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Lower limbs motion intention detection by using pattern recognition

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Abstract*—Electromyographic (EMG) signals processing allows to perform the detection of the intention of movement of the limbs of the human body in order to further use this decision to control wearable devices. For instance, robotic exoskeletons main objective consist of a human-robot interface capable of understanding the user's intention and reacting appropriately to provide the required assistance in an opportune way. In this paper, we study the performance of superficial EMG intended to design a intent pattern recognition based on Artificial Neural Networks (ANN) trained by the Levenberg-Marquardt method. Experiments consisting in 231 EMG records corresponding to 13 lower limbs muscles from 21 healthy subjects were considered. The EMG signals were randomly divided into the following sets: 70 % for training, 15 % for validation and 15 % for evaluation. The ANN-based pattern recognition was evaluated sample per sample with the movement intention annotations (target) and after the traininig operation end, the performance was evaluated in relation to the events (number of steps). The results show an accuracy of 90,96% sample per sample and 94,88% for an based on events evaluation. These findings motivates the use of this methodology for the classification of the motion intention detection in subjects with pathologies in the lower limbs.

***Index Terms*—EMG, ANN, Intended Motion, Lower limbs.**

I. Introduction

The Electromyogram (EMG) is used to evaluate muscle activity in cases where abnormal results or aberrant patterns of muscle activation occur [1], [2]. Another clear example of the use of EMG signals is in the patient's rehabilitation, since such EMG signals in combination with rehabilitation devices are widely used to help people suffering from a lack of muscle contractions [3]. And perhaps one of the most remarkable applications is in exoskeletons [4], [5]. Currently there is a large number of exoskeletons developed for the lower extremities, because they are more vulnerable to injuries of different types [5].

A very important issue, using EMG signals in exoskeletons is their classification and characterization. From the EMG it is possible to perform the detection of the intention of movement as part of the control of the exoskeleton. The ultimate goal of the skeletons is the design of a human-robot interface capable of understanding the user's intention and reacting appropriately to provide the required assistance in an opportune way.

There are several methods for detecting the motion intention from EMG. Among them are those based on thresholds, such as the simple threshold, which is the most intuitive and common, consisting in the comparison of the EMG rectified signals with a threshold [6]; there is the double threshold method that requires a preprocessing step to filter the EMG signal and is more time processing consuming [7]; also there are other proposed models, such as Lanyi and Adler method, which is based on the double threshold, increasing their sensitivity and decreasing computational cost [8].

Other algorithms based on Pattern Recognition through Artificial Neural Networks (ANN) have shown better performance. ANN can learn to map a series of inputs into a set of outputs, they represent a quick alternative for personalizing the system to the patient and a better patient-system adaptation. ANN could detect patterns which are not easily detected by other methods, this approach could improve device users satisfaction, providing effective movement assistance to patients. Veer and Sharma obtained a 92.5 % performance for a classification of upper arm movements performed on EMG signals using Backpropagation ANN [9]. With the same approach Backpropagation ANN, another research team [10] developed an EMG-angle model to be used for pattern recognition and so that the exoskeleton was adaptable to each subject. In this work it was concluded that the exoskeleton could be controlled by the intention user's motion in real time.

A different work, using pattern recognition [11], a system that allows to discriminate up to 19 different patterns of manual grip and individual movements of the fingers was reported, with an accuracy of 96% for subjects without amputations and 85% for patients with partial amputations in the hands. In fact, there are many approaches in which ANN are applied for the classification of EMG signals. Ahsan and collaborators [12] used ANN to classify EMG signals according to their characteristics using the Levenberg-Marquardt training algorithm. Those pattern recognition algorithm with ANN is one of the most used techniques to classify the EMG movements.

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Within the framework of a research project devoted to the development of a lower limb exoskeleton, which is aimed to assist the movement of the subject's leg ain a coordinated way, we propose a pattern recognition system for processing EMG signals that allow sending control/activation signals to the motors. In a previous work using this Exoskeleton prototype, the EMG intended movement were analyzed using threshold-based methods, a sensitivity higher than 85% was obtained using the static double threshold detector. In this paper, we study the performance of an EMG intended movement detector based on ANN using an architecture of Pattern Recognition trained by the Levenberg-Marquardt method on the lower limbs EMG database previously collected [13].

This document is structured as follows: section II describes the proposed methodology, section III describes the experiments performed, section IV presents the results and their analysis. Finally, conclusions and future work are outlined.

II. Methods

A. Database

The EMG Database consists of 231 EMG records corresponding to 11 muscles of 21 subjects without pathologies in the lower limb [13]. EMG signals correspond to seven muscles of the left lower limb:

1) rectus femoris (RF)
2) vastus lateralis (VL),
3) vastus medialis (VM),
4) sartorius (S),
5) biceps femoris (BF),
6) semitendinosus (ST)
7) semimembranosus (SM).

and four muscles of the right lower limb:

1) rectus femoris (RF),
2) vastus lateralis (VL),
3) vastus medialis (VM),
4) biceps femoris (BF),.

Each test subject made a coordinated paused walk based on a sequence of tones that indicated the time intervals in which to perform each step, in total they were carried out between 10 and 11 steps. The records were made sequentially. The annotations of contraction episodes, both activation and rest of the EMG signals, were made visually by two experts [14].

B. EMG Annotations

Although the database contains annotations of the steps (Section II-A), for this study, it is necessary to limit the start time of each step. A gap of $30ms$ was defined at the beginning of each step as an indicator of the start of the movement [15].

The Figure 1 shows the EMG processing block diagram to define the $30ms$ window.

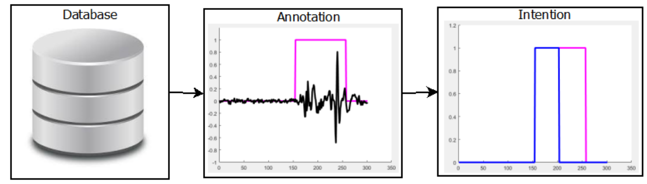

Fig. 1. Block diagram: Database and intention EMG annotation.

C. EMG signal preprocessing

The EMG preprocessing consists of three stages: filtering, normalization/rectification and envelope detection:

1) Filtering: EMG signals are passed through a Butterworth bandpass filter $(25 - 450Hz)$ in order to obtain the filtered version of each EMG signal [16].

2) Normalization/rectifcation: In order to reduce intersubjet variability and maintain the EMG signals with the same amplitude, normalization is performed using Eq. (1), where i, $i = 1, 2, \ldots, 13$ corresponds to each muscle in the study and j, $j = 1, 2, \ldots, 21$ is the subject number in correspondence.

$$EMG_{Nij} = \| \frac{(EMG_{Sijk} - E\bar{M}G_{Sij})}{\sigma_{EMG_{Sij}}} \| \tag{1}$$

where, EMG_{Nij} represents the corresponding i EMG normalized signal to the j subject, EMG_{Sijk} corresponds to the k sample of the i for the j subject, $E\bar{M}G_{Sij}$ and $\sigma_{EMG_{Sij}}$ correspond to the EMG mean and standard deviation.

Finally EMG_{Nij} is rectificated using a full wave procedure.

3) Envelope Detection - ANN entries: EMG_{Nij} is smoothed using a sliding RMS (Root mean Square) envelope with a window **W1**. This signal is defined as EMG_{RMS} Eq. (2) .

Then EMG_{RMS} is derivate and smoothed by a moving average windows **W2**, this signal was named δ_{EMG} Eq. (3).

To provide more information to the ANN, EMG_{RMS} and δ_{EMG} will be the inputs, since the derivative provides an approximation to the increasing, decreasing or stable behavior of the signal. This is because a single EMG_{RMS} signal represents few information to detect the step begining.

$$EMG_{RMS} = \sqrt{\frac{1}{W1} \Sigma_1^{W1} f^2(w)} \tag{2}$$

where, $W1$ is the window length and $f(w)$ equals the data whithin $W1$.

$$\delta_{EMG} = \frac{\Delta(EMG)}{\Delta(t)} = \frac{f_i - f_j}{i - j} \tag{3}$$

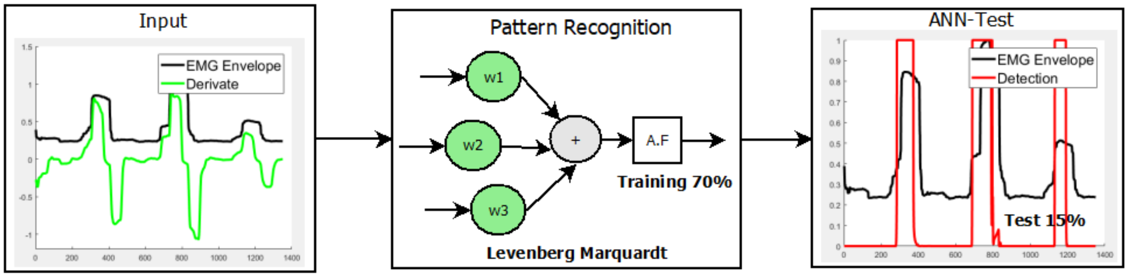

Fig. 2. Inputs, ANN architecture and Target vs Net Detection.

where, f_i and f_j are points of EMG_{RMS}.

D. Artificial Neural Network

An ANN consists of three fundamental layers, input layer, hidden layer and output layer. The artificial neurons are connected between theirs and this connection represents a weight [17]. Moreover, the node that performs the learning or where the processing is performed, adds the value of the input multiplied by the weight associated with the connection as seen in Eq. (4), in this sense, a learning network the weights must be modified so that the output is as close as possible to the *-target-* information delivered to the network.

$$net_j = \Sigma_j w_{ji} * pi \tag{4}$$

where, net_j represents the processing, w_{ji} represents the weight of conection between i input and j neuron, and p_i is the input value for i.

E. ANN Architecture

The pattern recognition method refers to the automatic discovery of regularities in data using computer algorithms, in which regularities are used to perform actions such as categorization or classification [18].

Additionally to training the ANN we have the Levenberg-Marquardt algoritm, that is a compromise between Newton's method, which, in a local or global minimum, presents rapid convergence, and the Gradient Descent method that appropriately selects the step size, however, converges slowly [17].

The chosen ANN architecture was *"Pattern Recognition"* trained by the *Levenberg-Marquardt* method. The Levenberg-Marquardt method is distinguished by its efficiency for the classification of single-channel EMG [19]. Consequently, it is used for this study.

The Figure 2 shows the block diagram ANN training and testing, with the inputs (E_{rms}, δ_{EMG}), target and net detection.

F. Performance Evaluation

Performance were evaluate sample to sample and for events (step). For each sample or event, we estimate true positives (TP) and true negatives (TN), corresponding to correct detection and correct rejection, and false positives (FP) and false negatives (FN), representing false detection and missed detection, respectively [20]. Sensitivity Eq. (5), specificity Eq. (6) and the accuraccy Eq. (7) were used to evaluate the ANN performance.

$$SEN = \frac{TP}{TP + FN} \tag{5}$$

$$ESP = \frac{TN}{TN + FP} \tag{6}$$

$$ACC = \frac{TP + TN}{TP + FN + TN + FP} \tag{7}$$

Additionally, time delay **Td**, is estimated. **Td** is defined as the time elapsed between the annotation of each step, (section II-B), and the detection time through the ANN.

III. Experiments

The experiments we performed to evaluate the ANN are described as follows:

1) **Sliding window width ($W1$):** The width of the sliding window ($W1$) was obtained by means of a linear optimization, $W1$ was iteratively varied from 50 to 150 ms, with intervals of 10 ms.

2) **Derivative E_{rms} window width ($W2$):** The window width for the derivative of E_{rms} ($W2$), was also obtained by linear optimization, varying the width iteratively from 20 ms to 100 ms , with intervals of 10 ms. In addition, the derivatives that provide more precise information of the slope changes according to the associated RMS envelope were visually compared.

3) **Number of neurons:** The number of neurons was obtained by linear optimization, varying iteratively the number of neurons and training the neural network

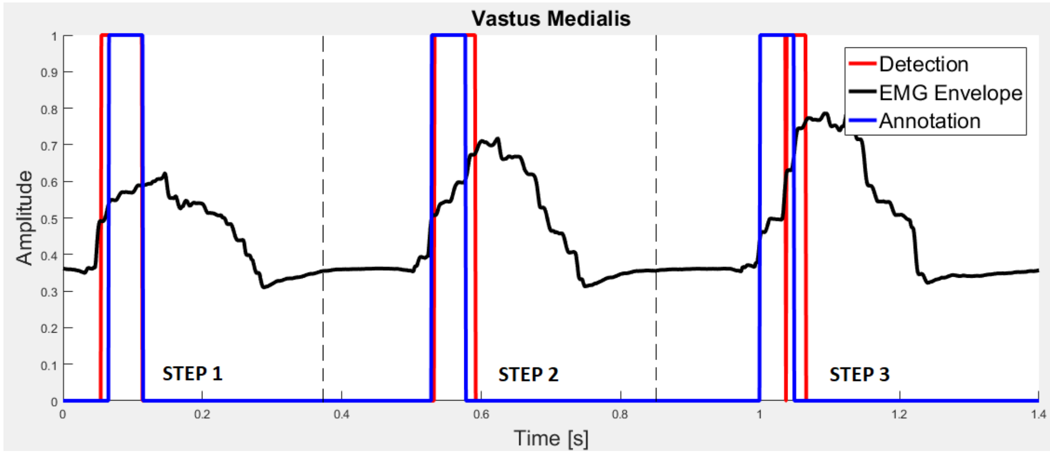

Fig. 3. Performance of the Artificial Neural Network (ANN) for Vastus Medialis: Envelope of filtered EMG signal (Black), Detection (Red), Annotation (Blue).

and comparing confusion matrix results. In the training process, some variants were used in the neural network architecture, as changing the number of neurons in the hidden layer. Several tests were performed, from 30 to 120 neurons with intervals of 10 neurons.

4) **Intention EMG detection:** The EMG signals were randomly divided into the following sets: 70 % for training, 15% for validation and 15% for evaluation.

The RMS envelope E_{rms} and its derivative δ_{EMG} are the ANN input data.

For training, the movement intention annotations are given as ANN Target. The ANN will perform a sample-to-sample training according to the inputs and the target.
To guarantee that the detection results can be generalized, these experiments have been repeated 10 times with different sets of the database for each muscle. The ANN was trained using MATLAB.

In the experiment 4, for each muscle, the ANN were trained using the initial characteristics, then the output was compared sample to sample with the movement intention annotations (target) and in each realization the accuracy lets to evaluated the ANN performance. Once the network has been trained, the performance was evaluated in relation to the events (number of steps).

IV. Results

For the RMS envelope length, the smallest possible window width with greater effectiveness was chosen. The value retained for **W1** was 100ms.

For **W2** it was found that the window width for the derivative gives better results with 60 ms. This was verified both with the training (accuracy values) and by visual observation on the slope change of the derivative of the signals.

	Intention EMG Detected		
Annotation	**TP=** 2720	**FP=** 275	**SEN=** 94,88%
	FN= 44	**TN=** 3190	**ESP=** 98,64%

Fig. 4. Event(number of steps) Confusion Matrix

Finally the best performances were obtained using 80 neurons in the hidden layer.

Table I, show the performance values, sample per sample (sensitivity, specificity, accuracy and time delay) obtained for each muscle. Accurracy and specificity are high however the sensitivity values are modest (mean 66.49 ± 2.36).

The sensitivity value seems low, however this is because the evaluation of network performance is calculated sample per sample and not by events (number of steps).

Figure 4 shows the confusion matrix by events. In this case, the performance of the network is really higher. The ratio of events detected for each muscle, indicates that on average 9 of 10 movement intentions can be correctly detected. Accuracy was 94.88%. Thus performance is higher than the one reported using detection methods based on thresholds on the same database [14]. Their performance was related to events ($SEN = 85,88 \pm 2,18\%; ESP : 86,11 \pm 3,55\%; Td = 6.24 \pm 2.42ms$).

In both performance evaluations sample-to sample and by events, the best accuracy results were observed in the vastus medialis, which may indicate that this is an important muscle

TABLE I
ANN PERFORMACE, SENSITIVITY, SPECIFICITY, ACCURACY AND TIME DELAY

Muscle	Leg	Specificity[%]	Sensitivity[%]	Accuracy[%]	Td [ms]
Rectus Femoris	Left	91.9±0.1	65.5±1.5	90.69±0.08	-5.88
Vastus Lateralis	Left	92.9±0.15	64.9±1.4	91,37±0.1	-19.9
Vastus Medialis	Left	94.56±0.26	68.66±0.75	92,5±0.1	-2.34
Sartorius	Left	92,41±0.15	64.12±1.8	90,83±0.22	-37.31
Tensor Fasciae Latae	Left	93,22±0.2	65.56±1.62	90,91±0.18	-4.25
Biceps Femoris	Left	93,35±0.22	66.97±5.43	91,46±0.21	-20.31
Semitendinosus	Left	93.31±0.15	62.81±0.94	90,8±0.18	-15.56
Semimembranosus	Left	93,42±0.17	66.7±3.38	91,49±0.21	-4
Popliteus	Left	92,03±0.13	67.46±1.41	91,13±0.29	1.125
Rectus Femoris	Right	90,51±0.08	71.7±0.95	89,8±0.06	-30.33
Vastus Lateralis	Right	91,79±0.13	63.45±1.83	90,31±0.1	-4.66
Vastus Medialis	Right	91,92±0.2	67.8±3.22	90,53±0.25	-14.5
Biceps Femoris	Right	91,57±0.1	68.7±1.12	90,61±0.08	-4.16
Average:		92.53±1.01	66.49±2.36	90.96±0.63	-12.6±10

TABLE II
EVENT DETECTION

Muscle	Leg	# Steps	% Detection
Rectus Femoris	Left	229	90.39
Vastus Lateralis	Left	229	89.95
Vastus Medialis	Left	229	93.44
Sartorius	Left	231	93.07
Tensor Fasciae Latae	Left	231	92.64
Biceps Femoris	Left	230	89.13
Semitendinosus	Left	231	90.04
Semimembranosus	Left	231	91.34
Popliteus	Left	231	91.341
Rectus Femoris	Right	231	90.90
Vastus Lateralis	Right	230	90.43
Vastus Medialis	Right	231	90.04
Biceps Femoris	Right	231	87.87
Total:		2995	90.81

for the control of the exoskeleton.

The performance by events of our work is also higher than that reported using : Backpropagation ANN [9] for the classification of arm movements with EMG signals ($SEN = 88.87\%; ESP = 92.5\%$), and Levenberg-Marquardt algorithm [19] to detection of hand movements ($SEN = 88.87\%; ESP = 92.5\%$).

In other work using pattern recognition algorithms, four patients with transfemoral amputation and four subjects without pathologies in the lower limbs were evaluated. EMG signals were recorded and evaluated with the subjects seated by surface electrodes in 9 muscles (semitendinosus, sartorius, tensor fasciae latae, adductor magnus, gracilis, vastus medialis, rectus femoris, vastus lateralis, and long head of the biceps femoris). Results shows high accuracy values, (91.8 % for amputees and 98.6 % for subjects without pathologies). These results are encouraging to use this methodology in subjects with pathologies in the lower extremities [21]. The pattern recognition in this case consists of classify combined EMG signals with a computer during performance of different movement. Moreover the classifier were used to decipher wich motion was being perfomed [22].

Figure 3 shows cases of early (Step 1) and later detection. Step 1, early detection occurs before the step has already begun. For steps 2 and 3, detection occurs after the annotation.

Although the time delay is decisive for real-time applications, and despite having a greater time delay than the one presented by Farfán and Rojas [14], this delay is still minor compared to the $250ms$ established for a system to be considered in real time.

V. CONCLUSION

We have considered the EMG intended movement detector based on ANN using an architecture trained by the Levenberg-Marquardt, for lower limbs EMG signals, the results give an accuracy of 90,96% sample to sample and 94,88% for step event with respect to manual annotations of the signals. In addition, the time delay obtained, allows its implementation in real time, in an exoskeleton.

These findings allow us to contemplate the use of the presented methodology for the classification of the intention of movement in subjects with pathologies in the lower limbs.

It should be considered that each EMG presents high morphologies variability from muscles and between subjects, without counting the noise problems during acquisition. It would be convenient to train an exclusive network for each exoskeleton user [23].

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