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Use of neural networks to differentiate wrist movements using muscle signals

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Abstract*– Currently, technological advances in bionics are considerable, providing the user with the possibility of regaining the ability to hold the elements and an adequate rehabilitation. Proper placement of electronic equipment on the prosthesis allows reading of muscle signals from the forearm, however measurements are mainly focused on the movement of the fingers when wrist movement is paramount to ensure a greater number of possible movements for the hand, for this reason, the use of processing algorithms as a neural network reduces dependence on this electronic equipment. In this research work, an algorithm of a mechanical control has been designed considering the six movements of the wrist, bending, extension, radial deviation, cubital deviation, pronation and supination using sensors that record data every 0.5 seconds by storing 50 signals per movement for neural network training. For best results, the training process was performed in the Matlab Program using its Deep Learning Toolbox package with a very near zero error. As a next step, two tests were performed on the neural network, the first with four movements of the wrist with a result of 88.9% accuracy and the second using the six movements of the wrist with a result of 92.9% accuracy. In addition, a validation was performed between the training and the tests performed with a regression with Pearson R correlation results for the neural network. The results indicate that deep learning and electronic elements favor the training of a neural network to control the movement of the wrist.

***Keywords*-- Deep learning, neural networks, muscle signals, prosthetics, wrist movement.**

I. Introduction

In recent years, technological advances in the field of bionics have increased considerably, new research has developed hand prostheses with better properties and characteristics in order to provide users with amputation of upper limb, the opportunity to regain the ability to gesture and prehensile, being favorable to their rehabilitation and development of their daily activities [1] [2] [3] [4].

Prosthetic equipment often employs components such as surface electromyography (SEMG), being non-invasive and accessible [5] alternative is innovation in materials by creating thin composite materials with high sensitivity to improve handling and precise grip [6] Manufacturers of recognized entities offer attractive bionic equipment solutions with considerable but limited functions in terms of intuitive and autonomous mobility [7].

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According to the way in which equipment interacts with external objects, the movements of the upper limb are divided into 3 categories: intransitive, transitive and gestures, that is, with the capacity for mobility and interaction between objects [8]. In this sense some researchers developed the intuitive capacity of the bionic equipment proposing that it is indispensable to consider the timely location of the electronic components that perform the reading of the muscular signal, therefore they considered focusing on the flexor muscles and forearm extenders for the proper decoding of hand movements, however it is important to also consider the limitation of the user in the amputated limb [9] [10].

Additional research aimed at analyzing the movements of human joints and other physiological signals has proposed combining multiple sensors paying greater attention to the evaluation of gestures based on muscle signals in such a way the use of other sensors could provide information from the external medium or other physiological data and EMG sensors can be combined and adjusted together to decrease signal processing time [11].

The latest advances have been in the design of learning algorithms employing muscle signals that capture the different muscle contractions characteristic of gestures [12] [13] [14]. In such sense the use of processing algorithms as a convolutional neural network (CNN) reduces dependence on myoelectric sensors thanks to CNN's ability to extract features automatically which provides intuitive control of the equipment because gestural commands are decoded directly from the patterns it generates the user's muscle vibration [15] [16]. Therefore, the present research is oriented in employing deep learning tools through the design of a neural network with the purpose of differentiating the joint movements of the wrist improving autonomous control in a prosthetic equipment.

II. Methods

The system proposed in the research focuses on the work of a mechanical control for wrist prostheses. The tools that served as transducers for data capture were myoelectric and inertial type as they will fulfill the purpose of identifying the joint movements performed by the wrist.

A. Data collection

To do this, an algorithm was designed that fulfills the corresponding functions in the process, Fig. 1 represents the flow diagram that the system will perform; the process begins with the preliminary calibration of the sensors for the reading of the signals. This task is executed every 0.5 seconds storing 50 signals per movement, obtaining a total of 300 samples during the reading. From this with the previous training of the neural network, the system will be able to identify the type of contraction recorded and make the movement to which it represents. To capture the data of the signals of muscular vibration of the movements of the wrist, the six movements were recorded: flexion, extension, radial deviation, ulnar deviation, pronation and supination, for these various electronic components such as an inertial sensor and a muscle sensor were used, both sensors were strategically placed in the forearm. In addition, a myoelectric sensor was located in the outer area of the forearm near the elbow, in this position it was decided because muscle activity will be recorded in response to minimal digital extensor muscles, digitorum extensor, carpal ulnar extensor, long radial carpal extensor and short radial carpal extensor, thus the recording of flexion, extension, radial deviation and wrist ulnar deviation is feasible [17]. Likewise, the inertial sensor used was located in the section proximal to the proximal insertion of the supinator arm muscle, an area that will allow the recording of the supination and pronation movements of the forearm [18].

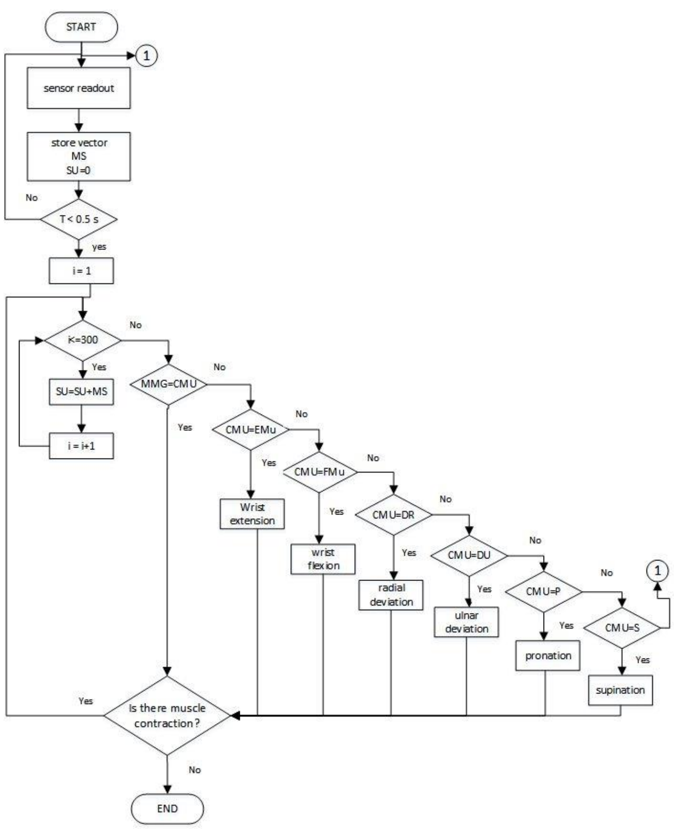


Fig. 1 Flow diagram identifying the type of contraction.

For each type of movement, it was essential to record and store the signals and then take them as a sample for the training of the neural network.

In Fig. 2, the muscle contraction is shown when the wrist is flexed and recorded by the myoelectric sensor and the inertial sensor respectively whose spectrum of greatest amplitude is recorded on the x-axis; it should be noted that in which of the axes (x, y, z) the signal registers greater amplitude will be of great help for its identification with respect to the other movements, filtering those signals of lesser range and avoiding that they interfere in the training.

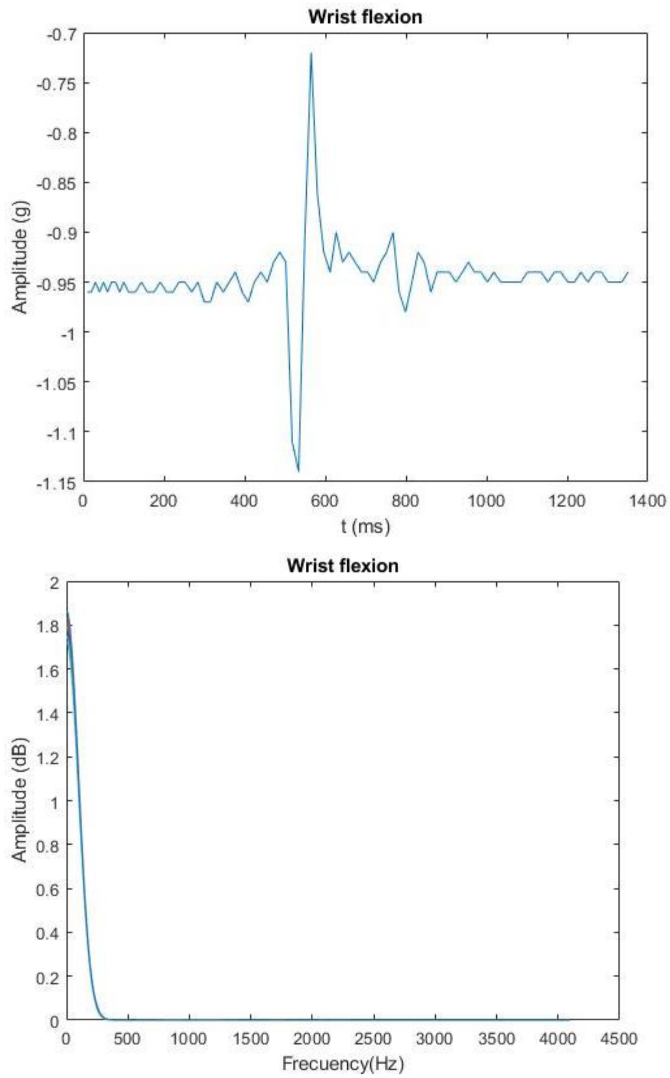


Fig. 2 Signs of muscle contraction in wrist flexion: up) muscle signal in flexion, down) spectrum of greater amplitude in flexion, x-axis.

Fig. 3 shows the muscle contraction when the wrist is in extension recorded by the myoelectric sensor and the inertial sensor respectively whose wider spectrum is recorded on the z axis.

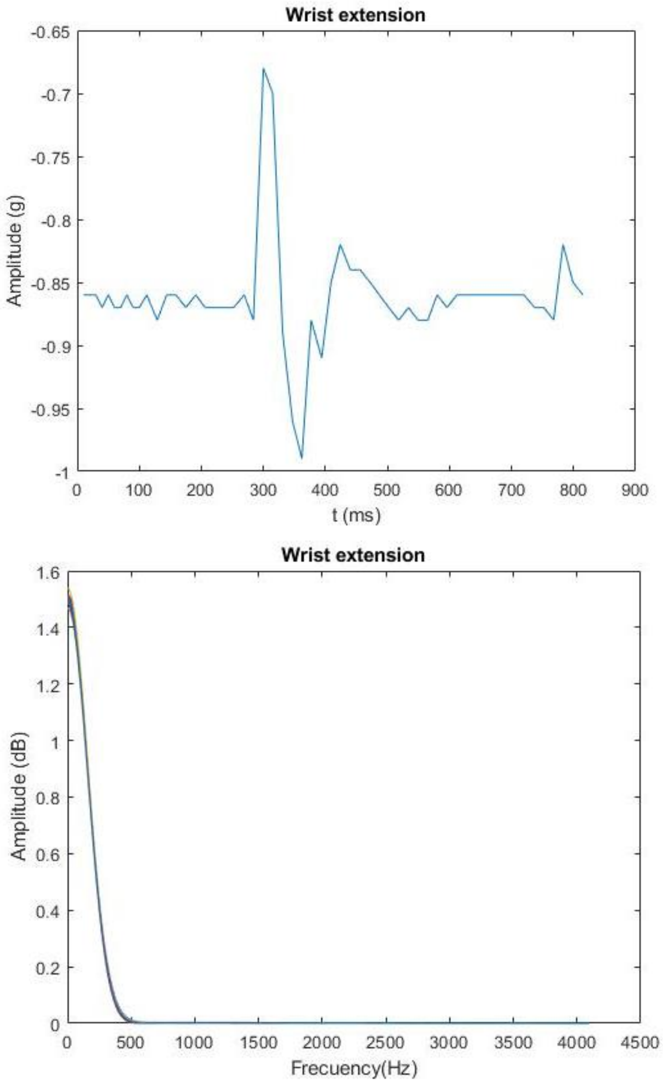
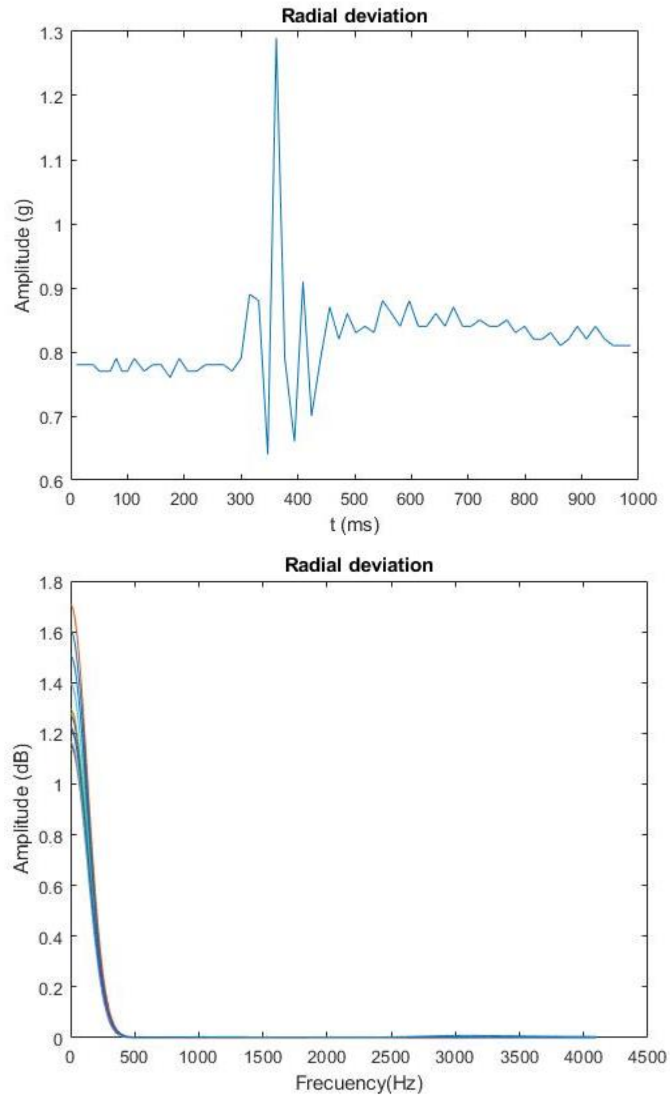


Fig. 3 Signals of muscle contraction as the wrist extends: up) muscle signal in extension, down) spectrum of greater amplitude in extension, z-axis.

Fig. 4 shows the muscle contraction when the wrist joint makes a radial deviation and that is captured by the myoelectric sensor and inertial sensor respectively and whose spectrum of greater amplitude is recorded on the x-axis.



(a) (b)

Fig. 4. Signals of muscle contraction when the wrist makes a radial deviation: up) muscle signal in radial deviation, down) spectrum of greater amplitude in radial deviation, x-axis.

Fig. 5 shows muscle contraction when the wrist joint performs a ulnar deviation and is captured by the myoelectric sensor and inertial sensor whose wider spectrum is recorded on the z axis.

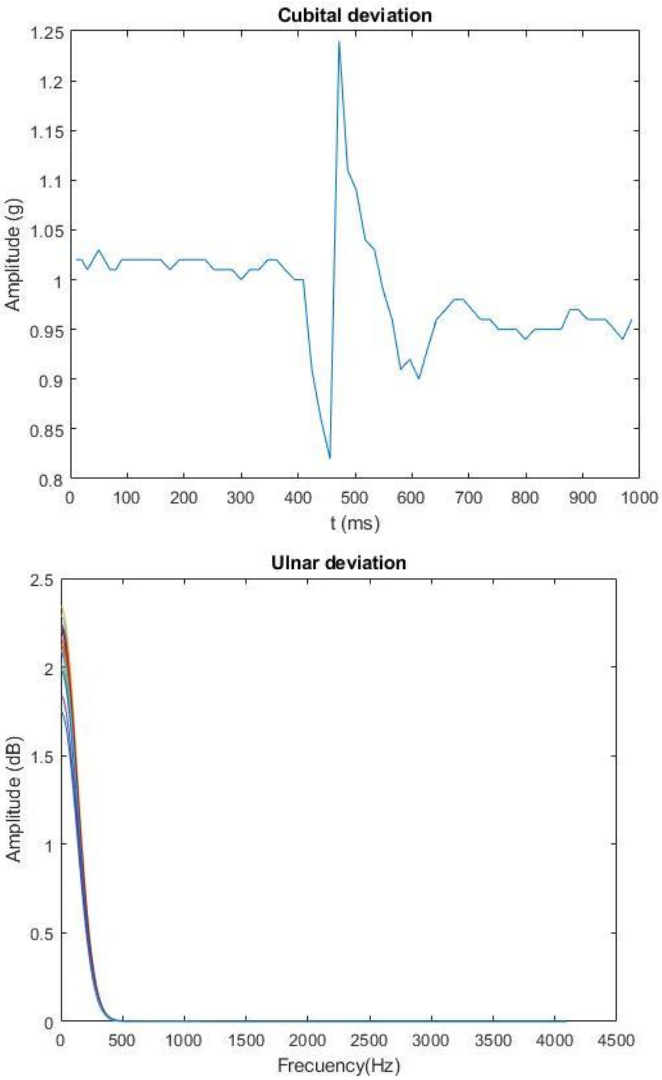
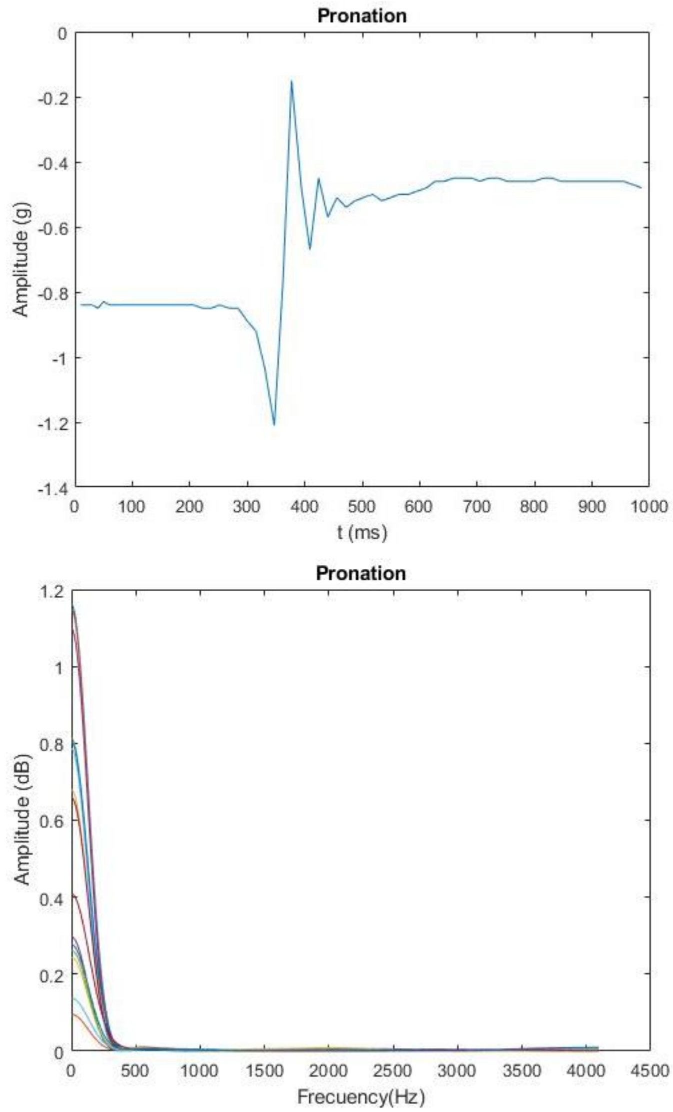


Fig. 5. Signals from the wrist joint when performing a ulnar deviation: up) muscle signal in cubital deviation, down) spectrum of greater amplitude in cubital deviation, z axis



(a) (b)

Fig. 6. Signals from the wrist joint in the pronation movement a) muscle signal in pronation, b) spectrum of greater amplitude in pronation, x-axis

Fig. 6 shows the muscle contraction when the wrist joint performs the pronation movement in conjunction with the elbow joint and is captured by the myoelectric sensor and inertial sensor whose wider spectrum is recorded on the x-axis.

Fig. 7 shows the muscle contraction when the wrist joint performs the supination movement in conjunction with the elbow joint and which is captured by the myoelectric sensor and inertial sensor whose spectrum of greater amplitude is recorded on the axis x.

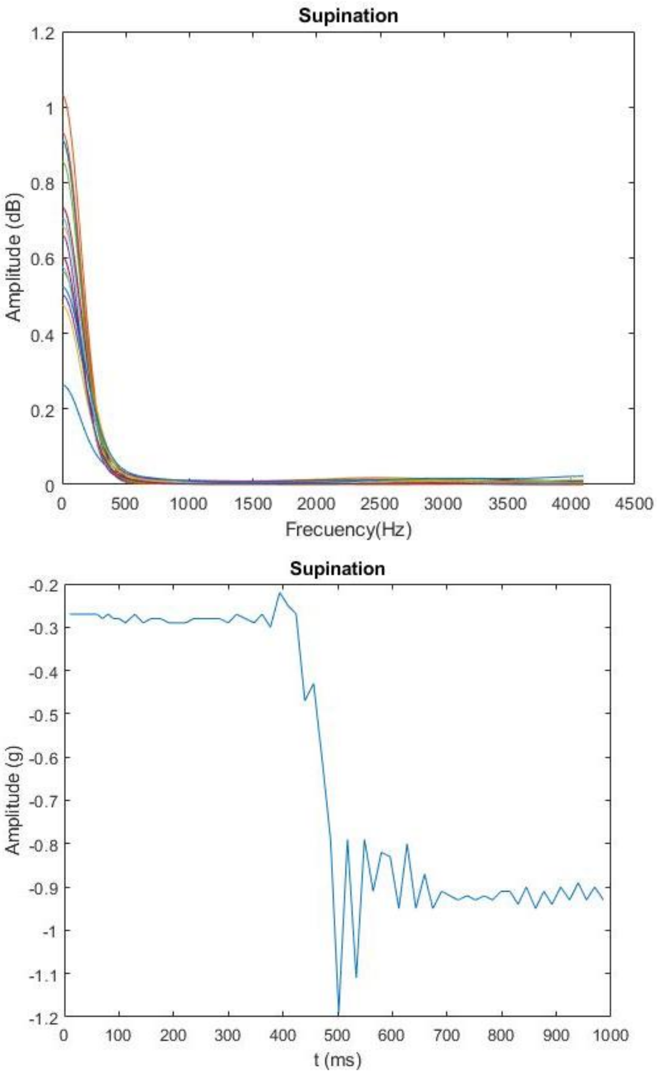


Fig. 7. Muscle contraction in the supination movement: up) muscle signal in supination, down) spectrum of greater amplitude in supination, x-axis

In the following process, an extraction of main characteristics was made for each sample of data, extracted from the 6 movements. The characteristics extracted included the absolute mean value (AVM), variance (VAR), standard deviation (STD), square mean root (RMS), Skewness (SKE) and kurtosis (KUR), these characteristics served as input data to the designed neural network [19] [20], as shown in Table 1.

TABLE I
CHARACTERISTIC VALUES FOR EACH MOVEMENT OF THE WRIST

	Flexion	Extension	Radial deviation	Ulnar deviation	Pronation	Supination
Function	Values					
MAV	-0.9492	-0.9615	0.8049	1.0153	0.7759	0.8559
VAR	0.0029	0.0047	0.0028	0.0025	0.2495	0.0036
STD	0.0525	0.0674	0.0498	0.0488	0.4995	0.0695
RMS	0.9507	0.9639	0.8066	1.0165	0.9218	0.9088
SKE	0.1279	1.1571	1.8018	1.1420	1.4503	1.7705
KUR	17.9655	10.7860	18.3899	10.7993	14.2408	14.0228

The recorded values of the indicated functions were obtained for each captured muscle signal belonging to the 6 groups of data representing the joint movements of the wrist. By group, an average value was obtained for each function and they are those shown in Table 1. Within the extracted parameters, the characteristic parameter RMS (mean square root) was considered, this parameter represents the value of the network that is usually used during the learning process with the function it represents when obtaining a better estimate in intuitive terms of the efficiency in prediction.

Likewise, the average absolute value of the digital signal EMG presents a useful property whose scale goes from 0 to 1, when the value approaches 0 indicates that the proposed model will present errors in the prediction and a value close to 1 will contribute to a more accurate prediction. Both parameters are considered the most important and work together with the other parameters for better training and network response.

B. *Neural network architecture*

The neural network was designed considering the following aspects in its architecture: 6 inputs (values of the main characteristics), 1 hidden layer and 6 outputs (6 movements) Likewise, for the start of the test, a TARGET representing the expected values for each output in the neural network training was considered. The diagram of the designed neural network is shown in Fig. 8.

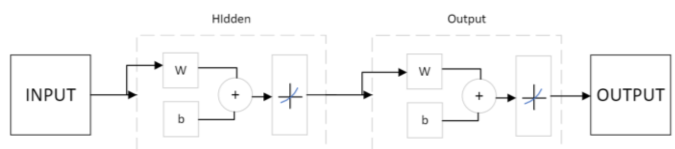


Fig. 8. Neural network architecture

III. RESULTS

A. *Training process with Matlab*

In the training process the Matlab program was used using the Deep Learning Toolbox extension, to implement deep neural networks with algorithms, obtaining the following results.

Fig. 9 shows the performance graph of the neural network which describes that with the times the MSE (Mean Square Error) of the network has decreased registering a low MSE, at the end of the training phase, taking a value of 0.0119 so being a value close to zero shows that the desired outputs and outputs of the RNA for the training set have been closest to each other.

The RMS parameter reflects how the network is getting correct answers; as the network learns, that value decreases. Similarly, because the values obtained at the network output and the expected outputs are real values, it is essential to define a cut-off parameter of the network error value RMS, to indicate that the output obtained by the network is approaching the desired output and to estimate that the response obtained is correct. Thus, the response obtained from the network presents a reasonable result since the final value of the quadratic error is small close to zero, the error of the validation set and the error of the test set have similar characteristics and no significant overadjustment is observed in the 48 epoch where the best validation performance occurs.

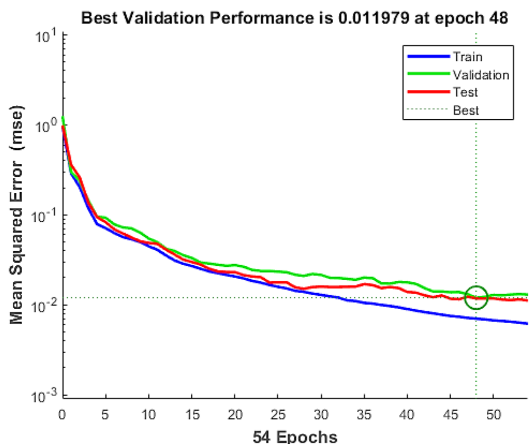


Figura 9. Gráfica de rendimiento usando Matlab - Toolbox Neural Network

Also the error histogram shown in Fig. 10 indicates an error value close to zero, as a result of the difference between the expected output and the output obtained from the network. From the graph described, the blue bars indicate the training data, the green bars the validation data and the red bars indicate the test data. The obtained histogram provides information on atypical values that would be the data in which the adjustment is significantly deficient than most data. On the other hand, it is advantageous to check outliers to define whether the data are poor or very different from the values that belong to the dataset.

It should be noted that in order to obtain a good performance of the network it is advisable to carry out a proper training of the network, to increase if necessary the number of neurons in the hidden layer and to employ a greater set of data for the training.

In addition, the error histogram shown in Fig. 10 was obtained, which indicates an error value close to zero, as a result of the difference between the expected output and the output obtained from the network.

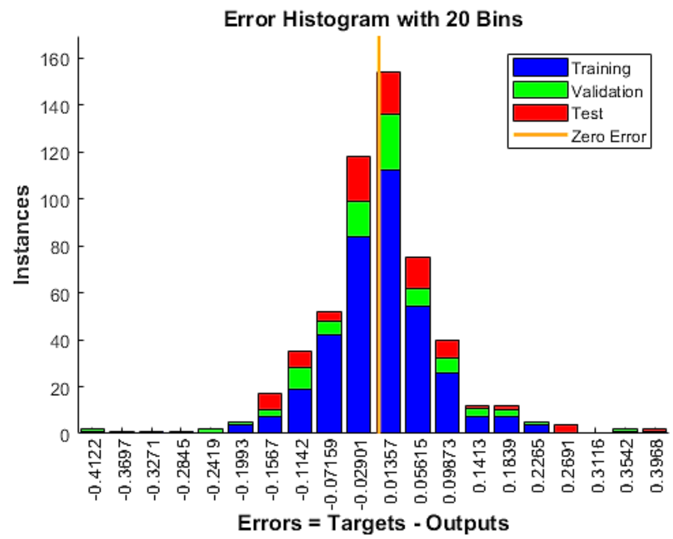


Fig. 10. Histogram of Mean Quadratic Error (MSE)

B. *Neural network test*

Two tests were performed on the neural network

1) First test: The first test consists of an evaluation of the network considering only the 4 characteristic movements of the wrist bending (1), extension (2), radial deviation (3), cubital deviation (4) and a confusion matrix was obtained that achieved an accuracy of 88.9% in movement differences and shown in Fig. 11.

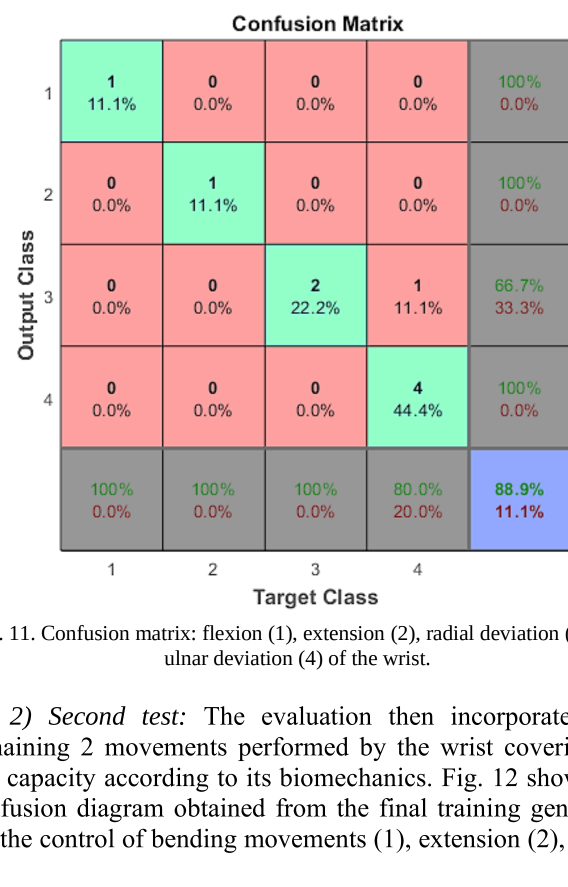


Fig. 11. Confusion matrix: flexion (1), extension (2), radial deviation (3) and ulnar deviation (4) of the wrist.

2) Second test: The evaluation then incorporated the remaining 2 movements performed by the wrist covering its full capacity according to its biomechanics. Fig. 12 shows the confusion diagram obtained from the final training generated for the control of bending movements (1), extension (2), radial deviation (3), cubital deviation (4), pronation (5) and supination (6) of the wrist, it is described that the training reached a precision value of 92.9% higher than the previous evaluation where only 4 movements were considered.

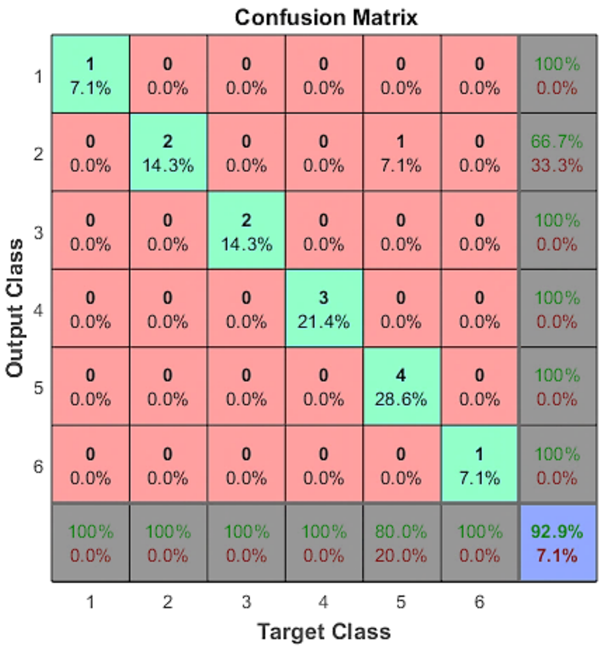


Fig. 12. Confusion matrix: flexion (1), extension (2), radial deviation (3), ulnar deviation (4), pronation (5) and supination (6) of the wrist.

C. Neural network validation

Finally, Fig. 13 shows the cross-validation diagram that represents the comparison of output or expected data (TARGET) with data simulated by the neural network. The purpose of this cross-comparison is to identify the proximity of training results and expected values in response to the system. In addition, this cross-validation allows to graphically represent the goodness of adjustment of the neural network for training data, validation, test and all data used.

This will be able to check whether an over-learning was presented or not. If the neural network continues its training with a greater number of data (captured signals) the results will be optimal in the differentiation of wrist movements.

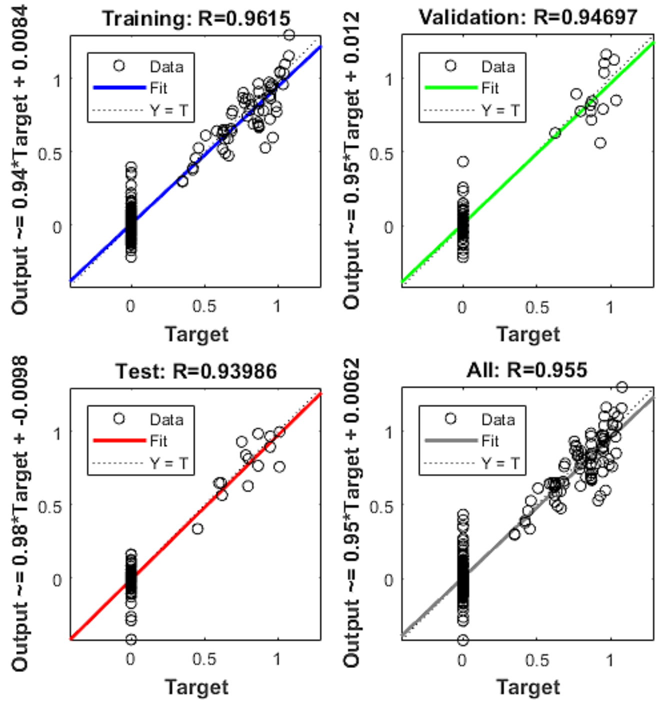


Fig. 13. Cross-validation diagram

The diagram described shows 4 regression graphs showing the results obtained from the Pearson R correlation coefficient for the designed neural network, the graph in the upper left represents the adjustment made by the network in the training phase, the graph in the upper right shows the adjustment in the validation phase and the graph in the lower left the adjustment in the test phase. Likewise the blue, green, red and black lines of the 4 graphs mentioned respectively, represent the adjustment of the network to the expected response and the black circles symbolize the predicted values of the data that were taken during the signal capture process.

It should be mentioned that, for a perfect fit, the data (represented by circular indicators) must be located in the area closest to the 45 degree line, where the values obtained at the output of the network are equal to the answers.

As long as the neural network continues its training with more data (captured signals) the results will be more accurate obtaining different initial weights and biases of the network achieving as a response an improved network after retraining.

IV. CONCLUSIONS

The use of deep learning tools and electronic input elements that allow the capture of data favor the training of a neural network allowing to obtain promising results in the analysis of muscle signals.

The purpose of the research was to use neural networks to learn a system whose focus was to differentiate the characteristic movements performed by the wrist joint, as the first evaluation was considered for the analysis only 4 movements (bending, extension, radial deviation, cubital deviation) achieving an accuracy of 88.9% but adding to the training 2 more movements that performs joint together with the forearm (pronation and supination) resulted in an accuracy of 92.9%. In this sense, the research shows that the training of the network was favorable and can be used to control an active hand prosthetic equipment by providing the equipment with an intelligent function that controls the movements of the wrist. This research can serve as a starting point for further research in the field of biomecatronics.

The system designed can be improved by being more optimized considering perhaps a greater number of data from the samples taken, other characteristic parameters and readjusted according to the objective function, in order to obtain a better response from the neural network. In this sense, the proposed research work can serve as a basis in the analysis of other articular movements of the human body, contributing to the control of prosthetic equipment with improved control and handling capabilities for user autonomy.

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