Real-Time Hand Gesture Recognition Using the Myo Armband and Muscle Activity Detection

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***Abstract*—Hand gesture recognition consists of identifying the class and the instant of occurrence of a given movement of the hand. The solutions to this problem have many applications in science and technology. In this paper, we propose a model for hand gesture recognition in real time. This model takes as input the surface electromyography (EMG) measured on the muscles of the forearm by the Myo armband. For any user, the proposed model can learn to recognize any gesture of the hand through a training process. As part of this process a user needs to record 5 times, during 2 s each, the EMG on his forearm, close to the elbow, while performing the gesture to recognize. The *k*-nearest neighbor and the dynamic time warping algorithms are used for classifying the EMGs seen through a window. As part of the proposed model, we also include a detector of muscle activity that speeds the time of processing up and improves the accuracy of the recognition. We tested the proposed model at recognizing the 5 gestures defined by the proprietary recognition system of the Myo armband, achieving an accuracy of 89.5%. Finally, we also demonstrated that the model proposed in this work outperforms other systems, including the recognition system of the Myo.**

Keywords—hand gesture recognition; EMG; real time; myo armband; muscle activity detection; machine learning

I. Introduction

Hand gesture recognition is the problem of identifying the class, from a predefined set of classes, and the instant of occurrence of a given movement of the hand. The information returned by a gesture recognition system can be used as the input for human-machine interaction systems, including the control of upper-limb prosthetics [1, 2] and robotics [3, 4]; human-computer interaction systems, including mouse control [5], gaming and virtual reality interfaces [6]; and medical applications, including data visualization [7] and image manipulation during medical procedures [8, 9].

A hand gesture recognition system can be divided into 5 modules: signal acquisition, preprocessing, feature extraction, classification, and posprocessing. Signal acquisition consists of measuring different types of signals generated when a user performs a movement of the arm. For signal acquisition different types of sensors have been used such as gloves [10]; vision sensors [11], including webcams [12], infrared cameras [13, 14], and lasers [15]; inertial measurement units (IMUs) [16, 17]; and electromyography (EMG) [18]. Some systems also combine different types of signals from different sensors [19, 20]. The main goal of the preprocessing module is to remove artifacts (i.e., noise) and condition the signals that will be fed to the feature extraction module. In the preprocessing, the most common operations are filtering and normalization. Feature extraction consists of obtaining meaningful and non-redundant information usually in the form of *n*-dimensional feature vectors [21]. Feature vectors need to have similar patterns between all the elements of a given class and different patterns between elements of different classes. For hand gesture recognition, the most common domains to extract features are: time, frequency, and the combination of these two (e.g., wavelets and spectrograms) [22]. The classification module takes as input a feature vector and returns a label that indicates the class to which such a feature vector belongs. The most common classifiers used for hand gesture recognition are support vector machines [23], feed-forward and recurrent neural networks [24], convolutional neural networks [18], decision trees [25, 26], *k*-nearest neighbors [10], linear discriminant analysis [27], hidden Markov models and ensembles of classifiers such as random forests [4]. The posprocessing is the last module of a recognition model and its function is to refine the decisions made by the classifier.

Among all the modules that compose a gesture recognition system, perhaps the most important and critical ones are signal acquisition, feature extraction and classification. Regarding signal acquisition, deciding which type of sensor to use usually depends on the application and environment where the system will work. Visual sensors, such as webcams, infrared cameras and lasers can be affected by changes in light conditions, occlusion, and variations of the distance between the hand and the sensor. Variations in the size of the hands are usually a problem for gloves. In addition to this, depending on the application, wearing a glove for a long period of time may be uncomfortable for some users. IMUs have the problem of returning noisy data. All the sensors described above are very difficult, and in some cases impossible, to be used with upper-limb amputees. For this case, we need a recognition system that is able to identify the gesture that the user wants to do with the hand that was amputated. For these people, EMG measured in muscles that went through a reinnervation surgery is an option for controlling artificial upper-limbs [28].

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Regarding feature extraction and classification, choosing the appropriate set of features and classification model is very difficult, especially when we constrain the time of processing of these modules. Usually, sophisticated feature extraction techniques combined with complex classifiers lead to good recognition accuracies at the expense of a high computational cost. For a hand gesture recognition system to operate in real time, it needs to return a response in less than 300 ms [29]. Some applications like robotics may even require faster recognition times. Choosing feature extractors and classifiers leading to high recognition accuracy with low computational cost is a very challenging problem, where there is still room for new approaches.

In this paper, we propose an improvement to a real-time hand gesture recognition model that we presented in [30]. The improvement consists of detecting the region of muscle activity on the surface EMG measured on the forearm by the commercial sensor Myo armband. For preprocessing, we use signal rectification. In the feature extraction module, we obtain the envelopes of the EMG. For classification, we use the *k*-nearest neighbors (*k*NN) [21, 31, 32] and the dynamic time warping (DTW) [33] algorithms. The last stage is a posprocessing module that refines the decision made by the classification module. The proposed model has the capability of learning to recognize any type of gesture of the hand through a training process. As part of this process, a user needs to record 5 times, during 2 s each, the forearm EMG while performing the gesture to recognize. This process has to include recording the EMG while the hand is resting or relaxed. It is important to emphasize that the proposed model is user-specific. This occurs because the force and speed with which a gesture is made varies between people. Additionally, the time and frequency features of the EMG change with the thickness and temperature of the skin, thickness of the fat between the muscle and the skin, velocity of the blood flow, and location of the sensors. Factors like muscle fatigue, aging, and neuromuscular diseases also degrade the EMG patterns for a given gesture [34].

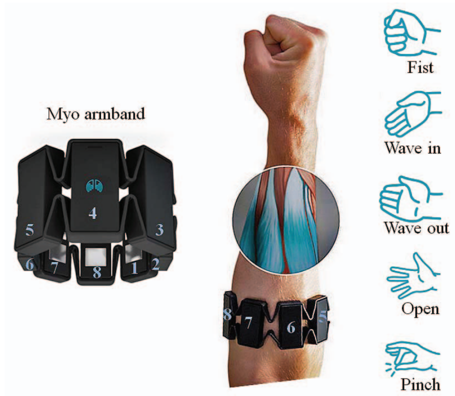
Following this introduction, this paper is organized as follows. In section 2, we describe each of the modules that compose the proposed model. In section 3, we present and analyze the results obtained in this work. Finally, in section 4, we draw some conclusions and outline the future work.

II. Materials And Methods

In this section, we describe the characteristics of the Myo armband, the nature and characteristics of the surface EMG measured on the forearm, and the modules that compose the proposed recognition model.

A. Myo Armband

The Myo armband is a commercial sensor that contains 8 dry and bipolar surface EMG pods (Fig. 1a). This sensor measures the electrical activity of the muscles of the forearm, close to the elbow, at 200 Hz with 8 bits (Fig. 1b). For a user it is very easy to adjust the diameter of the Myo to fit well his forearm. The length of the Myo circumference is expandable between 19 and 34 cm. Additional to the 8 EMG pods, the Myo also provides haptic feedback through vibrations and contains an IMU that measures acceleration, angular velocity, and orientation in the *x*, *y* and *z*, axes. In this work, we use only the data from the EMG pods. The data from all these sensors is transmitted to the computer via Bluetooth. The weight of the Myo is approximately 93 g. The Myo armband also contains a proprietary recognition system, which is capable of identifying in real time 5 gestures of the hand: wave in, wave out, fist, pinch and open (Fig. 1c).



(a) **(b)** **(c)**

Fig. 1. Myo armband: (**a**) number of the EMG pods, (**b**) location on the forearm and (**c**) gestures to recognize.

B. EMG: Nature and Mathematical Model

To understand the nature and mathematical model of EMG, we need to briefly review the anatomy and physiology of skeletal muscles. Regarding the anatomy, skeletal muscles are connected to bones through the tendons. A skeletal muscle is composed of a set of cells called muscle fibers, or simply fibers, which in turn have myofibrils. Myofibrils are formed by myofilaments (i.e., actin and myosin), which are the proteins responsible for the contraction and relaxation of a muscle. Functionally, a skeletal muscle can be divided into motor units. A motor unit is a set of fibers that are innervated by a single motor neuron. The number of motor units depends on the force that a muscle has to produce. One end of a motor neuron is the cell body, which is located in the spinal cord. The other end has axon branches, where each branch is connected to a single muscle fiber of a motor unit through the so called neuromuscular junction. The signals generated by the motor cortex of the brain travel to the muscle through the spinal cord and the motor neurons [35, 36].

Regarding the physiology of a skeletal muscle, the potential between the internal and the external part of a fiber is approximately -70 mV at rest. When the brain sends a pulse to the muscle, two action potentials are created in each fiber at the neuromuscular junction. These action potentials travel from the neuromuscular junction to the tendons. To produce force, the brain needs to send a train of pulses to some or all motor units of a muscle. The number of active motor units (i.e. recruitment) and the interval between two consecutive pulses are considered random quantities that increase with the muscle force. The train of pulses sent from the brain to a muscle fiber creates in it a train of action potentials. The summation of the trains of actions potentials of all the fibers of a motor unit is called a motor unit action potential (MUAP) train. The EMG measured by a surface sensor is the summation of the MUAP trains of the motor units that compose a muscle [37, 38].

Mathematically, the EMG measured by each pod of the Myo armband, when there is movement of any part of the hand, can be modeled by the non-stationary stochastic process

$$E(t) = w(t)s(t) + n(t), \tag{1}$$

where $w(t)$ is modeled by the Gaussian process $\mathcal{N}(0,\sigma_w)$, $s(t)$ is a stochastic process with low frequencies and non-negative amplitudes representing the movement of the hand, or any of its parts, and $n(t)$ is a Gaussian process $\mathcal{N}(0,\sigma_s)$ modeling the noise of the EMG, where $\sigma_s \ll \sigma_w$ [34, 39, 40].

C. Structure of the Propossed Model

The proposed model is composed of the following modules connected in the order that they are described:

- *EMG acquisition*: Here, we obtain the signal measured by the 8 EMG pods from the Myo armband. We model the measured EMG as time series represented by the matrix $\underline{\mathbf{S}} = (\mathbf{S}_1, \ldots, \mathbf{S}_8) \in [-1, 1]^{N\times 8}$, where the column vector $\mathbf{S}_i = (S_i(1),\ldots, S_i(N))^{\mathrm{T}} \in [-1, 1]^8$ contains the values of the ith channel of the EMG, with $i = 1, ..., 8$. The value of N denotes the window length used to observe the EMG. The stride between two consecutive window observations is denoted by M, where $M \in \mathbb{Z}^+$. For this work, we use two different window lengths: one, $N_{\text{train}} = 400$ points, for acquisition of training data and the other, $N_{\text{test}} = 200$ points, for testing. The window length for training is larger than the one for testing because, for training, the user needs to manually record 5 repetitions of each gesture to recognize. For testing, we need a shorter window length so that the time of processing of the following modules is not too large in order to achieve real time.
- *Preprocessing*: Here we rectify the EMG measured in the previous step. For this task, we compute the absolute value of each channel of the EMG, obtaining thus the new signal $abs[\underline{\mathbf{S}}] = (abs[\mathbf{S}_1], \ldots, abs[\mathbf{S}_8])$. Next, we estimate the envelope of each channel of $abs[\underline{\mathbf{S}}]$. Note that according to (1), the shape of the envelope of the EMG contains the information of the movement executed by the user's hand. For extracting the envelope, we used a digital low-pass Butterworth filter $\mathbf{\Psi}$ of 4th order with a cutoff frequency of 5 Hz. It is worth mentioning that the Myo measures EMGs in the spectrum between 0 and 100 Hz. In addition to extracting the envelope of each channel, this filter also reduces the noise of the EMG. The output from this step is the EMG envelope $\mathbf{\Psi}[abs[\underline{\mathbf{S}}]]$ (Fig. 2d).

  Muscle activity detection: In this module, we detect the region of the EMG corresponding to muscle activity (i.e. movement of the hand), removing thus the head and tail of each channel where the forearm muscles are at rest. To avoid increasing the time of processing during testing, this step is applied only to the training EMGs. The goal of this step is twofold: speed up the time and improve the accuracy of the classification. Here, we first obtain the sum $sum[\mathbf{\Psi}[abs[\underline{\mathbf{S}}]]] \in \mathbb{R}^{N\text{train}\times 1}$ of the EMG envelopes (Fig. 2a) and then compute the spectrogram $\boldsymbol{\mathcal{S}}[sum[\mathbf{\Psi}[abs[\underline{\mathbf{S}}]]]] \in \mathbb{C}^{26\times 26}$ (Fig. 2b). For obtaining this spectrogram, we split both the time [0, 2] s and frequency intervals [0, 100] Hz into 26 points each. Then, we compute the l^2-norm of the spectrogram to obtain thus the matrix $\|\boldsymbol{\mathcal{S}}[sum[\mathbf{\Psi}[abs[\underline{\mathbf{S}}]]]]\| \in \mathbb{R}^{26\times 26}$. Next, we sum this matrix along the columns, obtaining a row vector of 26 components (Fig. 2c). Then, we found all the instants of time where the components of this vector are greater than or equal to the threshold 10. The first of these instants is the beginning of the region of muscle activity, and the last instant is the end of this activity (Fig. 2d). If the length of the detected region is less than 100 points (500 ms), the detection is considered spurious. In this case, we return the start and end points of the signal $sum[\mathbf{\Psi}[abs[\underline{\mathbf{S}}]]]$.
- *Feature extraction:* Here we define two types of feature matrices, one $\underline{\mathbf{Z}} \in \mathbb{R}^{L\times 8}$ for each training EMG, with $L \in [100, N_{\text{train}}]$, and the other $\underline{\mathbf{X}} \in \mathbb{R}^{200\times 8}$ for each testing EMG. These matrices contain the data of the signals resulting from the preprocessing module.
- *Classification*: The inputs to this module are the preprocessed training set $\mathcal{D} = \{(\underline{\mathbf{Z}}^{(i)}, Y^{(i)})\}_{i=1}^{P}$ and the preprocessed window observation $\underline{\mathbf{X}}$. For the training pair $(\underline{\mathbf{Z}}^{(i)}, Y^{(i)}) \in \mathcal{D}$, $Y^{(i)} \in \{0, \ldots, c - 1\}$ denotes the label of the preprocessed EMG $\underline{\mathbf{Z}}^{(i)}$, c denotes the number of gestures to recognize, and 0 is the label of rest or the class no gesture. To label the observation $\underline{\mathbf{X}}$ using the kNN algorithm, we use the DTW algorithm to find in $\mathcal{D}$ the k nearest neighbors to $\underline{\mathbf{X}}$. For this task, we compute the optimal warping path [33] to align the channels $\mathbf{Z}_i \in \underline{\mathbf{Z}}$ and $\mathbf{X}_i \in \underline{\mathbf{X}}$ using the Manhattan distance, with $i = 1, \ldots, 8$. By doing so, we obtain 8 DTW distances $dtw(\mathbf{X}_i,\mathbf{Z}_i)$, where $i = 1, \ldots, 8$. We define the total distance between the testing $\underline{\mathbf{X}}^{(j)}$ and the training observations $\underline{\mathbf{Z}}$ as the sum of the DTW distances between their channels $dtw(\underline{\mathbf{X}}^{(j)},\underline{\mathbf{Z}}) = \sum_{i=1}^{8} dtw(\mathbf{X}_i,\mathbf{Z}_i)$. Note that we can compute the DTW distance in parallel to speed up the time of the classification process. Next, we find the k nearest neighbors to $\underline{\mathbf{X}}$ in terms of the DTW distance. The kNN algorithm is universally consistent if $k \to \infty$ and $k/P \to 0$ when $P \to \infty$, where P denotes the number of training examples [32]. Based on this fact, we can choose k to be the closest larger and odd integer to the value of $log_2(P)$. With the k

nearest neighbors to $\mathbf{X}$, we estimate the conditional probability $\mathbb{P}(Y = y|\underline{\mathbf{X}})$, with $y \in \{0, \ldots, c - 1\}$. Finally, this module returns the label of $\underline{\mathbf{X}}$ based on the rule

$$\psi(\underline{\mathbf{X}}) = \underset{y \in \{0, \ldots, c-1\}}{\arg\max} \ \mathbb{P}(Y = y|\underline{\mathbf{X}}), \tag{2}$$

subject to the condition that the probability of the label that maximizes (2) must be equal to or greater than a threshold $\tau \in [0, 1]$. Otherwise, we define $\psi(\underline{\mathbf{X}}) = 0$.

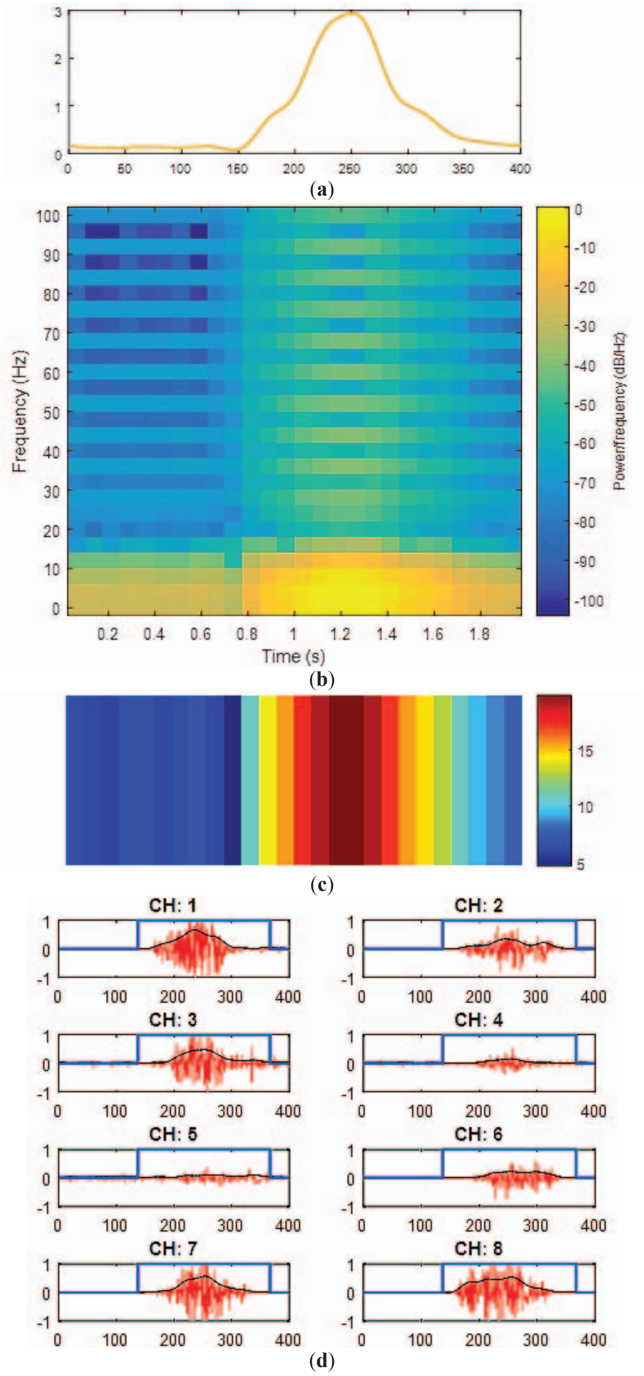


Fig. 2. Muscle activity detection of the forearm: (**a**) Sum of the EMG envelopes, (**b**) spectrogram of (**a**), (**c**) sum of the l^2-norm of (**b**) along the columns, and (**d**) EMG, envelopes and muscle activity region.

- *Posprocessing*: The goal of this module is to eliminate consecutive repetitions of the same label using a time delay of one step. For this task, let us assume we have the consecutive labels $\psi(\underline{\mathbf{X}})(n - 1)$ and $\psi(\underline{\mathbf{X}})(n)$ for some $n \in \mathbb{Z}^+$. If the previous label $\psi(\underline{\mathbf{X}})(n - 1)$ is equal to the current label $\psi(\underline{\mathbf{X}})(n)$, then we return $\psi(\underline{\mathbf{X}})(n) = 0$ at the current instant n. Otherwise, we return the label $\psi(\underline{\mathbf{X}})(n)$ unchanged.

III. Results And Discussion

In this section, we present and discuss the results obtained with the proposed model. For comparison purposes, we also evaluated the performance of a general system, which does not have to be trained for both each user and each test session. Additionally, we also compared the proposed model with the proprietary gesture recognition system of the Myo armband. Finally, we also make comparisons with the results of our previous work [30], where we did not apply muscle activity detection to the training data.

A. *Results of the Propososed Model*

For evaluating the recognition accuracy of the proposed model, we used the same protocol and dataset as in [30]. The gestures we defined for testing are the 5 ones indicated in Fig. 1c. The dataset we used is composed of EMGs acquired from 10 different people, including men and women, and is composed of 2 sets: one for training and the other for testing. In the training set, for each person we have 5 EMGs for each gesture and also 5 EMGs recorded while the hand was at rest. This means that, for each person, the training set contains a total of 30 EMGs of 8 channels each. Each of these EMGs has approximately 400 points recorded during 2 s at a frequency of 200 Hz. In the testing set, for each person we have 30 EMGs for each of the 5 gestures defined above. In this set, we do not have any EMG for the resting position because this position is part of the background, which in this work is referred as no gesture. In total, for the testing stage we have 300 EMGs for each gesture, where each EMG has 8 channels with 1000 points recorded during 5 s at 200 Hz. The length of the testing EMGs is larger than the length of the training ones because, the goal a recognition system is not only to recognize the gesture that user did but also the moment when it occurs.

For testing the proposed model, we used a window length of $N_{\text{test}} = 200$ points for each channel of the EMG. This length was determined heuristically. The stride between 2 consecutive observations was defined to be $M = 50$ points. This value was selected as a tradeoff between the time in which our model process a window observation and 300 ms, which is longest time in which a real-time system can give a response. For the kNN classifier, we used $k = 5$ that is the closest larger and odd integer to $log_2(30) = 4.91$. Additionally, we used $\tau = 0.8$ for thresholding the conditional probability $\mathbb{P}(Y = y|\underline{\mathbf{X}})$. It is worth mentioning again that the proposed model was trained and tested for each person of the dataset. Training the model took between 3 and 5 min for each user.

The results obtained in this work are presented in the confusion matrix of Table 1. The values of this table are the averages of the results obtained for each user. In the lower right corner of this table, we can see that the recognition accuracy of the proposed model is 89.5%. The highest and lowest sensitivities or recalls occur for the gestures wave in (99.3%) and pinch (77.3%), respectively. The highest and lowest precisions occur for the gestures pinch (99.6%) and open (88.4%), respectively.

TABLE I. CONFUSUION MATRIX OF THE PROPOSED MODEL

		Targets					%ACCURACY (PRECISION) % ERROR
		FIST	WAVE IN	WAVE OUT	OPEN	PINCH	
Predictions	REST	**10** 0.7%	**2** 0.1%	**9** 0.6%	**30** 2.0%	**25** 1.7%	**0.0%** 100%
	FIST	**278** 18.5%	**0** 0.0%	**0** 0.0%	**7** 0.5%	**5** 0.3%	**95.9%** 4.1%
	WAVE IN	**6** 0.4%	**298** 19.9%	**1** 0.1%	**1** 0.1%	**9** 0.6%	**94.6%** 5.4%
	WAVE OUT	**1** 0.1%	**0** 0.0%	**290** 19.3%	**18** 1.2%	**1** 0.1%	**93.5%** 6.6%
	OPEN	**4** 0.3%	**0** 0.0%	**0** 0.0%	**244** 16.3%	**28** 1.9%	**88.4%** 11.6%
	PINCH	**1** 0.1%	**0** 0.0%	**0** 0.0%	**0** 0.0%	**232** 15.5%	**99.6%** 0.4%
	%ACCURACY (SENSITIVITY) % ERROR	**92.7%** 7.3%	**99.3%** 0.7%	**96.7%** 3.3%	**81.3%** 18.7%	**77.3%** 22.7%	**89.5%** 10.5%

B. *Results of Different Recognition Models*

In the following table, we present the averages of the accuracies and the times of processing of the models we used for comparison:

TABLE II. RESULTS OF DIFFERENT RECOGNITION MODELS

Model	Accuracy (%)	Average time (ms)
Proposed model (with muscle activity detection)	89.5	193.1
Model without muscle activity detection	86.0	245.5
Proprietary system of the Myo	83.1	-----
General model	53.7	1803.5

For measuring the time of processing of all the algorithms presented in Table 2, we used a desktop computer with an Intel® Core™ i7-3770S processor and 4GB of RAM memory. The averages of time are computed as the mean of the times of processing window observations of 200 points. We do not report the average time of processing of the recognition system of the Myo because it is black-box model that provides only the labels of the gesture recognized.

For evaluating the accuracy of what we call the general model, we used the leave-one-out cross-validation method [21, 31, 32]. Under this method, we trained the proposed model using the EMGs of 9 out the 10 users of the dataset. Then, we evaluated the performance of this model on the 30 testing EMGs of the user whose EMGs were not included in the training process. This procedure was repeated 10 times, where in each repetition, we used a different user for evaluating the accuracy of the general model. For testing the proprietary system of the Myo armband, users were asked to synchronize it by performing a wave out and then relaxing the arm.

C. *Comparison of Results and Discusion*

The results of Table 2 show that the proposed model outperforms the other models presented in this paper both in accuracy and time of processing. These results also evidence that the detection of the muscle activity in the training EMGs speeds the time of processing up and improves the accuracy of the classification module. Additionally, the huge difference between the recognition accuracies of the proposed model (89.5%) and the general model (53.7%) clearly justifies the decision to train the model for each person and for each test session. We predict this result occurs because by training the proposed model for each person and test session, it can adapt its behavior to the particular attributes of each user's EMG. For a general model, this adaptation is not possible since the gesture recognition model is trained only once. Additionally, analyzing visually the EMGs of the dataset used in this work, we have observed that they vary between different people for the same gesture. This may be one of the reasons why a general model is harder to implement than a user-specific model. Finally, this also evidences that training with EMGs from several users a general model that is able to work well for all the users is a very difficult problem.

IV. CONCLUDING REMARKS

In this paper we have presented a real-time hand gesture recognition model based on the forearm EMG acquired with the Myo armband. The proposed model can learn to recognize any gesture of the hand through a training process. As part of this process a user needs to record 5 times, during 2 s each, the EMG on his forearm, close to the elbow, while performing the gesture to recognize. The model also requires recording 5 times, during 2 s each, the forearm EMG while the hand is relaxed or at rest. For classification, we used the *k*NN and the dynamic time warping algorithms. The proposed model was based on the detection of the envelopes and the region of muscle activity in the training EMGs.

We evaluated the performance of the proposed model at recognizing the following 5 gestures: fist, wave in, wave out, open and pinch. Both the recognition accuracy and time of processing indicate that the proposed model performs better than the model without detection of muscle activity in the training EMGs. Additionally, we also determined that the recognition accuracy of the proposed model is better than the one of proprietary system of the Myo armband. We also demonstrated empirically that implementing a user-specific hand gesture recognition model is easier than a general model.

Future work includes testing new models for feature extraction and classification in order to improve the recognition accuracy obtained in this work. We will also include the recognition of dynamic gestures of the arm, for which we will need to use the data from the IMU.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support provided by Escuela Politécnica Nacional for the development of the research project PIJ-16-13 "Clasificación de señales electromiográficas del brazo humano usando técnicas de reconocimiento de patrones y machine learning."

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