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Multifunctional Prosthesis Control with Simulation of Myoelectric Signals

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Abstract

The skeletal muscle activation generates electric signals called myoelectric signals. In recent years a strong scientific activity has been developed in the recognition of limb movements from electromyography (EMG) signals recorded from non-invasive (surface) electrodes, in order to design systems for prosthetic control. Surface EMG acquire the activation of surrounding muscles and for that reason the obtained signal needs to be conditioned and processed, with pattern recognition techniques for extraction and classification. In this work EMG signals were acquired for two hand movements, "hand close" and "hand open". The EMG electrodes were placed on the forearm and positioned over the extensor digitorum muscle, for the "hand open" and flexor digitorum muscle, for the "hand close". Using MATLAB software the signal conditioning, feature extraction and classification were performed. The feature extraction process was carried with the Wavelet Packet Transform (WPT) technique and the classification process was done with two different techniques for comparison purposes, Neural Networks (NN) and Support Vector Machines (SVM). The results show that the SVM classifier used presented better classification performance compared to NN classifier used.

Keywords: EMG, Signal conditioning, Wavelet Packet Transform (WPT), Neural Networks (NN), Support Vector Machines (SVM)

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1. Introduction

In the human body, muscular contraction is responsible for many processes, such as: force generation, body movement, posture maintenance, breath, body heat production, communication, organs and vessels constriction and heartbeat [1].

There are three types of muscle tissue: skeletal muscle, smooth muscle and cardiac muscle. The skeletal muscle is inserted in the bones, controlled voluntarily and involuntarily (reflexes), doesn't contain spontaneous contraction capacity and the main function is the body movement. The smooth muscle is in the walls of hollow organs, vessels, eyes, glands and skin, some of them having spontaneous contraction capacity and their main functions are mobilization of food in the digestive tract, regulation of blood vessels diameter, change of pupil size and gland contraction. The cardiac muscle in the heart has an involuntary control, having spontaneous contraction capacity and the main function is the heartbeat [1].

The muscular activation is triggered when an action potential is transmitted from motor neurons to the muscle fibers creating an action potential. A single action potential can only be recorded with invasive needle electrodes. However, non-invasive electrodes (surface electrodes) are more commonly used and multiple, superimposed action potentials are recorded. These electrical signals are referred as electromyogram (EMG) [2]. EMG signal is acquired by a technique called electromyography which consists of an amplifier with more than one channel, an acquisition board and a PC with software for signal visualization, acquisition, offline evaluation and processing. For signal amplification and filtering it is normally used a band pass filter, to reduce motion artefacts (high-pass filter) and noise (low- pass filter) [3].

In health care and rehabilitation engineering, the recognition of limb motions from EMG has been largely studied. Nowadays, EMG prosthesis motion is accomplished mainly with electric motors. The EMG activity is acquired from the remaining muscles in the stump, after amputation, with superficial non-evasive electrodes [4].

The EMG signals provide important information in a particular way. This information is useful if the signal can be quantified. The signal is sent to the conditioning signal block, for amplification, filtering and A/D conversion [3], [4].

In the past few years, various feature extraction methods have been used for pattern recognition, such as mean absolute value (MAV), number of zero crosses (ZC), number of slope sign changes (SSC), waveform length (WL), variance (VAR), root mean square (RMS), histogram (HIST), autoregressive (AR) coefficients, fast Fourier transform (FFT) coefficients, cepstrum coefficients (CC), wavelet transform (WT) coefficients and wavelet packet transform (WPT) coefficients [5]-[6].

Different approaches may be used for features classification to identify the intended movement. Some classification techniques used are for example: Linear Discriminant Analysis (LDA), K-Nearest Neighbour (K-NN), Neural Networks (NN), Fuzzy Systems, Neuro-Fuzzy classifiers and Support Vector Machines (SVM).

Figure 1 shows the block diagram of a myoelectric prosthesis that allows us to understand the integration of electronic and mechanical systems and to identify problems related to pattern recognition [5]-[6]. The EMG signals, presented in this work, were acquired from a healthy volunteer, to recognize two specific movements: “open hand” and “close hand”. To perform the signal conditioning, a Wavelet Packet Decomposition (WPD) was used. For feature extraction, a Wavelet Packet Transform (WPT) was used. Finally, the NN and the SVM classification methods were compared.

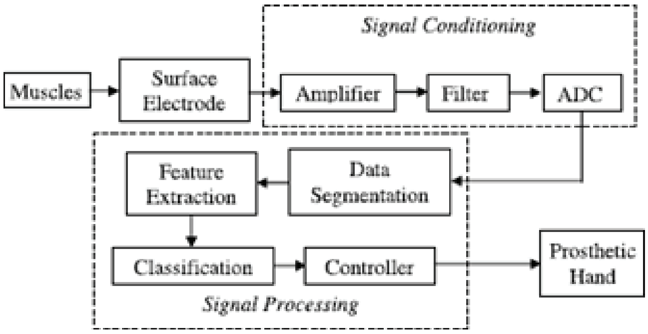

Figure 1: Block diagram of a myoelectric prosthesis device [6]

2. Background and Methods

2.1. Signal Acquisition

To proceed with signal acquisition two movements were tested: “open hand” and “close hand”. Two antagonist muscles were chosen for the signal acquisition, both located in the forearm: for the “open hand” movement the extensor digitorum muscle and for the “hand close” movement the flexor digitorum muscle [1], [2], [7], Fig. 2.

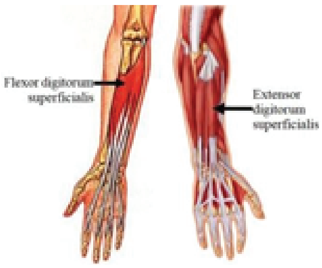

Figure 2: Representation of the muscles (Extensor digitorum and Flexor digitorum) used in signal acquisition [7]

Using the signal acquisition system “PowerLab/4st” from ADInstruments, connected to a PC with LabChart software installed, it was possible to perform the data acquisition. In the experiment, surface electrodes were used. From the acquired data, 6 frames were selected, and MATLAB software was used to perform the conditioning of the signals and perform the feature extraction and classification [8].

2.2. Signal conditioning

For signal acquisition, surface electrodes collect signals from different motor muscles activity, which cause an increase in noise. To remove the noise, Wavelet method was used. This method is better than filtering in the frequency domain because it does not alter feature signals while reducing noise. Wavelet Packet Decomposition (WPD) is a

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Wavelet Transform where discreet time signal (sample) is passed through many filters. For *n* decomposition levels WPD produces 2^n different sets of coefficients or nodes [9].

Using the functions of Wavelet Toolbox from MATLAB it is possible to perform signal conditioning with noise reducing [9], [10]. In this work the parameters were defined as "Haar" Wavelet with level 3 and "Shannon" entropy [11]. This type of entropy is a normalized entropy which involves logarithm of the squared value of each sample of the signal (s_i):

$$-\sum s_i^2 \log(s_i^2) \tag{1}$$

Stein's Unbiased Risk Estimate (SURE) method was used to obtain the thresholding value T:

$$T = \sqrt{(2\ log\_e(n\ log\_2(n)))} \tag{2}$$

where n is the number of signal samples. For thresholding parameters we selected the method "Fixed form", "soft" thresholding and a threshold value of 60 [9], [10].

2.3. Wavelet Packet Transform

Using the Wavelet Toolbox functions of the MATLAB software it is possible to perform feature extraction of the EMG signals [5], [6], [12]. The Fourier analysis is often used, but the transient information is lost in frequency domain. The biggest advantage in using Wavelet Transform is that time-frequency window is flexible and adapts such that there is always the same number of periods of the analysed frequency in the time window [13].

The Wavelet Transform is achieved by breaking up a signal in shifted and scaled versions of the original Wavelet [13]. The waves can be discreet or continuous waves, and the later can be divided in real or complex. Table 1 shows the different types of Wavelets [14].

Table 1: Different types of Wavelets Source: [14]

Discreet Wavelets	Continuous Wavelets	
	Real	*Complex*
Coiflet	Beta	Mexican Hat
Daubechies	Hermitian	Morlet
Haar	Mexican Hat	Modified Morlet
Symmlet	Shannon	Shannon

In Wavelet Transform (WT) the signals are divided in detail and approach. Those obtained from first level are divided in a new detail and approach and this process is repeated. Due to the fact that Wavelet Transform decomposes the signal, some problems can arise for applications where the most important information is located in higher frequency components [10], [14].

Wavelet Packet (WP) analysis is an expansion of classical Wavelet decomposition with advantages for signal processing. The main difference between Wavelet Transform and Wavelet Packet Transform (WPT) is that in WPT details are decomposed for each signal. Thus, with WPT, a better frequency resolution for decomposed signal can be obtained. Besides, the use of WPT extracts more features about the signal. Fig. 3 illustrates a signal decomposition tree with 4 decomposition levels [10], [13], [14].

The equation (3) represents a WP as a function of 3 indexes: integers *i*, *j* and *k* which are related with the modulation, scale and translation parameters:

$$\psi^{i}_{j,k} = 2^{j/2}\psi^{j}(2^{j}t - k),\;\; i = 1, 2, 3, \ldots \tag{3}$$

Wavelet functions Ψ^{j} are determined by the following recursive functions in Eqs. (4) and (5):

$$\psi^{2j}(t) = \sqrt{2}\sum_{-\infty}^{\infty} h(k)\psi^{i}(2t - k) \tag{4}$$

$$\psi^{2j+1}(t) = \sqrt{2}\sum_{-\infty}^{\infty} g(k)\psi^{i}(2t - k) \tag{5}$$

The original signal $f(t)$ after j decomposition levels is defined in Eq. (6) as:

$$f(t) = \sum_{i=1}^{2j} f^{i}_{j}(t) \tag{6}$$

while WP component $f^{i}_{j}(t)$ is a linear combination of Wavelet Packet functions $\Psi^{i}_{j,k}(t)$:

$$f^{i}_{j}(t) = \sum_{-\infty}^{\infty} c^{i}_{j,k}(t)\psi^{i}_{j,k}(t) \tag{7}$$

where WP coefficients $c^{i}_{j,k}(t)$ are calculated by:

$$c^{i}_{j,k}(t) = \int_{-\infty}^{\infty} f(t)\psi^{i}_{j,k}(t)dt \tag{8}$$

with functions satisfying the orthogonality given in Eq. (9):

$$\psi^{m}j,k(t)\psi^{n}j,k(t) = 0 \text{ if } m \neq n \tag{9}$$

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Energy E_k of a WP $\Psi^i_{j,k}$ is given by:

$$E_k = \sum_{-\infty}^{\infty} |c^i_{j,k}(t)|^2 \tag{10}$$

To calculate the rated energy of a WP, the energy is divided by the total energy of the signal:

$$NE_{j,k} = \frac{E_k}{E} \times 100\% \tag{11}$$

where E is the total energy of the signal, given by Eq. (12):

$$E = \sum_{-\infty}^{\infty} E_n \tag{12}$$

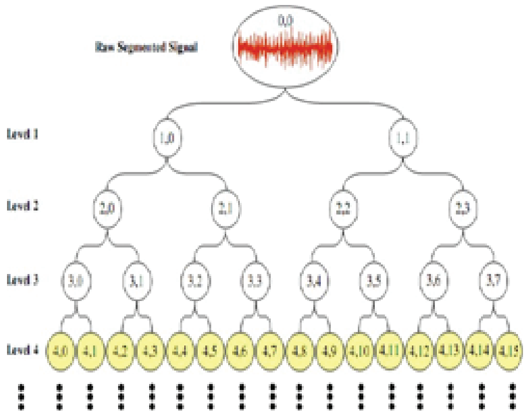

Figure 3: Decomposition tree with 4 decomposition levels [13]

For extraction parameters it was chosen a Symmlet Wavelet with 4 and 5 levels of decomposition because there will be greater preservation of signal information. After creation of the decomposition tree, the energy value for each terminal node is calculated and used as feature vectors to proceed with their classification [10], [13].

2.4. Neural Networks Classifier

Using Neural Networks Pattern Recognition Toolbox functions of MATLAB software was possible to perform the classification with Neural Networks Classifier [10]. The Artificial Neural Networks are bio-inspired algorithms that simulate low levels functions of biological neural networks, widely used in pattern recognition and deep learning [3], [11], [15].

In the training phase, feature vectors were used as input for the network. The network adjusts the parameter variables and weights, to recognize the relationship between input and output. The ability to learn from examples, the ability to reproduce nonlinear functions of arbitrary inputs and the highly parallel and regular structure, make the Neural Networks especially suitable for pattern classification tasks [3], [11], [15].

There are various architectures for Neural Networks but the most commonly used is Multilayer feedforward Perceptron Neural Network (MFPNN). The architecture of this type of network is characterized by an input layer, one or more hidden layers and an output layer. Each node (neuron) of a layer is connected to every node of the adjacent layers, however the information flows without any type of feedback.

The training algorithm chosen was the Back Propagation (BP) algorithm. This algorithm regulates the weights and bias value by back propagating the error of the predicted outputs and is widely applied in pattern recognition in prosthetic hands [3], [13].

This MFPNN with the BP training method is an adaptive network where each hidden node calculates the weighted sum of its inputs and applies a thresholding function to determine its output. The output of a node Y_j is described as the weighted sum of input signals plus a bias term, Eq. (13) and then apply a thresholding function (sigmoid in our case) given by Eq. (14),

$$x_j = \sum_i w_{i,j} x_i + b_j \tag{13}$$

$$Y_j = f(x_j) = \frac{1}{1 + \exp(-x_j)} \tag{14}$$

where x_i is an input set of node j, $w_{i,j}$ is the relative weight for the connection between nodes i and j and b_j is the bias threshold of node j.

The BP method is performed in two phases: in the first phase, the feed-forward process is performed to determine the predicted outputs; in the second phase the error to the desired output is calculated and it is back propagated (feed-backward) from the output layer to the input layer adjusting the weights and thresholds value in order to minimize the error rate. The error E_j for node j for a sample of the training set is given by Eq. (15):

$$E_j = d_j - Y_{out,j} \tag{15}$$

where d_j is the desired output for node j and $Y_{out,j}$ is the current output for node j for each sample of the training set. Figure 4 shows a typical architecture of NN classifier [15]. The NN used in this work has an input layer with 12 inputs, an hidden layer with 4 nodes and an output layer with 2 nodes. Data was with 80% for training and 20% for test [10].

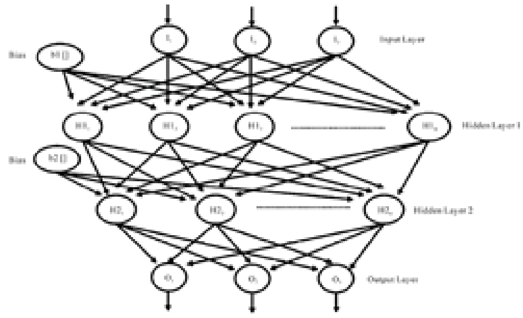

Figure 4: Architecture of a Neural Network [15]

2.5. Support Vector Machines Classifier

Using Classification Learner Toolbox functions of MATLAB software was possible perform the classification with Support Vector Machines (SVM) [10]. SVM maps the input vectors x in the high dimensional feature space Z with some non-linear mapping, chosen in advance. In this space a hyperplane is constructed to divide the input vectors [16]. SVM is a binary classifier $f : R^N \mapsto \{\pm 1\}$ which is estimated by empirical data:

$$(x_1, y_1), \ldots , (x_m, y_m) \in R^N \times \{\pm 1\} \tag{16}$$

For a non-linear classification, the solution is given by mapping the original data in feature space, wherein the mapped data are separated in a linear form by a hyperplane, Fig. 5 [16].

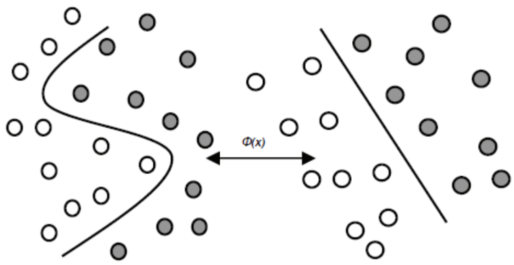

Figure 5: Mapping a non-linear and linear hyperplane [16]

For non-linear classification, a feature space with non-linear dimension builds a classifier as:

$$w \cdot \varphi(x) + b = 0 \tag{17}$$

A hyperplane not only properly separate classes of data points but also make a maximum margin (distance from the point closest to the hyperplane). Applying the Lagrande Transform, the classification function is given by Eq. (19):

$$f(x) = sgn(\sum_{i=1}^{l} a_i^* y_i K(x, x_i) + b) \tag{18}$$

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where x_i is the training vector, x is the recognition vector and a_i^* is the Lagrande operator.

The Kernel function is given by Eq. (20):

$$K(x, x_i) = \varphi(x_i) \cdot \varphi(x) \tag{19}$$

The Kernel functions given a convenient method to obtain high dimension features, mapped from data without non-linear transform calculation. The common Kernel functions are the linear, the quadratic, the polynomial and radial basis [6], [15], Table 2.

Table 2: Kernel Functions used in SVM Source: [15]

Função Kernel	Equação
Linear	$K(x, x_i) = x \cdot x_i$
Quadratic	$K(x, x_i) = (x \cdot x_i + 1)^2$
Polinomial	$K(x, x_i) = (x \cdot x_i + 1)^q$
Radial Basis	$K(x, x_i) = \exp \lvert x - x_i \rvert^2 / \sigma^2$

In SVM the training is reformulated and represented to obtain a quadratic programming problem. The solution for this problem is global and unique. In this approximation it's possible to choose many types of Kernel functions. There are many possible hyperplanes which separate the data, but there is only one hyperplane whit a maximum separation margin between classes. To construct this hyperplane it is necessary to solve the problem:

$$min_{w,b}\frac{1}{2}\|w\|^2 + c\sum_{i=1}^{m} \xi_i y_i(w\phi(x_i) + b) \geq 1 \quad i = 1, 2, \ldots, m \tag{20}$$

SVM is a powerful tool in binary classification, able to generate fast classification functions in sequence of a training period. There are many approaches with three or more classes (multi- class problem) $f : R^N \mapsto \{1, \ldots, k\}$ to calculate the most appropriate class from empirical data:

$$(x_1, y_{x_1}), \ldots, (x_k, y_{x_k}) \in R^N \times \{1, \ldots, k\} \tag{21}$$

The approaches used are: one-against-all (OAA) classification method and one-against-one (OAO) classification method. In OAA classification method, to classify a new sample, k classifiers are used that work separately and the one that generates a larger decision function value is selected as estimated class. This method is easy to implement and gives better results. In OAO classification method, $k(k-1)$ classification methods are trained separately to separate a pair of two classes. To classify a new sample, the class that has more votes of binary classifiers is chosen as final result. This is a fast method like OAA method. The advantage of OAO method is the binary classifications in all pairs of classes and estimation of probability of each class [6], [15]. Figure 6 shows the architecture of SVM classifier [15].

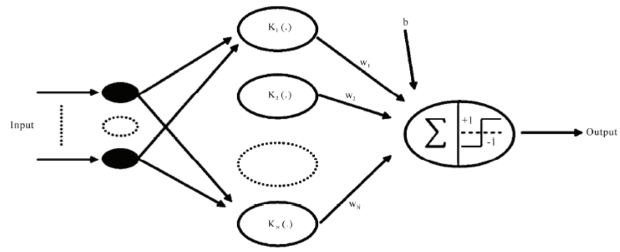

Figure 6: Architecture of SVM classifier [15]

In this work a Holdout validation method was defined. The Holdout validation method selects a percentage of the data to use as a test set. The toolbox trains the model on the training set and assesses the performance with the test set. The data was divided in the following manner: 80% for training and 20% for test [10].

2.6. Electrodes and Hardware

Surface electromyography was obtained using the PowerLab/4ST EMG acquisition system from ADInstruments. The common electrode was connected to the common channel and two pairs of electrodes were connected to channels 1 and 2. The pair of electrodes placed in the anterior forearm to acquire signals from the flexor digitorum muscle was connected to channel 1 and the pair of electrodes placed in the posterior forearm, to acquire signals from extensor digitorum muscle, was connected to channel 2 were located. Prior to electrode placement the skin of the volunteer was exfoliated (to remove dead skin) and cleaned with 70% v/v alcohol to remove any oil or dust from the skin surface. To hold the electrodes, adhesive tape was placed and between the electrodes and the volunteer's skin an electrolyte gel was used. Also, a MLT003/D transducer (load cell) was plugged into the differential input of the PowerLab/4ST to measure the force when the open/close movement is made.

3. Results

Figure 7 shows the obtained results. First signal corresponds to the measured force (load cell) and second and third signals correspond to the movements "hand close" and "hand open" respectively. The data acquisition generates a text file with obtained signal values. For each hand movement, 6 frames are selected to extract their characteristics and classification [16].

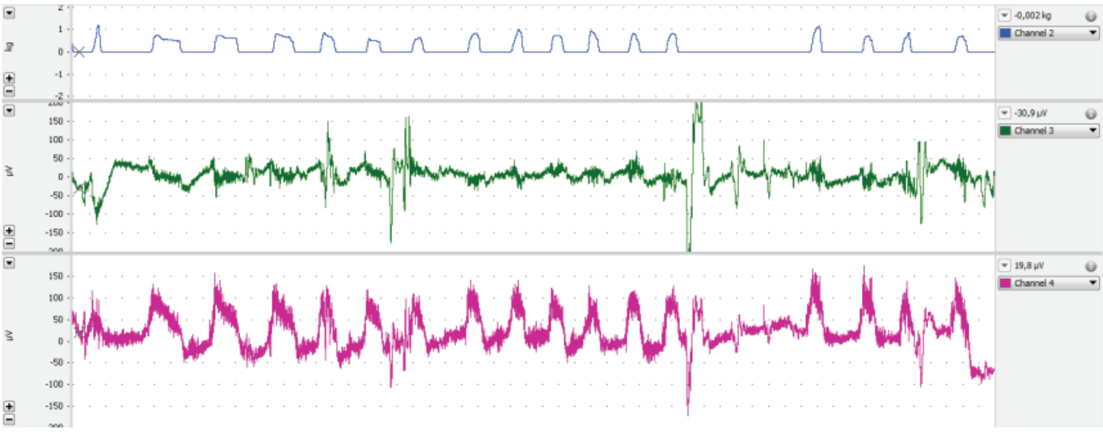

Figure 7: Signals obtained from the hand movements.

With the obtained EMG results, it was possible to perform signal conditioning through the Matlab software using the Wavelet Toolbox. After the feature extraction process with a Symmlet 4 type Wavelet with a 5 level decomposition, a 1X32 feature vector was obtained for each signal. The NN classifier created a 2x32 output matrix, where each column represents the output results for each hand movement and a 2x32 error matrix, where each column indicates the error for each hand movement (corresponds to the difference between the target matrix and the outputs matrix). A performance of 0.9359 (93,59%) was obtained.

After the classifier training, the confusion matrices were obtained for the training, validation, test and all combined data, showing the performance of the method, Fig. 8. Those matrices in Fig. 8 show a good classifier performance as the outputs are mostly classified as correct (green) than incorrect (red). The validation matrix has no results as no data was associated to the validation process. The Receiver Operating Characteristic, ROC, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. ROC curves represent the true positives (sensitivity) versus the false positives (fall- out). A perfect result should have 100% of sensitivity and 100% of fall-out. The classifier results, Fig. 9, show high performance for the training data, however, for the test data, the results were below expectations.

The SVM classifier creates a validation model, Fig. 10, from training data and their responses. From this model, the classifier can classify new samples through predict function. The predict function was used with the data test and two 2x2 matrices were created, one to classify the signal and other to score the classifications (how close the observation data are from the decision boundary). The Close and Open classes were positioned at a distance of $\pm$ 3.2001 and $\pm$1.1005 from the boundary, respectively, as shown in Fig. 11. The classifier allowed a 100% of accuracy with a null validation error.

Figure 8: Confusion matrix of the NN classifier.

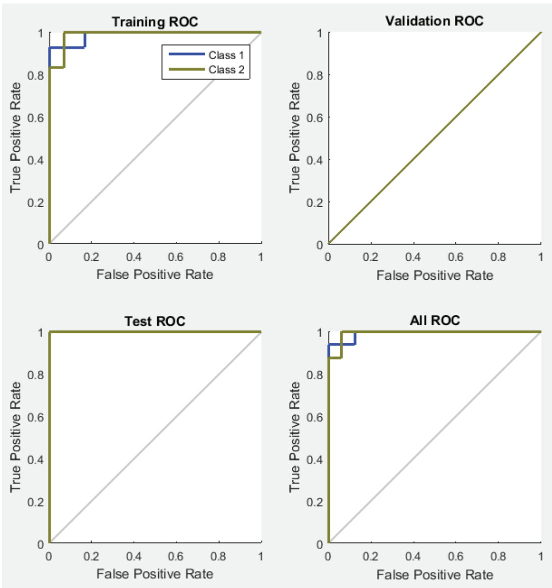

Figure 9: ROC curves of the NN classifier.

4. Conclusions

In this work two hand movements were used for EMG signal acquisition: “Close hand” and “Open hand”. The signals were obtained with Powerlab acquisition system from

```
>> svmtest
>> validationModel

validationModel =

  ClassificationSVM
      PredictorNames: {1x32 cell}
        ResponseName: 'Y'
          ClassNames: {'Close'  'Open'}
      ScoreTransform: 'none'
     NumObservations: 10
               Alpha: [5x1 double]
                Bias: -0.7391
    KernelParameters: [1x1 struct]
                  Mu: [1x32 double]
               Sigma: [1x32 double]
      BoxConstraints: [10x1 double]
     ConvergenceInfo: [1x1 struct]
     IsSupportVector: [10x1 logical]
              Solver: 'SMO'
```

Figure 10: Validation model of the SVM classifier.

```
>> validationPredictions

validationPredictions =

    'Close'
    'Open'

>> validationScores

validationScores =

    3.2001   -3.2001
   -1.1005    1.1005
```

Figure 11: SVM classifier validation scores.

ADintrumental, and the data was processed with MATLAB software because it has powerful toolboxes for the pattern recognition and classification processes.

After performing the classification with the Neural Networks (NN) and Support Vector Machines (SVM) techniques it was possible to conclude that the latter classifier offers better classification efficiency. However, the performance of both classifiers is strongly influenced by the division of data for training, validation and testing. The performance of the NN classifier is also strongly influenced by the network size of the classifier. The SVM classifier was originally designed for binary classification and that can be a reason for the better performance in the presented work.

Acknowledgments

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