifiers for different movements are the following: 1- hand open; 2-hand close; 3-wrist flexion; 4-wrist extension; 5-forearm supination; 6-forearm pronation; 7-resting.

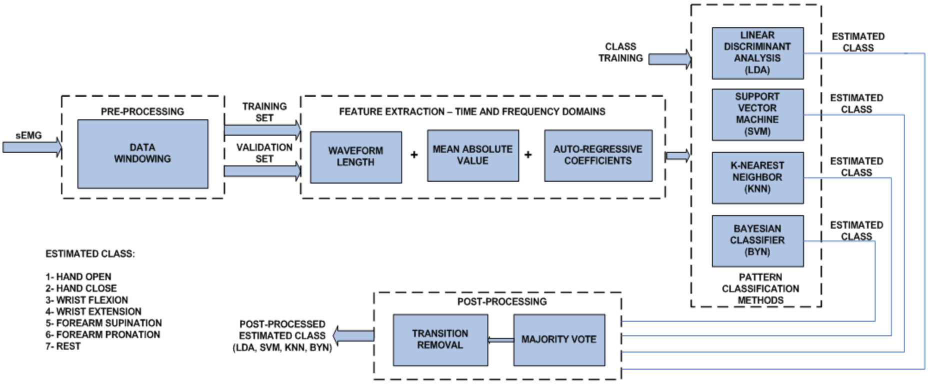

Fig. 1. Block diagram of the proposed myoelectric algorithms

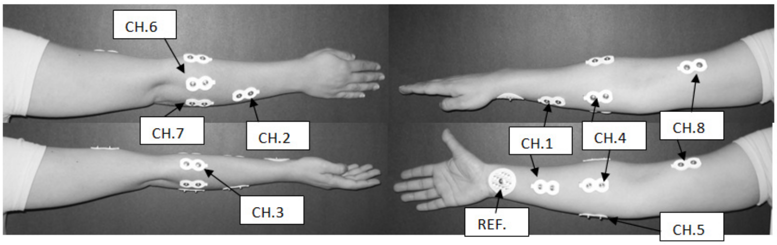

Fig. 2. Position of the bipolar electrodes associated to sEMG channels

2.2 Feature Extraction Methods

The feature extraction method includes a combination of time and frequency domain parameters. Recent researches have demonstrated that this mixture vectors is a functional and efficient configuration [2]. This configuration provides a good classification accuracy and, is computationally efficient, which facilitates its implementation on embedded systems. Furthermore, it is more robust to the displacement of the surface electrodes. In the temporal domain the mean absolute value (MAV) and the waveform length (WL) were used. The MAV provides the average amplitude of x_i in the segment i that is N samples in length, see equation (1). The WL provides the cumulative length of the waveform over the time segment, see equation (2).

$$MAV = \frac{1}{N}\sum_{l=1}^{N}|x_i|, \tag{1}$$

$$WL = \sum_{l=1}^{N-1} \left| x_{i+1} - x_i \right|, \tag{2}$$

In the frequency domain, an Auto-Regressive (AR) model was implemented, basically expressed by follow expression:

$$x_i = \sum_{p=1}^{P} a_p \, x_{i-p} + w_i, \tag{3}$$

where P is the order of the AR model and w_i the white noise error. In the sEMG-based pattern recognition process, the coefficients of the AR model a_p have been used as the feature vector. The AR model was based on Levinson–Durbin recursive method. This method is efficient at computation level in the calculus of the linear prediction coefficients, supported on the autocorrelation matrix [3]. Considering that any one of a four-order to six-order auto-regressive model is enough to represent the signal as a temporal series for the recursive method, a four-order model to obtain the linear prediction coefficients was defined [3]. Finally, in the feature extraction process, a concatenation of vectors of several parameters calculated from each sEMG channel was obtained: 1 MAV coefficients, 1 WL coefficients and 4 AR coefficients.

2.3 Myoelectric Pattern Classification

After extracting feature vectors, four classification methods (classifiers) were applied independently, according to the proposal myoelectric algorithms (LDA, SVM, KNN, BYN), see figure 2. Each sEMG channel and theirs characteristic vectors were concatenated from the first four auto-regressive coefficients, *MAV* and *WL* values, resulting in 48 coefficients (8 channels x 6 characteristic vectors/channel). Those feature vectors are the input to the different classifiers. The output of each classifier represents in each time anyone the seven motion class, see figure 2. Linear Discriminant Analysis technique [5] maximizes the ratio of between-class variance to the within-class variance in any particular data set, thereby guaranteeing maximal separability. This classification algorithm does not require iterative training, avoiding the problems with over-training that appear in artificial neural networks. Support Vector Machine constructs an optimal separating hyperplane in a high-dimension feature space of training data that are mapped using a nonlinear kernel function [9]. Therefore, although it uses a linear learning machine method with respect to the nonlinear kernel function, it is in effect a nonlinear classifier. The high generalization and classifying linearly-inseparable patterns with small computational complexity are capabilities of the SVM, which can be useful for classifying sEMG signal patterns whose features tend to change with time and can allow real-time motion classification, respectively [9]. K-nearest neighbor algorithm [10] is a non-parametric method for classifying objects based on closest training examples in the feature space. The k-nearest neighbor algorithm is one of the simplest of all machine learning algorithms. Bayesian classifier [4] is applied for use when features are independent of one another within each class, but it appears to work well in practice even when that independence assumption is not valid. The class-conditional independence assumption greatly simplifies the training step since it is possible to estimate the one-dimensional class-conditional density for each feature individually. The stages of training and validation of proposed algorithms were implemented using cross-validation technique evaluating the results based on partitioning the data into training and test sets. Specifically, k-fold cross-validation was used based on the partition the k samples sub-conjunct. One subset is used as testing data and the rest (k-1) as training data. For this evaluation the k value ($k = 6$) is equal to the number of sEMG recordings acquired in one trial. For implementation of the four myoelectric pattern classifiers, the information of the classes during the training process was used.

2.4 Post-processing Techniques

The post-processing methods are designed to manage excessive outflows in the classification process and improve the system performance. The majority vote method (MV) uses the current classification result along with the n previous classification (for this case, the eight previous classifications results) and makes a classification decision based on the class that appears more often [8]. The resulting effect is a smooth operation that removes spurious misclassification. The number of decisions that can be used in majority vote depends upon the length of the analysis window, the system processing delay, and the total system delay tolerable by the user for the exoskeleton control. On the other side, the errors that are present normally occur during transitional periods, which are expected as the system is in an undetermined state between contractions. Indeed, it is possible to remove them using transition removal algorithms [8].

3 Results

Feature extraction and patterns classification algorithms were implemented in an off-line mode using functions in Matlab (Mathworks Inc., Natick, MA). The performance of the proposed algorithms was evaluated based on quantitative measures that include sensitivity (SS), specificity (SP), predictive positive value (PPV), total error rate of classification (TER) and active error rate (AER). An active decision is a single output class from the classifier resulting in limb motion. Figure 3 presents the scatter plot based on the feature vectors and the representative motion class from the proposed myoelectric algorithms, for the eight myoelectric channels. From a qualitative evaluation, the four classifiers provide a good discrimination of the wrist flexion and extension motion class, based on *MAV*, *WL* and auto-regressive feature vectors. The others motion class (hand open, hand close, supination, pronation and rest) were grouped in homogenous and similar way from the four classifiers. Figure 4 shows the statistical dispersion based on the total error rate, sensitivity, specificity, active error rate and predictive positive value without post-processing techniques (majority vote and transition removal).

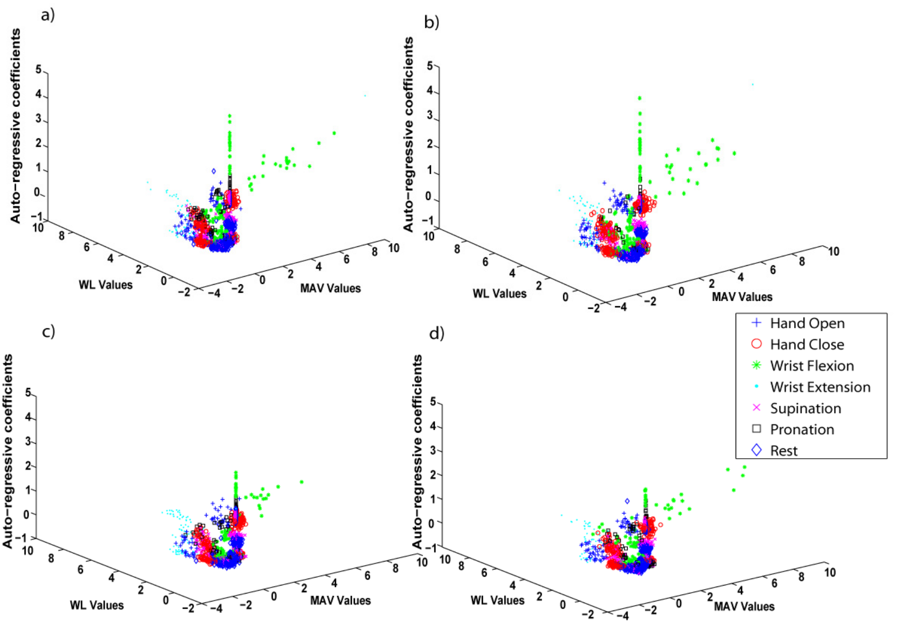

Fig. 3. Scatter plot the feature vectors and the motion class from the proposed myoelectric algorithms: a) LDA classifier; b) KNN classifier; c) SVM classifier; and d) BYN classifier

LDA, KNN and SVM classifiers (Fig.4a, b and c) present a similar performance from quantitative parameters. The total and active error rate (TER and AER) in the Bayesian classifier (Fig. 4d) is higher respecting to others classifiers, meaning lower accuracy during the movement action classification. Additionally, the specificity (SP) accuracy is lower, expressing that the movement actions proportion correctly rejected is lower respect to the previous classifiers. Therefore, the false positive number is higher during the classification process. From the above results and taking as example the Bayesian classifier, table 1 shows the confusion matrix from one working section the experimental protocol. Rows in the matrix represent the inputs related to classes that are required to obtain, and columns represent obtained patterns as classifier outputs. The main diagonal in both matrices represents the concordance between the true and obtained classes. Shared cells in the confusion matrix of the first table, under the main diagonal, present positive falses, i.e., a number of occurrences of motion class with the class that should be obtained. This is caused by the dispersion of the feature vectors and their relation with the motion class based on the assumption that not always is accurate, for Bayesian classifiers, that the predictor variables are independent. The second table shows the results obtained with the combinations of the majority vote and transition removal technique. The total removing of the positive falses with the combinations of these techniques is observed. Nevertheless, a considerable reduction of the motion class corrected classified from main diagonal is generated, as well as the motion class execution time. This is caused by removing the transition periods at the beginning and end of the motion class period while contractions occur.

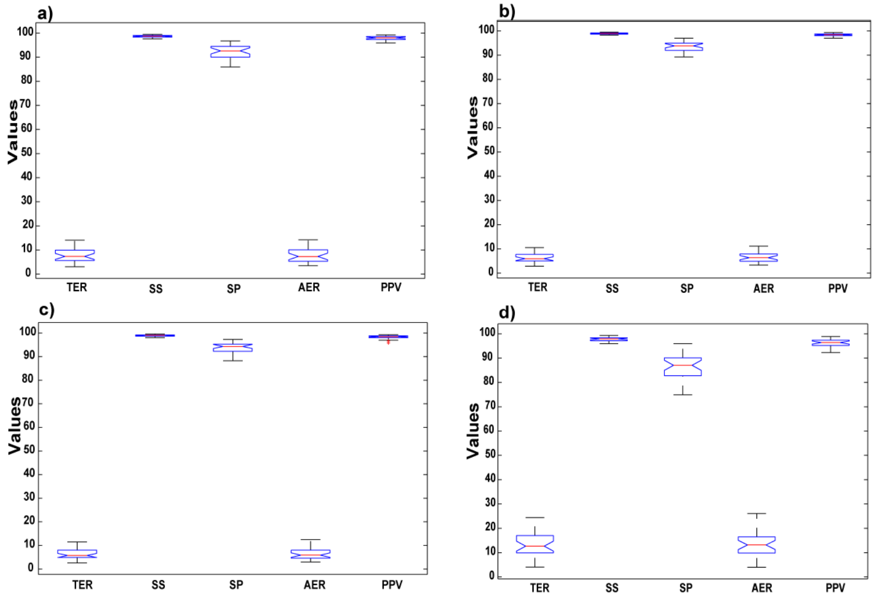

Fig. 4. Statistical results for a representative classification from the proposed myoelectric algorithms: a) LDA classifier; b) KNN classifier; c) SVM classifier; and d) BYN classifier.

Table 1. Confusion matrix of the Bayesian classifier

	Bayesian Classifier without post-processing						
	Hand Opened	**Hand Close**	**Wrist Flexion**	**Wrist Extension**	**Forearm Pronation**	**Forearm Supination**	**Rest**
Hand Opened	293	2	1	0	1	0	4
Hand Close	2	292	2	0	0	1	0
Wrist Flexion	2	4	287	0	1	1	3
Wrist Extension	7	1	1	287	0	0	0
Forearm Pronation	5	3	14	3	280	0	1
Forearm Supinatio	5	3	8	1	4	280	3
Rest	3	5	3	1	3	0	506
	Bayesian Classifier with majority vote and remove transitions						
Hand Opened	29	0	0	0	0	0	0
Hand Close	0	72	0	0	0	0	0
Wrist Flexion	0	0	27	0	0	0	0
Wrist Extension	0	0	0	23	0	0	0
Forearm Pronation	0	0	0	0	57	0	0
Forearm Supinatio	0	0	0	0	0	7	0
Rest	0	0	0	0	0	0	152

4 Conclusions

The control of exoskeletons working as an assistance or rehabilitation tools requires special considerations such as robustness, reliability and safe. These are mandatory requirements taking into account that the device must identify the user movement intention, analyze the information in real-time and compute the mechanical power to release in the right instant. This paper described the obtained results in a comparative study of four proposed algorithms to approach the detection of movement intentionality. Selected algorithms aim to control a robotic upper limb exoskeleton using sEMG signals. LDA, SVM and KNN have presented better accuracy than Bayesian classifier. Nevertheless, the execution time during the training and evaluation process of the Bayesian classifier (292 ms) is considerably lower than the other classifiers (LDA − 1.22 s, SVM − 700 ms and KNN − 428 ms). This result is an important parameter to be considered for its implementation in on-line mode. In this mode, the performance of the proposal algorithms could be improved using the post-processing techniques (majority vote and transition removal), but it is important to evaluate the number of decisions that can be used, as well as the length of the analysis window, taking into account that delays in myoelectric control. As future work, it is required to implement other algorithms and evaluate them under other conditions in order to obtain an optimal solution for myoelectric control.

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