Feature Extraction from sEMG of Forearm Muscles, Performance Analysis of Neural Networks and Support Vector Machines for Movement Classification

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Abstract: The propose of this work is to extract different features from surface EMG signals of forearm muscles such as MAV, RMS, NZC, VAR, STD, PSD, and EOF's. Signals are acquired through 8 channels from "Myo Armband" sensor that is placed in the forearm of the human being. Then, identification and classification of 5 types of movements are done, including open hand, closed hand, hand flexed inwards, out and relax position. Classification of the movement is performed through machine learning and data mining techniques, using two methods such as Feedforward Neural Networks and Support Vector Machines. Finally, an analysis is done to identify which features extracted from the sEMG signals and which classification method present the best results.

1 INTRODUCTION

Nowadays advances in robotics have made life easier for human beings, both domestically and industrially. An application of the first one, is to assist people with different types of disabilities, helping them to lead their lives in the most normal way possible. Specifically, in the case of people who have suffered the loss of a superior member such as the amputation of a hand, it is indispensable that the disabled person recovers the ability to take or manipulate objects. The muscular groups present in the forearm of the human being are directly related to the different states of the hand (Khushaba, Al-Timemy, Kodagoda, and Nazarpour, 2016), for example, completely open, closed, flexed inwards, flexed out, relax position, etc.

The surface EMG can be measured easily and non-invasively (Nakajima, Keeratihattayakorn, Yoshinari, and Tadano, 2014), through the use of dry sensors, which measure the potentials generated by muscle contractions. EMG signals are widely used to perform medical diagnoses (Abel, Zacharia, Forster, and Farrow, 1996), as well as to determine movements of the upper limbs and thus control hand prosthetics (Kawano and Koganezawa, 2016). With multisensory information is possible identify human hand motion via feature extraction and classification (Ju and Liu, 2014)(Ju, Ouyang, Wilamowska-Korsak, and Liu, 2013). There are different studies that have allowed the estimation of mathematical models that establish the generation of potentials in muscle groups as in the case of those belonging to the forearm, to study its behavior and its mechanism which may be potentially used for assessment or neuromuscular rehabilitation (Nakajima et al., 2014). Other studies have focused on identifying different states of the hand through myoelectric sensors placed in the forearm, to control robotic prostheses establishing states of supination, pronation, open and closed hand, this through the classification of the signals through the harmonic wavelet packet transform (Wang, Zhiguo, Xiao, Hongbo, and Zhizhong, 2006), and detection of the angle of the hand, considering the position of relax, semi-flexed and flexed to replicate those movements in an orthopedic hand that may be useful for rehabilitation (Kavya, Dhatri, Sushma, and Krupa, 2015), the classification of these states is done through Support Vector Machines (SVM). The force generated between each of the fingers and the thumb is also considered to determine the behavior of EMG signals of the forearm (16 channels) and its relation to these

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movements which may be useful to identify precise movements (Fang, Ju, Zhu, and Liu, 2014), and may help identify which muscle group interacts in greater proportion with each of these movements. There are a lot of features that can be obtained from the signals in time, frequency and wavelet domain. (Boostani and Moradi, 2003), studying which of them improves the results in the classification process.

This work proposes to identify and classify 5 types of movements, including open hand, closed hand, hand flexed inwards and flexed out and relax position, through different patterns such as: Mean Absolute Value “MAV”, Root Mean Square “RMS”, Number Zero Crossing “NZC”, Variance “VAR”, Standard Deviation “STD”, Power Spectral Entropy “PSD”, and Empirical Orthogonal Functions “EOF's”, extracted from the surface myoelectric signals in 8 channels from "Myo Armband" sensor that is placed in the forearm of the human being. Classification of the movement is performed through machine learning and data mining techniques, using two methods such as Neural Networks and Support Vector Machines, finally an analysis is done to identify which pattern extracted from the signal and which method of classification present the best results, through subjects/users of training and test groups.

2 METHODOLOGY

The system to be tested consists of the steps shown in Figure 1, for the proposed analysis using different features extracted for the sEMG signals, and classified by two methods such as Feedforward Neural Networks and Support Vector Machines.

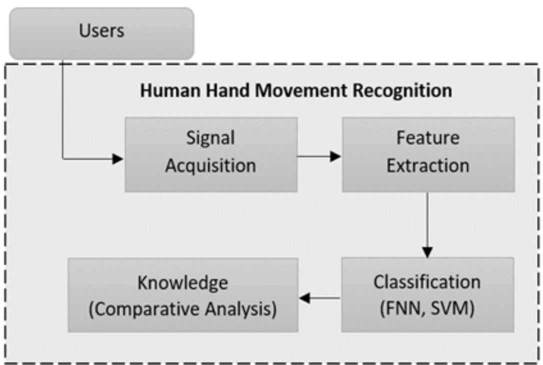

Figure 1: Scheme of the proposed approach.

2.1 Signal Acquisition

In this work is performed feature extraction and pattern recognition of a sEMG signals from the forearm to identify different class of movements. Signals are acquired using “Myo Armband” sensor, which is a gesture recognition device worn on the forearm and manufactured by Thalmic Labs. It uses a set of electromyographic sensors that sense electrical activity in the forearm muscles, combined with a gyroscope, accelerometer and magnetometer to recognize gestures.

The sensor consists of 8 channels (Figure 2) to acquire the myoelectric signals of muscles of the forearm from users/subjects.

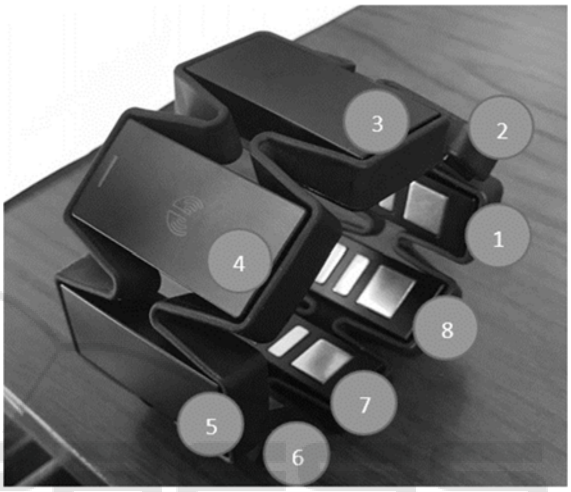

Figure 2: Myo Armband Sensor and its channels.

This sensor allows to know the myoelectric signals of the muscular groups present in the forearm (Figure 3), the signals are acquired at a sampling frequency of 200 Hz, and are normalized to values between -1 and 1 as shown in Figure 4.

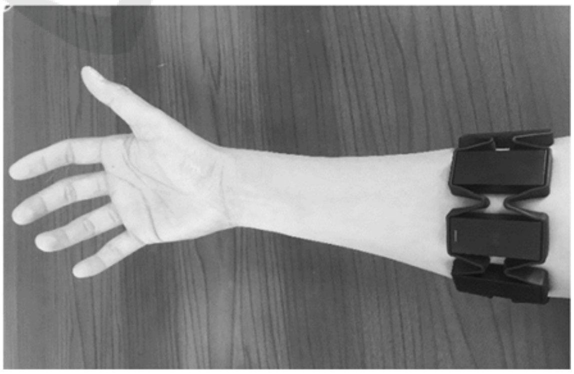

Figure 3: Positioning the sensor for signals acquisition.

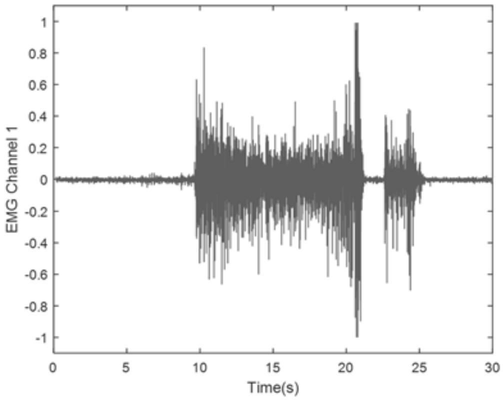

Figure 4: EMG signal acquired by Myo Armband Sensor.

The electrodes are in contact with the different muscles around the forearm as shown in Table 1.

Table 1: Electrodes distribution in muscles of the forearm.

Myo Armband	Muscle
Channel 1	Extensor Digitorium Cummunis
Channel 2	Extensor Carpi Radialis
Channel 3	Brachioradialis
Channel 4	Pronator Teres
Channel 5	Flexor Digitorum Sublimas
Channel 6	Flexor Carpi Ulnaris
Channel 7	Flexor Digitorum Profundus
Channel 8	Extensor Carpi Ulnaris

The signals acquired by the 8 channels of sensor (S1, S2, ... S8) allow detecting 5 hand movements (M1, M2, ... M5) which are produced by the combination of contraction and relaxation of different muscles in the forearm. Figure 5.

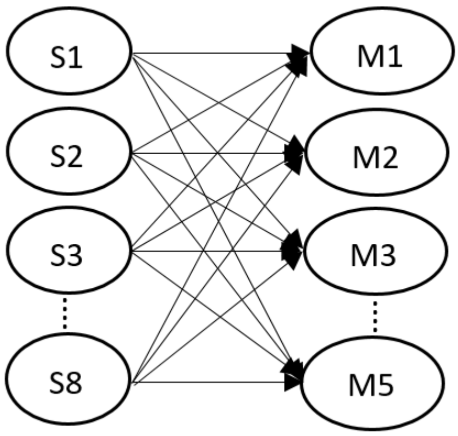

Figure 5: Multi-channel sensor and its relation with the movements of the hand scheme.

Signal acquisition is made to fifteen user/subjects who were separated in seven subjects for training and eight subjects for test. They were asked to perform the movements that are to be detected. Figure 6.

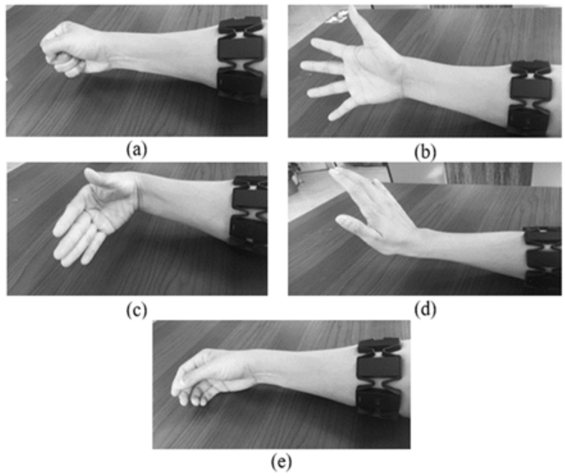

Figure 6: Proposed movements to identify a) closed hand, b) open hand, c) hand flexed inwards d) hand flexed out e) relax position.

2.2 Feature Extraction

Different features can be extracted from the obtained signals (Boostani and Moradi, 2003), in this work has been calculated parameters in time domain such as: MAV, NZC, RMS, VAR, STD, and EOF, in the frequency domain is calculated PSD. With these parameters, is desired to reduce the number of signal data to facilitate pattern recognition and movement classification.

- MAV (Mean Absolute Value): This feature determines the mean value of the difference in amplitudes of consecutive samples in a time segment.

$$MAV = \frac{1}{n}\sum_{i}^{n}|x_i| \quad (1)$$

Where: x_i is the value of i-th sample, n is the number of samples.

- RMS (Root Mean Square): This feature determines the root mean square of consecutive samples in a time segment.

$$RMS = \sqrt{\frac{1}{n}\sum_{i}^{n} {x_i}^2} \quad (2)$$

- NZC (Number Zero Crossing): is the number of times that signal passes the zero-amplitude axis.

$$NZC = \sum_{i}^{n} sign(-x_i x_{i+1}) \quad (3)$$

$$sign(x) = \begin{cases} 1 & if\ x > 0 \\ 0 & otherwise \end{cases}$$

- VAR (Variance): This feature measures the spread of data from the mean ($\bar{x}$) of consecutive samples in a time segment.

$$VAR = \frac{1}{n-1}\sum_{i}^{n}|x_i - \bar{x}| \quad (4)$$

Where $\bar{x}$ is the mean of data in a time segment.

- STD (Standard Deviation): this feature measures the data dispersion of consecutive samples in a time segment from its mean.

$$STD = \sqrt{\frac{1}{n-1}\sum_{i}^{n}|x_i - \bar{x}|^2} \quad (5)$$

- EOF (Empirical Orthogonal Function): is a time series data mining technique that allows decomposing time series into a sum of a set of discrete functions namely EOF's (Cepeda and Colome, 2014).

In this work time series correspond to the signals obtained from eight channels of the forearm F.

$$\mathrm{F_{np}} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix} \quad (6)$$

The SVD of F matrix has the form:

$$\mathrm{F_{np}} = \mathrm{U_{nn}}\Lambda_{\mathrm{np}}^{1/2}\mathrm{V_{pp}}' \quad (7)$$

Where $\Lambda_{\mathrm{np}}^{1/2}$ is a diagonal matrix with the square roots of eigenvalues from $\mathrm{U_{nn}}$ or $\mathrm{V_{pp}}$. $\mathrm{U_{nn}}$ and $\mathrm{V_{pp}}$ are an orthogonal matrix whose columns are the orthonormal eigenvectors of $\mathrm{FF'}$ and $\mathrm{F'F}$ respectively.

The number of selected eigenvectors of $\mathrm{V_{pp}}$ is defined by eigenvalues of Λ, which allow a measure of the corresponding explained variability (EVi), and whose elements are known as EOF's.

$$EV_i = \frac{\lambda_i}{\sum_{i=1}^{p}\lambda_i} \times 100\% \quad (8)$$

Then the EOF's will be used for training of classifiers.

- PSD (Power Spectral Entropy): is used to extract information content in a discrete signal. To calculate PSD is necessary to apply the FFT to the signals in a finite time. The algorithm to calculate this parameter is summarized to the following steps (Zhang, Yang, and Huang, 2008):

- The discrete Fourier Transform $X(\omega_i)$ can be computed by FFT. Considering ω_i is the i-th frequency of the spectrum.
- The Power Spectral Density is computed by:

$$P(\omega_i) = \frac{1}{n}|X(\omega_i)|^2 \quad (9)$$

- In this work, the sum of the $\boldsymbol{P(\omega_i)}$ corresponding to each frequency is the pattern that will be used.

$$PSD = \sum_{i}^{n} P(\omega_i) \quad (10)$$

2.3 Classification

In this work two methods of pattern recognition are presented: Feedforward Neural Networks and Support Vector Machines, then it is done a comparison between the performance of the classifiers when they are tested with different patterns that are obtained from the acquired signals.

2.3.1 Feedforward Neural Networks (FNN)

Neural Networks are processing algorithms whose operation simulates a biological brain. They can process large parallel amounts of information, even if it is partial and diffuse. This method can learn and memorize very varied information and formalize it and, of course, predictions from the data with which it has been trained. They provide a powerful non-linear interpolation tool and multidimensional. So, they have been used mainly in identification and prediction of patterns.

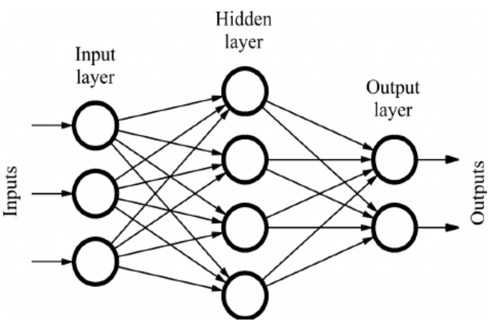

Figure 7: Feedforward Neural Network Scheme.

The feedforward topology is characterized by running the processing in one direction only (Russell and Norvig, 2009). Distinguishing three layers of computation called neurons: input layer where the data to be processed is received; the intermediate layer or layers, where is the processing itself and the output layer. (See Figure 7).

2.3.2 Support Vector Machines (SVM)

SVM is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, is plotted each data item as a point in n-dimensional space (where n is number of features) with the value of each feature being the value of a particular coordinate. Then, is performed classification by finding the hyper-plane that differentiate the two classes. In Figure 8, is shown the representation of SVM's and the optimal hyperplane.

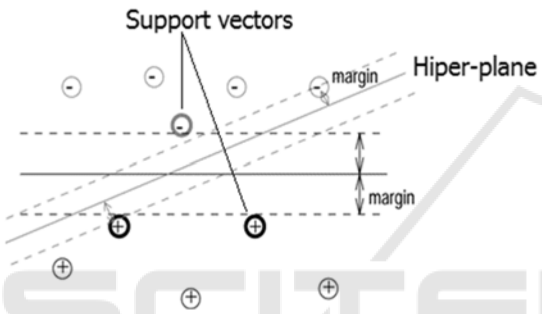

Figure 8: Representation of SVM's.

Support Vector Classifiers (SVC) needs a priori an off-line learning stage, in which the classifier must be trained using a training set of data. Each element in the training set contains one ¨target value¨ and several attributes (Cepeda, 2013). Training involves the minimization of the error function:

$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i \qquad (11)$$

Subject to the constraints:

$$y_i(w^T\phi(x_i) + b) \geq 1 - \xi_i \text{ and } \xi_i \geq 0 \qquad (12)$$

Where: C is the margin parameter, w is the vector of coefficients, b is the bias constant, and ξ_i represents parameters for handling nonseparable data (inputs). The index i labels the N training cases. y_i represents the class labels and x_i represents the independent variables. The kernel ϕ is used to transform data from the input (independent) to the feature space. Radial Basis Kernel function used in this work, it has the form (Chih-Wei Hsu, Chih-Chung Chang, 2008):

$$K(x_i, x_j) = e^{-\gamma\|x_i - x_j\|^2}, \gamma > 0 \qquad (13)$$

In this work, the inputs are the different features extracted of the signals of the forearm muscles and the targets are the hand movements.

2.3.3 K-Fold Cross Validation

It is a technique used to measure how accurate is the classification algorithm. In this method, the sample data are divided into K subsets. One of the subsets is used as test data and the rest (K-1) as training data. The cross-validation process is repeated during K iterations, with each of the possible subsets of test data. Finally, the arithmetic mean of the results of each iteration is performed to obtain a single result. This method is very accurate since we evaluate from K combinations of training and test data. In practice, the choice of the number of iterations depends of the measurement of the data set.

2.3.4 Reduction of Dimensionality of the Data

In this work, it is identified the clusters belonging to the 5 movements of the hand to verify its separation. Data have been obtained through the 8 channels of the sensor, then it necessarily to reduce their dimensionality to show the information in the space.

Through the principal component analysis (PCA) is proposed to reduce the dimensionality of elements to represent the clusters in the plane (2-dimensions) or space (3-dimensions) without excessive loss of accuracy.

Principal component analysis (PCA) is a data mining technique that allows transform the original data into a new set of variables which are uncorrelated (Cepeda, 2013), and can be obtained through calculation of singular value decomposition (SVD) of the covariance matrix (S).

Considering a data matrix X:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix} \qquad (14)$$

The covariance matrix is calculated from data matrix (X):

$$S = \frac{1}{n}X'\left[I - \frac{1}{n}11'\right]X \qquad (15)$$

where:

I: identity matrix

1: all ones vector

Applying spectral decomposition (SVD) to S matrix:

$$S = U\Lambda U' \qquad (16)$$

Where Λ is a diagonal matrix containing eigenvalues (λ_i) of S, U is an orthonormal matrix containing the eigenvector of S.

The number of selected eigenvectors of U is defined by eigenvalues of Λ, which allow a measure of the corresponding explained variability Ec (8).

Thus, the new data matrix Y is the projection of original data X on the hiper-plane defined by U.

$$Y = XU \tag{17}$$

3 RESULTS

Feature extraction has been for time window of 100 milliseconds as shown Figure 9. Once the data for these segments are obtained, it is calculated: MAV, NZC, RMS, VAR, STD, and EOF, and PSD.

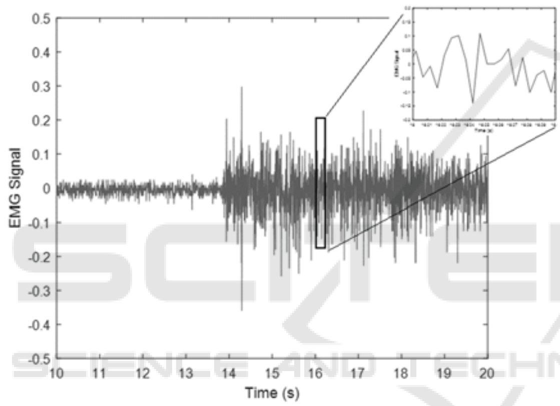

Figure 9: Time window used for feature extraction (example).

Figure 10, shows clusters obtained with 3 PC´s which have an Explained Variability EV_3=93.3%.

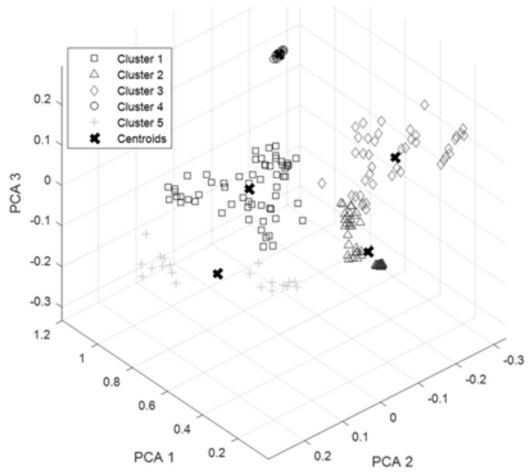

Figure 10: Clusters identified for 5 hand movement.

In Table 2, the results obtained to measure the robustness of the implemented classifiers are presented, taking the signals of 7 subjects/users (4 men, 3 women) for off-line training of Feedforward Neural Networks (10 hidden layers and backpropagation method for training phase) and Support Vector Machines with 350 time windows of signals corresponding to the 5 movements of the hand, that is: 70 open hand, 70 closed hand, 70 hand flexed inwards, 70 hand flexed out and 70 hand relaxed, the accuracy of the classifiers is done using K-fold cross validation algorithm for K = 10.

Tests were performed with independent features and with the best combinations of them to find the best accuracy.

Table 2: Classification accuracies throw K-fold cross validation method.

Pattern	Feedforward Neural Network	Support Vector Machines
MAV	79.2 %	63.2 %
NZC	34.5 %	29.5 %
RMS	87.5 %	66.0 %
VAR	77.0 %	55.5 %
STD	86.0 %	69.0 %
PSD	45.0 %	35.5 %
EOF	22.5 %	39.0 %
MAV-STD	86.0 %	67.0 %
RMS-STD	86.5 %	67.5 %
MAV-RMS-STD	78.8 %	62.4 %
MAV-RMS-VAR	82.4 %	62.4 %
MAV-RMS-VAR-STD	78.0 %	63.2 %

It is recommendable to identify the best parameters C and γ of SVM classifier to obtain better results (Chih-Wei Hsu, Chih-Chung Chang, 2008). Differential evolution algorithm has been used to identify the constants, obtaining the accuracy results shown in Table 3.

Table 3: Classification accuracies throw K-fold cross validation method with identified parameters of SVM.

Pattern	Feedforward Neural Network	Support Vector Machines
MAV	79.2 %	100 %
NZC	34.5 %	61.0 %
RMS	87.5 %	99.5 %
VAR	77.0 %	98.5%
STD	86.0 %	100 %
PSD	45.0 %	65.5 %
EOF	22.5 %	56.0 %
MAV-STD	86.0 %	99.5 %
RMS-STD	86.5 %	100 %
MAV-RMS-STD	78.8 %	99.6 %
MAV-RMS-VAR	82.4 %	99.2%
MAV-RMS-VAR-STD	78.0 %	99.6 %

In Table 3, it can be evidenced when using a method of optimization for calculation the SVM constants, the performance of the classifier can be greatly improved.

Table 4: Classification accuracies in the test group.

		Classification accuracy with different features (%)				
Test	CLA	MAV	STD	RMS STD	MAVR MS STD	MAV RMS VAR STD
User 1	*FNN*	79.0	84.0	74.0	40.0	50.0
	SVN	94.0	92.0	92.0	82.0	94.0
User 2	FNN	80.0	38.0	50.0	74.0	74.0
	SVN	90.0	84.0	84.0	90.0	92.0
User 3	FNN	70.0	58.0	68.0	72.0	42.0
	SVN	88.0	84.0	84.0	76.0	76.0
User 4	FNN	50.0	34.0	28.0	36.0	22.0
	SVN	64.0	62.0	62.0	78.0	90.0
User 5	FNN	74.0	84.0	44.0	84.0	96.0
	SVN	92.0	92.0	100	100	100
User 6	FNN	80.0	74.0	56.0	52.0	46.0
	SVN	99.0	98.0	100	100	100
User 7	FNN	46.0	20.0	18.0	82.0	52.0
	SVN	88.0	86.0	84.0	84.0	88.0
User 8	FNN	58.0	30.0	36.0	52.0	50.0
	SVN	82.0	96.0	78.5	92.0	96.0

After the training of the FNN and SVM algorithms, accuracy measurements, were performed taking the signals of 8 subjects/users (6 men, 2 women) of the test group, with 400 time windows of signals corresponding to the 5 movements of the hand, that is: 80 open hand, 80 closed hand, 80 hand flexed inwards, 80 hand flexed out and 80 hand relaxed. It has been done with the better features such as: MAV, STD, RMS-STD (R-S), MAV-RMS-STD (M-R-S) and MAV-RMS-VAR-STD (M-R-V-S) which exceed 99.5% accuracy in the training phase of SVM. This results are shown in Table 4.

Table 5, shows the average accuracies for each classifier, and Figure 11 a comparative graph of these values.

Table 5: Average accuracies in the test group.

	Feedforward Neural Network	Support Vector Machines
MAV	67.1 %	87.1 %
STD	52.8 %	86.8 %
R-S	46.8 %	85.6 %
M-R-S	61.5 %	87.8 %
M-R-V-S	54.0 %	92.0 %

Results presented in Figure 11, show the best feature for the classification of movements in users who did not participate in the training phase, this is the combination of the features M-R-V-S, with the SVM classifier, which have an average accuracy of 92.0%.

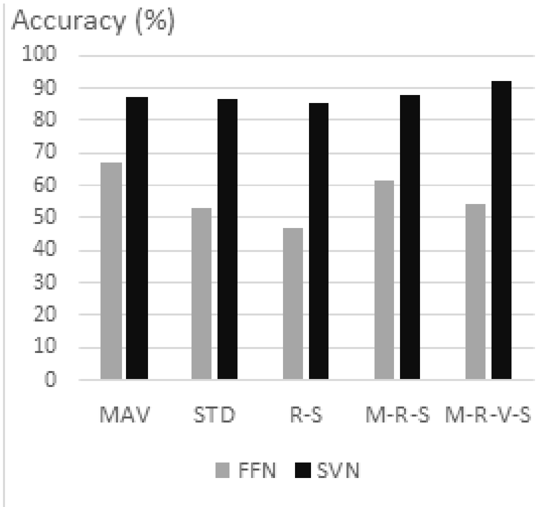

Figure 11: Average accuracies of classifiers test.

4 CONCLUSIONS

The present work has allowed to determine the identification of different movements of the hand through the acquisition of sEMG signals of the forearm. In this work, it has been shown that SVM presents better accuracy regarding the FNN for classification, and the feature that is considered the best for this aim is the combination MAV-RMS-VAR-STD with 92% of accuracy.

In future works, it is proposed to detect other movements, especially including the fingers of the hand and to verify other classification techniques such as Linear Discriminant Analysis (LDA) among others to transfer these movements ton robotic orthotic prostheses.

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