Classification of Myoelectric Surface Signals of Hand Movements using Supervised Learning Techniques

Marisol Cristel Galarza Flores[a], Juan Felipe Miranda Medina[b] and Cristian López del Álamo[c]
Universidad Nacional de San Agustín de Arequipa (UNSA), Arequipa, Peru

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Abstract: This work presents a comparative study of techniques to classify four hand movements (flexion, extension, opening and closure) using myoelectric signals measured at the forearm in two separate channels: the brachioradialis and the flexor carpi ulnaris (FCU) muscle. The process of signal acquisition is described, as well as signal normalization, hybrid feature extraction and classification using two supervised learning techniques; i.e., backpropagation and support vector machines. The classifiers were trained using the raw data from the input signal. It was verified that the accuracy of the classification is improved by feature extraction up to 2.25%, yielding a successful average classification rate of 91.00%.

1 INTRODUCTION

Experiments related to electromyography (EMG) are linked to the discovery of electricity in the late 16th century (Kazamel and Warren, 2017). The array of possibilities arising from the measurement of EMG signals, however, was better understood only in the 20th century with the development of electronics and programming: myoelectric prosthesis for amputees, bionic exoskeletons, and teleoperated robots for microsurgeries or explosive deactivation are all current applications that continue to be researched (Cabrera and Jaramillo, 2010). The analysis of EMG signals, however, is not exempt from challenges, since the measured potentials present low amplitude and are strongly non-stationary and the initial data is poorly structured. There is thus the need to "develop new effective methods" for the analysis of EMG signals and for their application to the study of human motricity (Kurkin et al., 2019).

Earlier studies about the classification of myoelectric signals deployed neural networks (Hudgins et al., 1993; Haihua et al., 2005; Durgesh and Lekha, 2010), ARTMAP (Carreño and Vuskovic, 2005) and Euclidean distance (Ferguson and Dunlop, 2002) as classification methods. More recent research, such as the survey by (Kehri et al., 2016) identifies Wavelets, Principal Component Analysis (PCA), Support Vector Machines (SVM) and Neural Networks (NN) as key techniques for EMG signal analysis. Furthermore, the studies by (Gupta et al., 2017) and (Satapathy et al., 2019) emphasize on SVM and neural networks as particularly relevant classification techniques.

This work is aimed towards the classification of four different hand movements (i.e., flexion, extension, hand opening and hand closure) utilizing measurements of EMG signals in the forearm. In this respect, the comparative study by (Wołczowski and Zdunek, 2017) shows that in general, higher rates of accuracy (approximately 95 %) with lower computational complexity can be achieved utilizing feature extraction techniques, thus outperforming conventional methods such as Principal Component Analysis (PCA). This is a key motivation in the methodology of this work, since its chief contribution is a comparison accross two different processes. The first one refers to feature extraction, where we resort to a hybrid approach combining (1) univariate selection with a Chi-square distribution (henceforth referred to as $\chi 2$) with Principal Component Analysis (PCA), (2) $\chi 2$ with Wavelets, and (3) $\chi 2$ with PCA and Wavelets. The second process corresponds to classification algorithms; we present a comparison of classification accuracy of back-propagation neural networks against Support Vector Machines (SVM) for each of the three feature extraction methods. Although the methods

[a] https://orcid.org/0000-0001-6419-0761
[b] https://orcid.org/0000-0002-5239-2718
[c] https://orcid.org/0000-0002-2568-650X

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deployed in this research have already been used by other research groups for EMG signal classification, the novelty of this work is the comparative study that can be helpful to plan similar experiments in the future.

2 PREVIOUS WORK

(Yücel and Mehmet, 2001) and (Ferguson and Dunlop, 2002) proposed the extraction of signal features prior to classification. For their study they deployed the Wavelet transform with principal components as a feature extractor. In 2004, hybrid feature vectors were proposed. In this regard, (Kilby and Hosseini, 2004) made a comparison of different Wavelet families with DWT and WPT, concluding that the Wavelets that yielded the best results for EMG signals where Daubechies, Summlet and Coiflet. On the other hand, (Hargrove et al., 2007) classified 6 patterns of movement based on surface EMG signals and EMG intramuscular signals. Their hypothesis was that crosstalk would be weaker in intramuscular signals, which would allow for a better classification. Nevertheless, they found that there was no significant difference in the accuracy of the classification. In 2015, (Quinayás-Burgos and Gaviria-López, 2015) developed a two-channel system to detect the intention of movement, achieving an accuracy percentage of 85 and 92.5% in the classification of four different movements, utilizing a hybrid vector of statistical components as a feature extractor. In 2016 they developed a classifier based on a backpropagation neural network utilizing wavelength as the feature in the time domain for the feature extractor, extracting EMG signals to classify five different movements, obtaining an accuracy percentage of 75.54% $\pm$ 5.17 and 67.37% $\pm$ 8.75. It was thus shown that accuracy in movement classification is not dependent on the number of electrodes deployed. A better classification rate can be achieved by placing the electrodes on the main muscles relative to the movement being performed, instead of utilizing a large amount of electrodes (Irastorza-Landa et al., 2017).

3 METHODOLOGY

Upon reviewing the state of the art, we concluded that the classifier that was most deployed was the backpropagation neural network. In order to have a reference of comparison for this classifier, we decided to use *support vector machines* (SVM) as well. Regarding feature extraction, we chose a hybrid vector with Wavelet transform components, for it was the most deployed method. We chose principal component analysis as well because it had the best results in the literature and we added the *univariate selection* method to our list, utilizing the Chi-square ($\chi 2$) distribution. The methodology we suggest is represented in Figure 1.

In the development of this work, the following activities were carried out: signal acquisition (Section 3.1), signal preprocessing (Section 3.2), extraction of signal features (Section 3.3), signal classification (Section 3.4), result comparison (Section 4) and conclusions from test analysis and results (Section 5).

3.1 Signal Acquisition

3.1.1 Features of the EMG Signal

An EMG signal has a typical amplitude that varies between 0 and 6mV, and its useful frequency lies in the range of 0 to 500 Hz although most part of the energy is concentrated between 50 and 150 Hz (Gerdle et al., 1999). According to the Nyquist-Shannon theorem, if the highest frequency contained in an analog signal $x_a(t)$ is $F_{max} = B$ and the signal is sampled at a rate $F_s > 2F_{max} \equiv 2B$, then $x_a(t)$ can be fully recovered. If this criterion is not satisfied, there will be frequency overlapping, otherwise known as aliasing. For this project, the sampling frequency had to be at least greater than 300 Hz, therefore we chose to sample every 2 ms, which is equivalent to a 500 Hz sampling frequency. On the other hand, according to (Birkedal et al., 2002), the first 400 ms of a muscular movement are enough for the identification of the movement, therefore the signals were recorded with a window of 400 ms. With these considerations, samples of four movements were taken in 10 different participants, 10 samples for each one of them. The participants did not perform any significant physical effort 24 hours prior to the experiment.

3.1.2 Electrode Placement

One of the most controversial aspects of surface EMG is the placement of the electrodes (Aaron, 2010). That is why, the Surface Electromyography for Non-invasive Assessment of Muscles (SENIAM) standard was elaborated in Europe to provide specific recommendations regarding the location, the size and the shape of the electrodes (Hermens and Freriks, 1997). According to the SENIAM standard, the recommended value for the diameter of the electrodes is 10 mm, while the inter-electrode distance, defined as the center-to-center distance of the conductive area of the electrodes, should be 2 cm. For the shape of

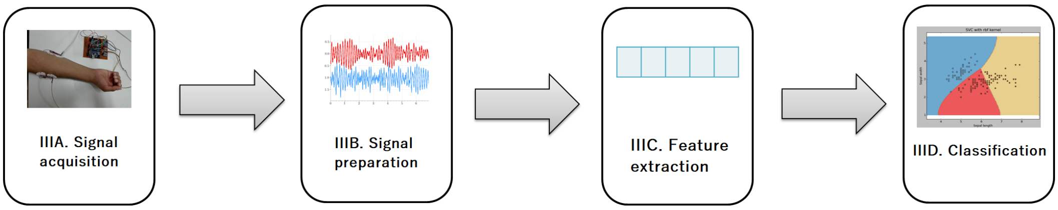

Figure 1: Suggested methodology for signal classification. Source: prepared by the authors.

the electrode, defined as the conductive area that is in touch with the skin, most of the literature recommends a circular shape (Merletti and Parker, 2004).

In this study, the following signal characteristics and process for signal acquisition where selected:

1. Superficial (non-invasive) Ag-Cl electrodes.
2. The participants' skin was disinfected with alcohol. In addition, the electrodes carried the saline solution for the transmission of the electric impulse.
3. The participant's initial posture for signal acquisition is shown in Figure 2.

Figure 2: Initial position for signal acquisition. Source: prepared by the authors.

4. For this study we chose the motor points of the brachioradialis and the *flexor carpi ulnaris* muscle (FCU) muscle as shown in Figures 3 and 4.
5. The inter-electrode distance is 2 cm, and the grounded electrode will be placed in the area nearest to the elbow.
6. After placing the electrodes, the signals will be visually inspected on the oscilloscope.

3.2 Signal Preprocessing

3.2.1 Sensing of the EMG Signal

Myoelectric signals are characterized by low amplitude levels (typically between 0 and 6 mV) and therefore the sensing mechanism must include a low noise amplifier. A passband filter is also required since the

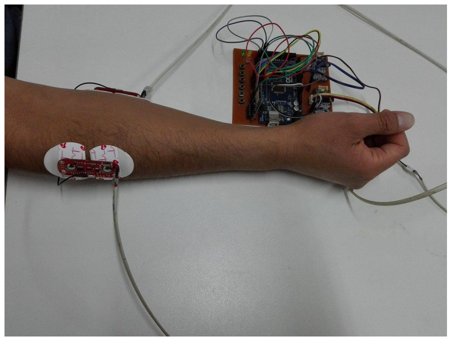

Figure 3: Electrode position in the brachioradialis. Source: prepared by the authors.

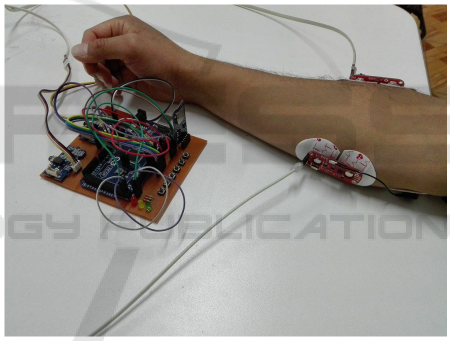

Figure 4: Electrode position in the FCU muscle. Source: prepared by the authors.

signal's energy is concentrated around a 50 to 150 Hz bandwidth. Furthermore, the signal must be conditioned according to the input of the microcontroller carrying out the signal processing. A sensor was fabricated that included the stages of amplification, filtering and conditioning following the method proposed by (Gomero et al., 2009). Upon comparing its performance to the MyoWare Muscle sensor (MyoWare., 2015), however, the latter yielded better results and was therefore chosen for this project.

The resulting architecture of the sensing interface was compact: it consisted of two MyoWare muscle sensors (each of which includes low-noise amplification, passband filtering and signal conditioning), an Arduino Mega microcontroller (that converts the analog input into a digital binary stream), and an SD memory that stores the digitized version of the electromyographic signal into a CSV file. The reason for using two sensors rather than one is that, according to our medical consultant Dante Condori, at least two different channels are needed in order to detect four different hand movements.

3.2.2 Signal Normalization

Each channel was normalized separately subtracting the average offset amplitude to each measured input signal. This is because each participant had a different average offset amplitude value which corresponds to the average of the signal measurement when the arm is at rest.

3.3 Feature Extraction

3.3.1 Wavelet Transform

The Wavelet transform provides simultaneous information both in the time and the frequency domains. One of its most important parameters is the resolution of the transform, associated with the level of decomposition to be deployed (Mallat, 1991). The Wavelet transform is used to analyze time series that contain non-stationary signals in a wide frequency range (Torrence and Compo, 1998), and is given by:

$$W_f(s,\tau) = \int f(t)\psi^*_{s,\tau}(t)dt \ , \qquad (1)$$

where $f(t)$ is the signal being analyzed, $\psi^*_{s,\tau}(t)$ is the expansion function or basis, i.e., the Wavelet function, and $W_f(s,\tau)$ is the resulting Wavelet transform. Wavelets are generated from the translation and scale variation of the same Wavelet function $\psi(t)$, known as the "mother Wavelet". In this work, we deploy as part of the characteristic vector of the EMG signal the approximation coeficients (cA) of the mother Wavelet Daubechies 4 (db4).

3.3.2 Principal Component Analysis (PCA)

The PCA algorithm starts from a mutually correlated data set, and returns a set of information without any linear correlation. The extractor of PCA characteristics is most effective when there is a high correlation in the variables of the input data (Daniel, 2015). In this work, the first 100 principal components were taken to form the characteristic vector.[1]

[1]The determination of the number of principal components is also possible by means of statistical inference methods, as the work of (Liu, 2017) illustrates.

3.3.3 Univariate Selection

This feature selection is based on picking the N characteristics with greater correlation with the expected output. The Chi-square function was chosen for this test. It was used to compare the observed frequencies with the expected frequencies. In our classification method each of the four hand movements corresponds to a class. The classifier returns one of the four classes as an output given the measured input signals for a given participant. To verify that the number of observed results in each class corresponds approximately to the expected number, we make use of hypothesis contrast utilizing the Chi-square distribution:

$$\chi^{2^*} = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{O_i}. \qquad (2)$$

From this equation we have that the lower the χ^{2^*} value is, the higher the correlation between the observed and the expected frequencies.

3.4 Classifiers

3.4.1 SVM

Support vector machine (SVM) is a classification technique based on exact mathematical models. To achieve optimal results, cross-validation (Durgesh and Lekha, 2010) on ten different test groups was deployed.

SVM maps an input vector (input data) in a higher spacial dimension, in which a maximal separation hyperplane is constructed. Two parallel hyperplanes are constructed on each side of the hyperplane separating the data. The separation hyperplane (MMH) is the hyperplane that maximizes the distance between two parallel hyperplanes. It is assumed that the higher the margin or distance between the parallel hyperplanes, the better the class separation will be (Vapnik, 2013).

If we consider Figure 5, we can see that the hyperplane of maximal margin is the medium line of the widest "block" that we can insert between the two classes so that they are perfectly separated.

3.4.2 Non-linear SVM

Not every problem is linearly separable. Therefore, different kernels are required depending on the sets of classes that are separated. The use of other kernels offers a greater flexibility, allowing for a greater separability margin of non-linear and multidimensional classes. SVM allows for non-linear kernels such as the polynomial and radial kernels shown in Figure

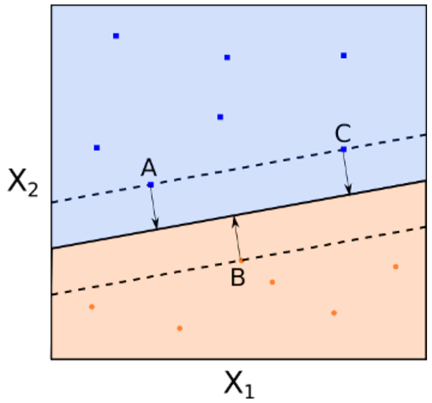

Figure 5: Maximal margin of the hyperplane with SVM for points A, B and C. X_1 and X_2 represent each dimension of a linearly separable two-dimensional hyperplane. Source: (Quantstart., 2014).

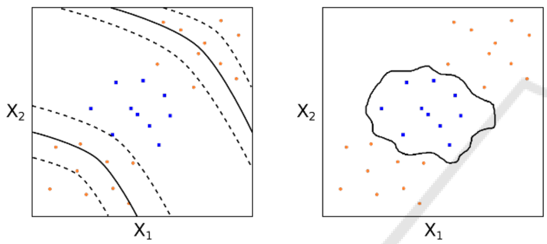

Figure 6: SVM classification with polynomial and radial kernels, respectively. X_1 and X_2 represent each a dimension of a two-dimensional non-linearly separable hyperplane. Source: (Quantstart., 2014).

6. In this work, the radial kernel was deployed because the set of signals was not linearly separable, and cross-validation was utilized for tests.

3.4.3 Neural Networks

Artificial neural networks are a computational representation of complex biological systems formed by numerous nervous cells that work in parallel and implement learning functions in the form of iterative adaptation of their parameters. They aim at characteristics such as auto-organization, learning capacity, generalization capacity and robustness against failure (Anderson, 1995).

For this research we used a backpropagation neural network with a sigmoid activation function shaped as a hyperbolic tangent that maps values in the range $(-1, 1)$. The network has two hidden layers, the first one with 100 neurons and the second one with 30 neurons. This was the distribution that performed best in a number of trials varying the number of neurons and hidden layers.

4 TESTS AND RESULTS

Two classifiers were proposed: the support vector machine (SVM) and backpropagation neural networks. Four different hand movements were studied (flexion, extension, hand opening and hand closure) and hundred samples were extracted for each movement. This data was gathered from ten test participants.

Figures 7, 8, 9 and 10, display the hundred registered signals for the movements of flexion, extension, hand opening and hand closure, respectively. In the X axis an interval of 400 is observed which represents the first 200 movement takes of the corresponding movement in the brachioradial muscle and the second 200 takes represent the corresponding movement in the FCU muscle. In the Y axis an interval of 100 is observed, where each number is a registered signal (from the 100 signals taken for each movement). Low and high amplitudes of the input in the Z axis correspond to blue and red colors, respectively.

The figures show that there are clear identification patterns for each movement, where the pattern of the brachioradialis and FCU muscle is different in amplitude and activation instant for each movement. This is why a supervised learning method can classify these patterns in one of the four movements that this work studies. All tests were conducted using cross-validation as a technique for statistical analysis to guarantee that the results are independent from the partition between training data and test data.

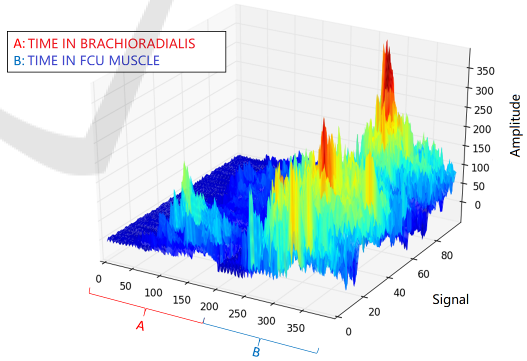

Figure 7: Signals for the flexion movement. The X axis represents the 200 takes in the brachioradialis and FCU muscle. The Y axis represents each registered signal, and the Z axis represents the signal amplitude. Source: prepared by the authors.

4.1 Results

Three hybrid feature vectors were deployed in the tests: (1) PCA and Chi-square, (2) Wavelet approximation coefficients and Chi-square, and (3) PCA

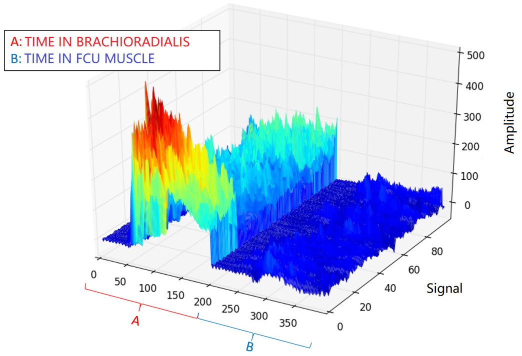

Figure 8: Signals for the extension movement. The X axis represents the 200 takes in the brachioradialis and FCU muscle. The Y axis represents each registered signal, and the Z axis represents the signal amplitude. Source: prepared by the authors.

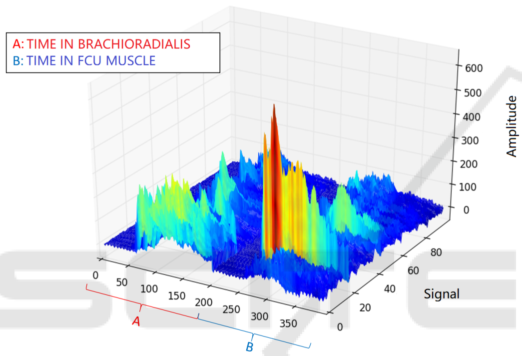

Figure 9: Signals for the hand opening movement. The X axis represents the 200 takes in the brachioradialis and FCU muscle. The Y axis represents each registered signal, and the Z axis represents the signal amplitude. Source: prepared by the authors.

combined with Wavelet approximation coefficients and Chi-square. Each of these vectors was tested with the two classifiers, namely SVM and backpropagation neural networks. Some tests were also conducted with the normalized original data, using the same classifiers, to test if the feature extraction improved the detection percentaje of the corresponding class.

4.1.1 Results with SVM

In this work we utilized the radial basis function kernel. Tests were conducted with the four movements. The results were estimated on the sample of 100 signals for each movement, deploying cross-validation with 10 different groups of 90 signals of training and 10 test signals.

Different characteristic vectors were explored thus obtaining a classification accuracy of 88.75 % for the original data without feature extraction, 91.00 % for PCA and Chi-square, 91.00 % for Wavelet and Chi-square, 89.00 % for PCA, Wavelets and Chi-square. The details of the classification for each movement can be observed in Table 1.

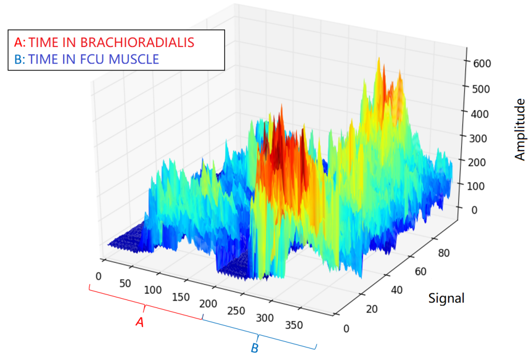

Figure 10: Signals for the hand closure movement. The X axis represents the 200 takes in the brachioradialis and flexor cubital muscles. The Y axis represents each registered signal, and the Z axis represents the signal amplitude. Source: prepared by the authors.

From Table 1 we can see that the movement that was hardest to detect with SVM was flexion, while the movement that is detected with highest accuracy is extension. The best results were achieved with hybrid features vectors: Chi-square and PCA; and Chi-square and wavelets, where an average detection accuracy of 91.00 % in the classification of the four movements was achieved. These vectors improved in 2.25 % respect to classification without feature extraction. The vector composed of Chi-square, PCA and Wavelets did not improve the classification accuracy significantly.

4.1.2 Results with Neural Networks

The results are estimated from the sampling of 100 signals for each movement, using cross-validation with 10 different test groups of 90 training signals and 10 test signals.

Different feature vectors were tested yielding a detection accuracy of 86.25 % for the original data, 82.00 % for PCA and Chi-square, 82.00 % for Wavelet and Chi-square, and 89.00 % for PCA, Wavelet and Chi-square. The details of the classification for each movement can be observed in Table 2.

From the Table 2 we can see that the movement that was most difficult to detect using backpropagation neural networks is hand opening, while the movement that is detected with the highest accuracy is extension. This movement is the same as the highest detection accuracy movement using SVM. The best results were obtained with the hybrid feature vector: PCA, χ^2 and Wavelets, where an average detection accuracy of 89 % was achieved in the classification of

Table 1: Classification accuracy with SVM.

	Raw data	χ^2, PCA	χ^2, Wavelets	PCA, Wavelets χ^2
Flexion	86.00%	85.67%	85.67%	85.33%
Extension	94.67%	96.00%	96.00%	93.00%
Opening	86.00%	91.00%	91.00%	89.00%
Closure	88.33%	90.33%	90.33%	87.00%
Total	**88.75%**	**91.00%**	**91.00%**	**89.00%**

Table 2: Classification accuracy with backpropagation neural networks.

	Raw data	χ^2, PCA	χ^2, Wavelets	PCA, Wavelets χ^2
Flexion	83.00%	81.33%	81.33%	88.67%
Extension	92.67%	92.00%	92.00%	92.00%
Opening	81.33%	72.67%	72.67%	82.33%
Closure	88.00%	82.00%	82.00%	92.00%
Total	**86.25%**	**82.00%**	**82.00%**	**89.00%**

the four movements. This vector improved in 2.75 % the result of the classification. It is also observed that the vectors formed by χ^2 and PCA; as well as χ^2 and Wavelets, did not improve the accuracy of the classification without feature extraction.

In general, the highest average classification accuracy obtained in this work (over 90 %) is at the level of the state of the art in the literature utilizing sofisticated but more complex methods such as machine learning (Mora Rubio et al., 2020), ternary pattern and discrete wavelet based iterative feature extraction (Tuncer et al., 2020) and convolutional neural networks with intrinsic feature extraction capabilities (Zia ur Rehman et al., 2018).

5 CONCLUSIONS

This work has provided a comparison of different methods for the classification of four different hand movements (extension, flexion, hand opening, hand closure) across two different lines. First, a comparison of methods for feature extraction (χ^2 and PCA, χ^2 and Wavelets) and second, a comparison of methods for classification (namely neural networks and support vector machines). We have shown that the SVM supervised classifier has a better performance than backpropagation neural networks for the classification of these four movements, and that these can be recognized taking the first 400 ms of the brachioradialis and *flexor carpi ulnaris* muscle (FCU) as an input. With SVM, an accuracy of 91.00 % was achieved using a hybrid characteristic vector with components of approximation coefficients of Wavelet transform and Chi-square. Likewise, an accuracy of 91.00 % was also achieved deploying a hybrid characteristic vector constituted by the hundred principal components (PCA) and Chi-square.

It was also observed that for the SVM classifier, flexion was the most difficult movement to detect, while opening the hand was the most difficult movement for neural networks. On the other hand, in all confusion matrices, the movement causing the most classification errors was closing the hand in the case of SVM, while for backpropagation neural networks both opening the hand and flexing were problematic. A greater number of distinct movements could be detected if more channels were used. Nevertheless, the high accuracy obtained with SVM, i.e., over 90 % is comparable to other methods in the state of the art that are computationally more expensive.

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