Implementation of a neural network of low computational cost for its application in arm prostheses

Implementación de una red neuronal de bajo coste computacional para su aplicación en prótesis de brazo

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Abstract

A prostheses implementation represents a design challenge in its different stages. The control systems and the total system cost play a very important role. In this work, a control proposal is presented using artificial neural networks (ANN) for pattern recognition using electromyographic (EMG) signals, which are obtained from the arm muscle (biceps). A single channel EMG surface sensor is used to acquire the EMG signals and by means of adjacent windows the feature extraction is carried out in order to reduce the input values to the neural network. The neural network is trained with the features extracted from the EMG signals, using a method of muscle tension thresholds for activation and a labeling technique for the output called One Hot Encode. The resulting ANN was embedded in a low-cost microcontroller and an accuracy of approximately 93% was achieved.

Pattern recognition, Neural networks, Surface EMG sensor

Resumen

El polietileno de baja densidad (LDPE), se encuentra La implementación de una prótesis representa un reto de diseño en sus diferentes etapas. Los sistemas de control y el coste total del sistema juegan un papel muy importante. En este trabajo se presenta una propuesta de control mediante redes neuronales artificiales (RNA) para el reconocimiento de patrones utilizando señales electromiográficas (EMG), que se obtienen del músculo del brazo (bíceps). Se utiliza un sensor de superficie EMG de un solo canal para adquirir las señales EMG y mediante ventanas adyacentes se realiza la extracción de características para reducir los valores de entrada a la red neuronal. La red neuronal se entrena con las características extraídas de las señales EMG, utilizando un método de umbrales de tensión muscular para la activación y una técnica de etiquetado para la salida denominada One Hot Encode. La RNA resultante se incrustó en un microcontrolador de bajo coste y se consiguió una precisión de aproximadamente el 93%.

Reconocimiento de patrones, redes neuronales, sensor EMG de superficie

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Introduction

Myographic signals have played a very important role in the design and implementation of gesture classification systems and prosthesis implementation. Prostheses require control systems that allow the user to perform basic tasks such as those performed by the real member (Oziomek et al., 2022; Polo Hortigüela, 2022). The synergy between the control system and the myographic signals should provide an accessible and economical methodology in the implementation. A methodology that has been recently used in the literature consists of the characterization of gestures through the use of myographic signals and Artificial Neural Networks (ANN) (Talib et al., 2019). In recent decades, artificial neural networks have become popular as a control method due to their advantages in efficiently and effectively modeling complex problems. Neural networks can find relationships or patterns inductively through learning algorithms, based on the data that the user specifies (Asghari Oskoei & Hu, 2007). The combination of tools such as neural networks and the acquisition of myographic signals has provided control systems for limb prostheses. EMG signals are rich in information, which is used by neural networks to generate control signals, but they usually require a high consumption of computational resources that complicate the implementation of lightweight and portable models(Zhang et al., 2019a).

On the other hand, the extraction of the characteristics of the EMG signals is a methodology that allows to know certain information about the signal. Features can be time domain (TD), frequency domain (FD), or time-frequency domain (TFD). However, the best performing data for neural networks is in the time domain (Zhang et al., 2019b). Most of the gesture prediction models are based on the use of sensors for EMG signals that require a large number of channels, which translates into higher cost and complexity of the system (S. Ahmed et al., 2020). Surface electrode EMG sensors are safe and easy to use. Although surface electrodes provide a better approximation of superficial muscle activity, they cannot be used to detect selective signals from small and deep muscles due to the problem of crosstalk. Even signals from superficial muscles are contaminated by crosstalk from muscles adjacent to and below the target muscle (Aljobouri, 2022).

The application of a microprocessor for the control of myoelectric signals has advantages of both functionality and cost. In addition, to adapt easily, which translates into a greater responsiveness. Pattern recognition-based control increases the variety of control functions and increases robustness (Amato et al., 2013; Antonelli et al., 2022).

In this work, we propose a pattern recognition control model based on EMG signals of the biceps muscle. For data acquisition, we used a DFROBOTS EMG Gravity sensor to identify three voltage thresholds. For signal processing, we use the extraction of temporal characteristics using the most representative ones such as the mean absolute value (MAV), the root mean square (RMS) and the wavelength of the waveform (WL) (Artemyev & Bikmullina, 2020; Barandas et al., 2020). An Arduino Nano board was chosen for its size and flexibility. For the classification we applied the labeling technique called One Hot Encoding and the artificial neural network was trained in Matlab.

Materials

An analog electromyographic (EMG) sensor of the DFROBOT brand, shown in figure 1, was used for the experiments. It consist of a single-channel sensor that has two plates. One of the plates is a metallic surface contact electrode that is attached to the arm by means of an elastic band and the other is the part of the interface between the electrode and the Arduino Nano board. The main advantages of this sensor compared to other EMG sensors is that its electrode is not like conventional suction suckers that adhere to the skin by glue and/or conductive liquid, so it is not necessary to replace the electrodes frequently. The EMG sensor electrode was placed on the biceps since this muscle will have the function of activating the prosthesis (Cote-Allard et al., 2019).

Figure 1 Analog EMG sensor
Source: dfrobot.com

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The microcontroller used is an Arduino nano, as shown in figure 2. This board is based on the ATmega328P microcontroller, with an operating frequency of 16 MHz. According to the manufacturer's specifications, sampling frequencies of 10 KHz can be achieved, which is sufficient for the activity to be carried out.

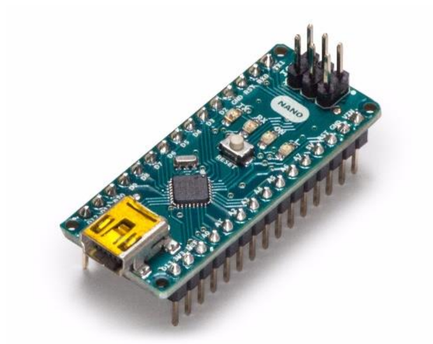

Figure 2 Arduino nano
Source: Arduino community

Data Adquisition

Through the EMG sensor, the necessary tests are carried out and the data that will be processed later in an artificial neural network is stored. In this work three levels of tension are distinguished that will be processed and classified by the ANN. For the implementation of a pattern recognition ANN, a training phase is required where the data to be learned and the category to which it must be assigned are presented. Then, for the first stage, the EMG signals from the biceps are sampled at three voltage thresholds (Cote-Allard et al., 2019; Hagengruber et al., 2022; Setioningsih, 2021). Figure 3 shows the thresholds distinguished by vertical dotted lines, on the left "low voltage", in the middle "medium voltage" and on the right "high voltage". Sampling was done at 100 Hz, in other words, one sample every 10 ms.

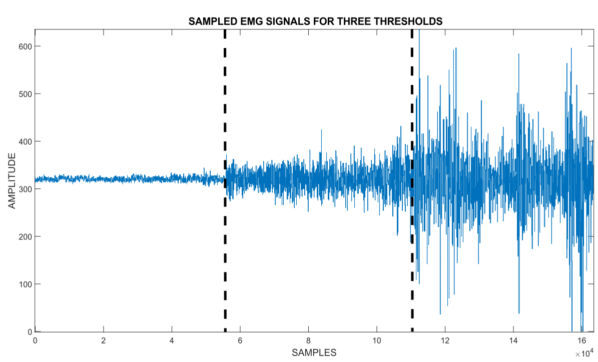

Figure 3 Sampled EMG signals for three thresholds
Source: Own elaboration

For the processing of the input signals, the temporal characterization of the signal was applied. The data was separated into separate windows of fifty values and the mathematical formulas for the time domain characterization were applied. The most representative characteristics are the mean absolute value (MAV), the root mean square (RMS) and the waveform length (WL) (S. S. Ahmed et al., 2021; Lee et al., 2021).

$$MAV = \frac{1}{N}\sum_{n=1}^{N} |x_n| \quad (1)$$

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

$$WL = \sum_{n=1}^{N} |x_n - x_{n-1}| \quad (3)$$

Having the input data for training the neural network, it is necessary to determine the classes to classify. For the output classes we use a labeling technique called "One Hot Encode", as shown in Table 1 (Samuel et al., 2019; Witman et al., 2019). This technique consists of proposing a vector of size equal to the number of thresholds of the input signal, in this case the vector is of size three since that is the number of thresholds to classify. The characteristic of this vector is that it has only one value equal to one and the rest are zero.

One Hot Encode			Threshold value
0	0	1	Low muscle tension (S1)
0	1	0	Medium muscle tension (S2)
1	0	0	High muscle tension(S3)

Table 1 Labeling the One Hot Encode output classes
Source: Own elaboration

Implementation of the ANN

For the implementation and training of the ANN, Matlab was used. First, the data is preprocessed using standard normal normalization. When we refer to the data, we are talking about the temporal characteristics MAV, RMS and WL, respectively. With the preprocessed input data and the output classifications, a neural network is proposed that will have three inputs, two neurons in the hidden layer and three neurons in the output layer. The activation function for the proposed hidden layer is known as Poslin (Positive Linear), also known as ReLu (Lin Wang & Buchanan, 2002). The behavior of the ReLu function is shown in Figure 4.

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$a = 0 \quad n < 0$ $a = n \quad 0 \le n$	

Figure 4 ReLu activation function range and symbol
Source: Neural Network Design 2da edition.

For the activation function of the output layer, the Softmax function was used, expressed in equation (4). The characteristic of this function is that a probability value is determined for each of the outputs, where the element of the vector with the highest value in probability is corresponding to the estimated output, in addition, it must be fulfilled that the sum of the probabilities of all its elements of the vector equal to one (Chambon et al., 2018; Nam et al., 2022).

$$\sigma(\vec{z})_i = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \quad (4)$$

The structure of the pattern recognition neural network is shown in Figure 5. The network consists of three inputs, two neurons in the hidden layer and three neurons in the output layer.

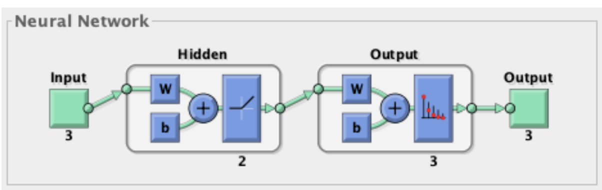

Figure 5 Structure of the neural network
Source: Own elaboration

Results

The results obtained from the training of the neural network show that the network can achieve the tolerable error reduction after 115 training epochs. Figure 6 shows the cross-entropy behavior of the training data, the validation data, and the test data during execution. It can be observed that the cross entropy tends in all cases to the best performance, which implies that the error approaches a relatively low value, close to zero.

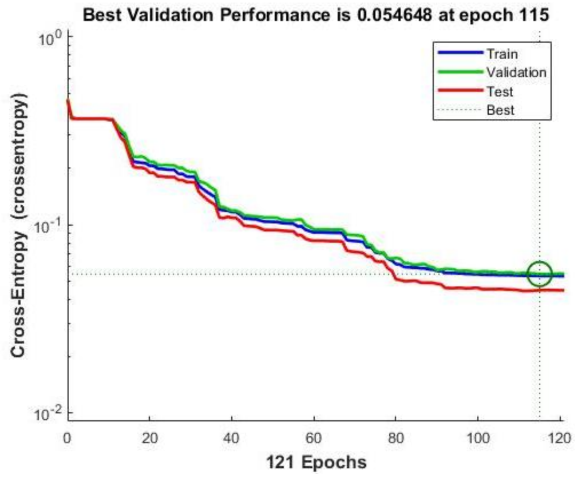

Figure 6 Performance validation
Source: Own elaboration

Figure 7 shows the confusion matrix for the training data of the neural network. In this matrix, the cases of detection (correct or incorrect class) of the input signal that can be obtained by the neural network are grouped. At this stage, 93.8% accuracy is achieved. This indicates that the training data globally provide an adequate precision in the classification of muscle tension levels.

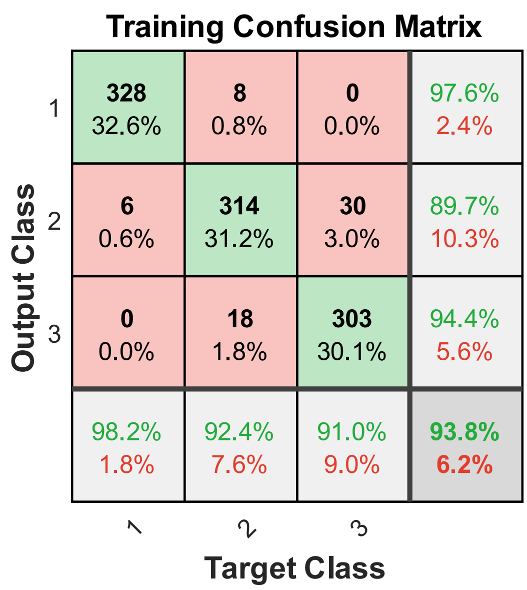

Figure 7 Confusion matrix of the training values
Source: Own elaboration

As shown in Figure 8, the confusion matrix for the validation data reaches 93.1% detection accuracy. Validation allows us to see the capacity of the network for data that was not used in the training and adequate precision is observed.

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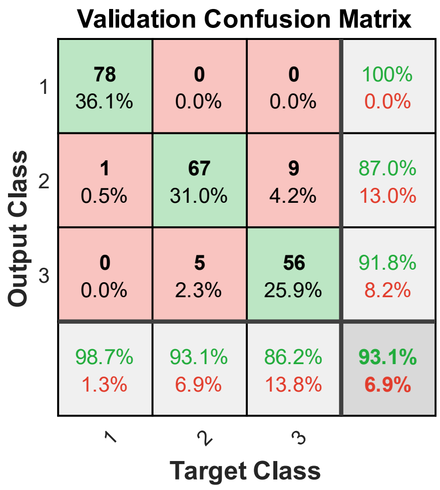

Figure 8 Confusion matrix of validation values
Source: Own elaboration

The confusion matrix indicated in figure 9 for the test data, reaches a 94% correct detection. Note that the test data is reserved for testing the already trained network. This result shows that the trained network offers excellent accuracy on new data.

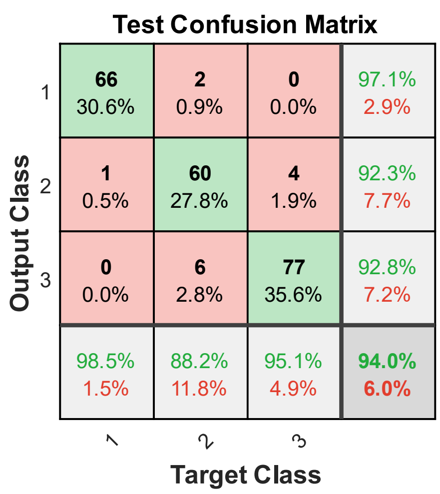

Figure 9 Confusion matrix of test values
Source: Own elaboration

Lastly, the general confusion matrix shown in figure 10 shows the general average of RNA detection, with a precision of 93.7%, which implies a detection of errors of 6.3%, which is sufficiently low.

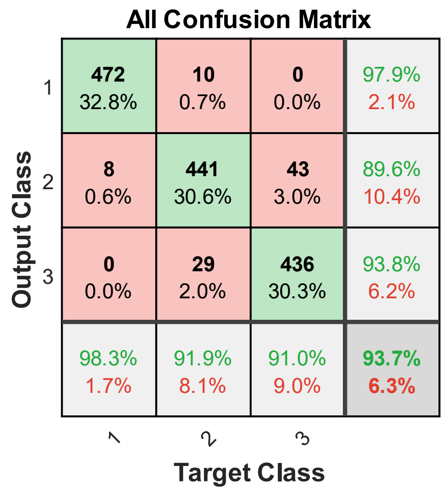

Figure 10 Confusion matrix of the general average of the values
Source: Own elaboration

The error histogram in Figure 11 is a graph that groups the cases by their variability of error obtained. It is observed that the maximum of the graph is very close to zero, which implies that the behavior of the error, in this network, is low enough, allowing an adequate detection.

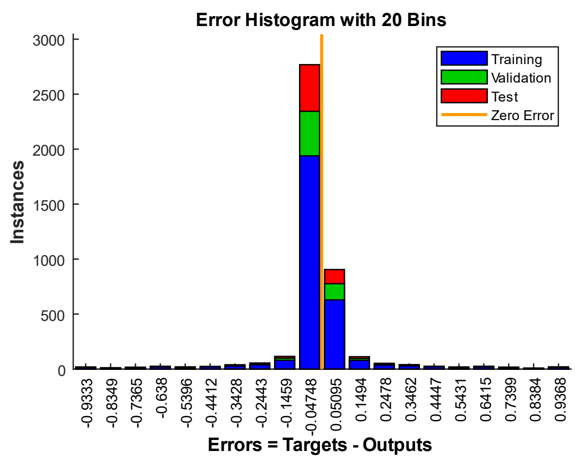

Figure 11 Error Histogram
Source: Own elaboration

On the other hand, equations (5), (6), (7) and (8) represent the weights corresponding to the hidden layer, the layer weights of the output layer, the biases of the hidden layer and the biases of the output layer, respectively.

$$W1 = \begin{bmatrix} -0.926 & 1.81 & 1.292 \\ -0.492 & 2.761 & 0.566 \end{bmatrix} \quad (5)$$

$$w2 = \begin{bmatrix} -1.51 & -7.614 \\ -3.178 & 1.95 \\ 1.903 & 0.692 \end{bmatrix} \ldots. \quad (6)$$

$$b1 = [0.974 \quad 2.564] \quad (7)$$

$$b2 = [4.501 \quad -0.76 \quad -3.001] \quad (8)$$

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These weights and biases are used to implement the trained neural network within any microcontroller, in this case an Arduino Nano. Figure 12 shows the block diagram for the implementation.

Figure 12 Block diagram for implementation
Source: Own elaboration

Conclusions

An artificial neural network was trained and an accuracy of 93.7% was achieved for an application with electromyographic signals. The network inputs were obtained from the signal produced by an EMG sensor and the extraction of the MAV, RMS and WL temporal characteristics. The use of the temporal characteristics allows to obtain a good enough precision for this application, this small ANN with only two input neurons in the hidden layer and three output neurons requires a low computational cost and can be easily implemented in an Arduino Nano.

One of the problems faced by this proposal is the limitations due to crosstalk caused by the adjacent muscles of the biceps, which could be reduced by increasing the number of electrodes of the EMG sensor.

artificial neural network fulfills its purpose, being cheap to implement compared to other more sophisticated systems, in addition to its low energy and computational cost.

Regarding EMG control, it is recommended that the user carries out muscle therapies and exercises in the area to improve the quality of muscle signals, in such a way as to facilitate control of thresholds and prolong the time of use of the sensor. The system could cause muscle fatigue when used for long periods of time.

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