Real-Time Hand Gesture Recognition With EMG Using Machine Learning

Andrés G. Jaramillo and Marco E. Benalcázar
Departamento de Informática y Ciencias de la Computación
Escuela Politécnica Nacional, EPN
Quito, Ecuador
{andres.jaramilloy, marco.benalcazar}@epn.edu.ec

***Abstract*—In this paper, we propose the development of a model for real-time hand gesture recognition. We use surface electromyography (EMG) and Machine Learning techniques. The recognition of gestures using EMG is not a trivial task because there are several physiological processes in the skeletal muscles underlying their generation. In the scientific literature, there are several hand gesture recognition models, but they have limitations both in the number of gestures to be recognized (i.e., classes) and in the processing time. Therefore, the primary goal of this research is to obtain a real-time hand gesture recognition model for various applications in the field of medicine and engineering with a higher recognition accuracy than the real-time models proposed in the scientific literature and a higher number of gestures to recognize (i.e. in the order of the dozens). The proposed model has five stages: acquisition of the EMG signals, preprocessing (e.g., rectification and filtering), feature extraction (e.g., time, frequency and time-frequency), classification (e.g., parametric and nonparametric) and post-processing. Generally, the main difficulties of the hand gesture recognition models with EMG using Machine Learning are: the noisy behavior of EMG signal, and the small number of gestures per person relative to the number of generated data by each gesture (e.i., curse of dimensionality). Solving these two issues could also lead to solutions for other problems such as face recognition and audio recognition, for which these two issues are a major concern.**

***Index Terms*—Hand Gesture Recognition; EMG(Electromyography); Machine Learning; Real-Time**

I. Introduction

Every day, more than five hundred people lose a limb [1]. Nowadays, there are several solutions for these problems; a solution is to develop a hand gesture recognition model with Electromyography (EMG) to use for different applications, including the intelligent prosthesis. There are several types of research works about real-time hand gesture recognition models, but with two limitations. First, the real-time hand gesture recognition models recognize few gestures. For example, in [2] is proposed a real-time hand gesture recognition model with a recognition accuracy of 94%, but it recognizes only four types of gestures (i.e., classes). Second, the recognition accuracy is low when the processing time of hand gesture recognition model is low (i.e., real-time model). For example, in [3] is proposed a real-time hand gesture recognition model with a recognition accuracy of 89.38%, but it recognizes 16 types of gestures (i.e., classes). Therefore, it is necessary for several applications, including intelligent prostheses, the development of a hand gesture recognition model with a higher recognition accuracy than the real-time models proposed in the scientific literature and the number of gestures to recognize in the order of the dozens.

978-1-5386-3894-1/17/$31.00 ©2017 IEEE

There are several hand gesture recognition models that use different devices to data acquisition. Among the main types of sensors we have: gloves [4], vision sensors [5], inertial measurement units (IMUs) [6], EMGs sensors [2] and, the combination of these devices, including EMG and IMUs [7]. The data acquisition devices have the following main limitations: the gloves and vision sensors can not be used in various applications, including intelligent prostheses for amputees; the vision sensors have occlusion problems; the IMUs generate noisy data and the EMG too, but the EMG data carry the information of the hand movement. Therefore, we will use EMG for the development of a hand gesture recognition model.

An arm muscle of the human body is structured by skeletal muscle tissue. A skeletal muscle is a set of overlapping motor units, where each motor unit is a collection of several fibers (i.e., muscular cells) innervated by a single motor neuron. The neuromuscular junction is the connection of fibers with motor neurons, which in turn are connected to the spinal cord. The fibers have an electric potential difference of -80 mV between its extracellular and intracellular environments when a muscle is at rest. When a muscle is active, the motor neuron activates the neuromuscular junction, and then two intracellular action potentials (i.e., waves) propagate along each fiber to the tendons with constant speed and without attenuation. These waves result from the depolarization and re-polarization of the fibers [8]. The motor unit action potential (MUAP) is the sum of the intracellular action potentials from all the fibers of a motor unit.

EMG is a measure of the electrical activity produced by the muscles of the human body [8]–[12]. The EMG signal is a linear summation between several trains of MUAPs. The amplitude and frequency of the EMG signals are affected by on the muscular fatigue, the age of the person, neuromuscular diseases, and the temperature and the thickness of the skin. A mathematical model for the EMG is to consider it as the sum of two zero-mean Gaussian processes [13], [14], where the first process is produced by the muscle activity modulation $S(t,w) = S(0,\sigma_{signal(t)},w)$ and the second one is an independent additive noise $N(t,w) = N(0,\sigma_{noise},w)$ [10]. In [8], [10], [15]–[18] it is shown the EMG mathematical model approximation of an EMG signal. Even though we have mathematical models that describe the behaviour and nature of the EMG, these models have not allowed us to infer an exact solution for the problem of hand gesture recognition. For this reason, we propose to use Machine Learning algorithms to estimate the distribution underlying the generation of gestures of the hand. When the mathematical model of the problem is known, the solution is computed directly from the model. If the mathematical model of a problem is unknown, we can obtain data and find the solution using Machine Learning algorithms. Therefore, Machine Learning algorithms are viable tools to solve the hand gesture recognition with EMG [19].

Hand gesture recognition means to identify which gesture is performed by the hand of a given user at any time. The EMG signals have medical and engineering applications (i.e., hand gesture recognition). In the engineering field, the applications of hand gesture recognition with EMG are the development of prosthesis, rehabilitation devices, and human-machine interaction systems [2], [10], [16], [18], [20], [21]. Humans with amputated arms have limitations in daily activities; this problem can be solved by designing prosthesis with a hand gesture recognition model using EMG because these signals can be captured even though the hand does not exist anymore and these signals are used as input for the hand gesture recognition model [9], [22].

In the scientific literature, we can find several types of offline models, for example, models with accuracies of 90% using Backpropagation (BP) neural network algorithm [22], 98.3% in average using three parallel BP neural networks [23], and 88.2% using four decomposed multi-class support vector machines (SVM), four decomposed linear discriminant analyses (LDA) and a multi-class LDA [24]. However, there are only a few works that propose real-time models. For example, in [2] authors propose a real-time model that has a recognition accuracy of 94% with a k-NN and Bayes model, but recognizing four types of gestures (i.e., classes). Therefore, the problem of the real-time hand gesture recognition is still open for innovative approaches.

In engineering and medical applications, the number of gestures per person is small respect to the number of generated data by each gesture. For example, assuming that the duration of a gesture is equal to two seconds and the feature extraction phase has 8 EMG surface sensors with a sampling frequency of 200 Hz, the number of generated data is 3200 for each gesture. In order to avoid overfitting, the number of gestures per person to develop a hand gesture recognition model must be much greater than the number of generated data per gesture. If the number of gestures per person is ten times greater than the number of generated data per gesture of each person, the data collected by each person to train the model would have a duration of about 32000 seconds (i.e., approximately nine hours) without pauses. Therefore, this is complicated and non-functional for engineering and medical applications. In this paper will train a real-time hand gesture recognition model with the number of gestures per person in the order of units, avoiding overfitting (i.e., curse of dimensionality).

In this project, we will develop a real-time hand gesture recognition with EMG using machine learning, with the following characteristics:

- Recognition accuracy greater than the proposed models in the scientific literature.
- Real-time recognition. A gesture must be recognized in less than 300 ms so that the human can perceive the processing in real time [22].
- Number of gestures to recognize (i.e., classes) must be in the order of dozens.
- The number of gestures per person must be in the order of units (i.e., training data), avoiding overfitting.

II. Methodology

We will develop a hand gesture recognition model with EMG and Machine Learning that is composed of the five following stages Figure 1:

- Acquisition of the EMG signals.
- Preprocessing.
- Feature extraction.
- Classification.
- Post-processing.

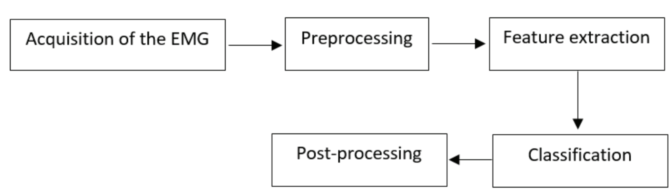

Fig. 1: Proposed Hand Gesture Recognition Model

A. Acquisition of the EMG signals

There are two types of EMGs: surface and intramuscular. In surface EMG, non-invasive surface sensors are placed on the skin to record the electrical activity of the muscles under it [8], [10].In intramuscular EMG, a needle is introduced in the muscle. In this project, we will use surface EMG. Sensors used to acquire the EMG can be homemade [20], [23]–[27]

and commercial, such as the Myo armband [21]. Additional some projects use EMG sensors with other types of sensors such as inertial magnetic units (IMUs) [2], [20].

In this project, we will use the Myo armband sensor Figure 2. We chose this sensor because of the following reasons: low cost, small size and weight, software development kit (SDK) and because the Myo is a small and open source sensor that is easy to wear. The Myo armband has eight EMG surface dry sensors, and an inertial measurement unit (IMU). The eight surface sensors measure 200 samples per second of the electrical activity of the muscles. The IMU has 9 degrees of freedom (accelerometer, gyroscope, and orientation in the X, Y, and Z-axes). The Myo armband uses Bluetooth technology for transmitting the data to the computer. Finally, the Myo armband has incorporated a proprietary system capable of recognizing five gestures of the hand: pinch, fist, open, wave in, and wave out.

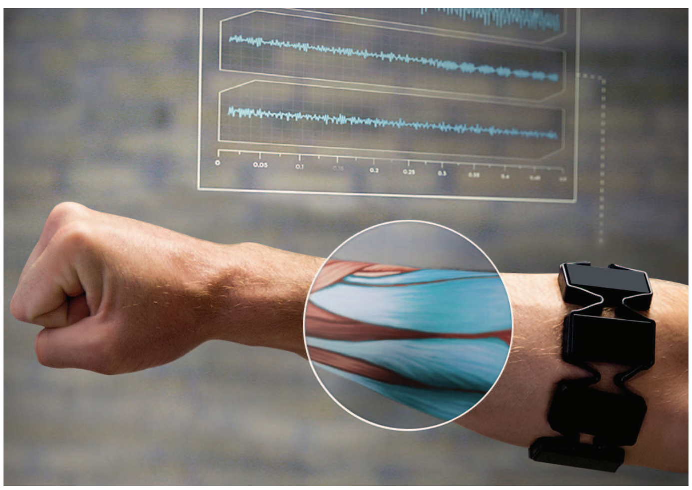

Fig. 2: Myo Armband

B. Preprocessing

The preprocessing stage is necessary to obtain only the information of EMG signals without noise. In Figure 3 EMG signals are shown without preprocessing. We will use two types of preprocessing:

- Rectification.
- Filtering

The rectification is used because the EMG signals have negative and positive values for the repolarization and depolarization of the fiber.

It is necessary to filter the EMG signals to extract the essential information (e.g., discarding noise). Prior to the filtering, we will make an exhaustive analysis of the frequency components of the EMG signal, in order not to lose valuable information in the filtering process. We will test the following type of filters: infinite impulse response and finite impulse

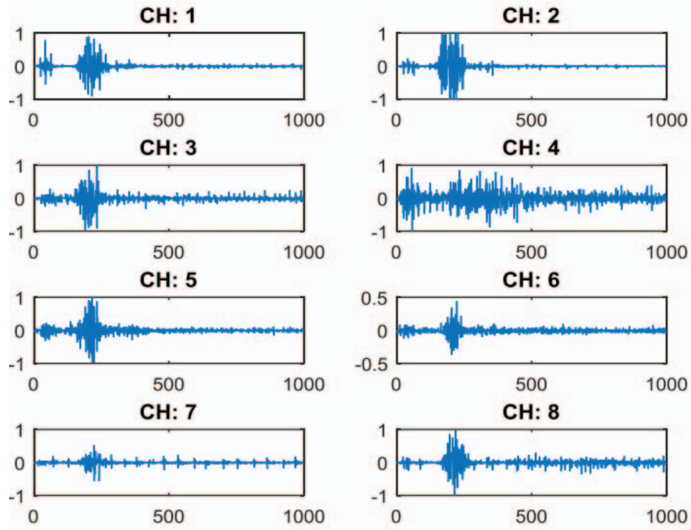

Fig. 3: EMG signals without preprocessing of Myo armband

response. In this project, we will use rectification and filtering of the EMG signals to determine the input data required by the classifiers. In Figure 4 we show EMG signals after being rectified and filtered.

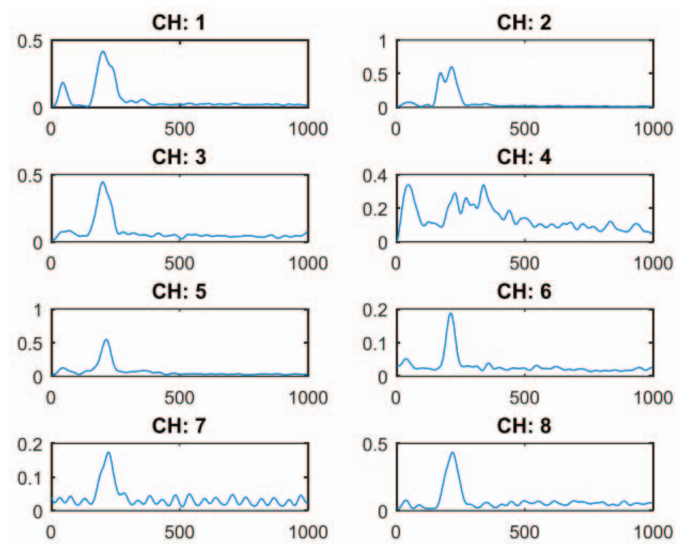

Fig. 4: Rectified and Filtered EMG signals of Myo armband

C. Feature Extraction

In this stage, we will apply different techniques in time, frequency, and time-frequency domains to obtain meaningful information for each class to be recognized. In the time domain, we will test features like the mean absolute value, nth-order autoregressive coefficients, zero crossing, length of the signal, sign of slope changes, modified mean absolute value, simple square integral, root-mean-square value, sample mean and variance, log detector, average amplitude change, maximum fractal length, EMG integral, Willison amplitude, histogram, cepstral coefficients, and sample entropy [2], [16], [18], [20], [21], [23]–[28]. In the frequency domain, we will test features like the power spectrum, mean and median frequencies, frequency histogram, mean power, and spectral moments [16], [18], [24], [25], [28]. In the time-frequency domain, we will test features like the wavelet transform [16], [18]. We will analyze the classifiers to develop a classification model.

D. Classification

The classification stage determines to which class (gesture) a feature vector extracted from the EMG signals belongs to. We will use two types of classifiers: parametric and nonparametric. The complexity of parametric classifiers is constant with the change in the number of training examples. We will test the parametric classifiers, including the logistic regression, linear discriminant analysis, naive Bayes, perceptron, artificial neural networks, and support vector machine. The characteristics of the parametric classifiers are simple to understand, fast to learn from data and can work well even if the fit to the data is not perfect.

The nonparametric classifiers have a potentially infinite number of parameters. We will test the nonparametric classifiers, including k-nearest neighbors, and decision trees. The nonparametric classifiers can fit several functional forms and not assume the underlying function.

The most common classifiers used in the hand gesture recognition with EMG are support vector machines [2], [25], [26], and neural networks [23], [27], [28]. The combination of classifiers are used in several researches, in [20] authors used a combination of decision trees, k-means clustering, and hidden Markov, and in [27] authors used a combination of support vector ma-chines and hidden Markov models.

E. Post-processing

In the post-processing stage, we will adapt the result of the classification stage for different applications of the proposed model. Therefore, in this stage, we will refine the output of the classifiers to obtain high recognition accuracy. For example, in Figure 5 a person makes a gesture in a time interval and a classifier performs four classifications during the time interval. The hand gesture recognition model must deliver a single result. Therefore, the model executes a post-processing technique (e.g., mode) to obtain a single result.

III. Stage of the Research

We developed a first model of hand gesture recognition, in this work, we proposed a model for real-time hand gesture recognition based on the EMG. For the classification of five classes of gesture, we used the k-nearest neighbor rule together with the dynamic time warping algorithm. The Myo

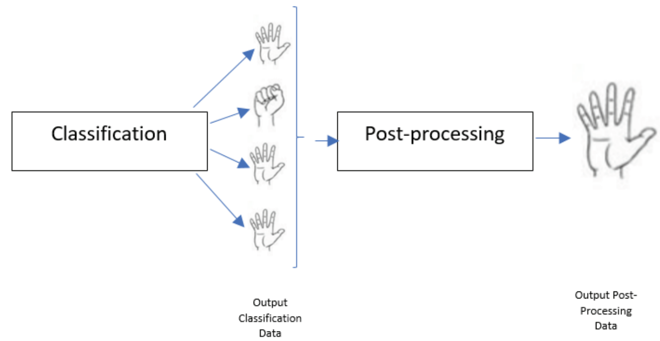

Fig. 5: Post-processing stage

armband recognition system has a recognition accuracy of 83%, and our model has 86%, This analysis was with five classes of gesture: pinch, fist, open, wave in and wave out [29].

IV. Conclusions

In this paper, we presented a doctoral proposal for developing a real-time hand gesture recognition model using EMG and Machine Learning.

In this project, we will develop a hand gesture recognition model able to recognize dozens of gestures of the hand, with a recognition accuracy greater than the real-time models proposed in the scientific literature and the number of gestures per person (i.e., training data) must be in the order of units, avoiding overfitting. In order to achieve these goals, we will use Machine Learning algorithms for the mathematical model of the EMG signal is unknown. In the proposed hand gesture recognition model, we will analyze: preprocessing techniques(e.g., rectification and filtering), feature extraction techniques (e.g., time, frequency and time-frequency), classifiers (e.g., parametric and nonparametric), and post-processing techniques.

References

[1] L. L. T. Force and A. Coalition, “Roadmap for preventing limb loss in america: Recommendations from the 2012 limb loss task force,” *Knoxville, Tennessee*, 2012.

[2] J. Kim, S. Mastnik, and E. André, “Emg-based hand gesture recognition for realtime biosignal interfacing,” in *Proceedings of the 13th international conference on Intelligent user interfaces*. ACM, 2008, pp. 30–39.

[3] G.-C. Luh, Y.-H. Ma, C.-J. Yen, and H.-A. Lin, “Muscle-gesture robot hand control based on semg signals with wavelet transform features and neural network classifier,” in *Machine Learning and Cybernetics (ICMLC), 2016 International Conference on*, vol. 2. IEEE, 2016, pp. 627–632.

[4] L. A. E. Jiménez, M. E. Benalcázar, and N. Sotomayor, “Gesture recognition and machine learning applied to sign language translation,” in *VII Latin American Congress on Biomedical Engineering CLAIB 2016, Bucaramanga, Santander, Colombia, October 26th-28th, 2016*. Springer, 2017, pp. 233–236.

[5] P. K. Pisharady and M. Saerbeck, “Recent methods and databases in vision-based hand gesture recognition: A review,” *Computer Vision and Image Understanding*, vol. 141, pp. 152–165, 2015.

[6] A. Moschetti, L. Fiorini, D. Esposito, P. Dario, and F. Cavallo, "Recognition of daily gestures with wearable inertial rings and bracelets," *Sensors*, vol. 16, no. 8, p. 1341, 2016.

[7] X. Zhang, X. Chen, W.-h. Wang, J.-h. Yang, V. Lantz, and K.-q. Wang, "Hand gesture recognition and virtual game control based on 3d accelerometer and emg sensors," in *Proceedings of the 14th international conference on Intelligent user interfaces*. ACM, 2009, pp. 401–406.

[8] J. M. Weiss, L. D. Weiss, and J. K. Silver, *Easy EMG: a guide to performing nerve conduction studies and electromyography*. Elsevier Health Sciences, 2015.

[9] M. Haris, P. Chakraborty, and B. V. Rao, "Emg signal based finger movement recognition for prosthetic hand control," in *Communication, Control and Intelligent Systems (CCIS), 2015*. IEEE, 2015, pp. 194–198.

[10] J. Rodriguez-Falces, J. Navallas, and A. Malanda, "Emg modeling," in *Computational Intelligence in Electromyography Analysis-A Perspective on Current Applications and Future Challenges*. InTech, 2012.

[11] L. Xu and A. Adler, "An improved method for muscle activation detection during gait," in *Electrical and Computer Engineering, 2004. Canadian Conference on*, vol. 1. IEEE, 2004, pp. 357–360.

[12] J. Singh, "Emg: Hand gesture recognition," Ph.D. dissertation, Indian Institute of Technology, Kanpur.

[13] H. Mizuno, N. Tsujiuchi, and T. Koizumi, "Forearm motion discrimination technique using real-time emg signals," in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*. IEEE, 2011, pp. 4435–4438.

[14] P. Bonato, T. D'Alessio, and M. Knaflitz, "A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait," *IEEE Transactions on biomedical engineering*, vol. 45, no. 3, pp. 287–299, 1998.

[15] E. Petersen, "A mathematical model of surface electromyographic measurements," in *Proceedings of the workshop Biosignal Processing*, 2016.

[16] D. F. Stegeman, J. H. Blok, H. J. Hermens, and K. Roeleveld, "Surface emg models: properties and applications," *Journal of Electromyography and Kinesiology*, vol. 10, no. 5, pp. 313–326, 2000.

[17] M. Mordhorst, T. Heidlauf, and O. Röhrle, "Mathematically modelling surface emg signals," *PAMM*, vol. 14, no. 1, pp. 123–124, 2014.

[18] M. B. Reaz, M. Hussain, and F. Mohd-Yasin, "Techniques of emg signal analysis: detection, processing, classification and applications," *Biological procedures online*, vol. 8, no. 1, pp. 11–35, 2006.

[19] C. E. Rasmussen and C. K. Williams, *Gaussian processes for machine learning*. MIT press Cambridge, 2006, vol. 1.

[20] N. Stifani, "Motor neurons and the generation of spinal motor neuron diversity," *Frontiers in cellular neuroscience*, vol. 8, 2014.

[21] X. Zhang, X. Chen, Y. Li, V. Lantz, K. Wang, and J. Yang, "A framework for hand gesture recognition based on accelerometer and emg sensors," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 41, no. 6, pp. 1064–1076, 2011.

[22] Y. Li, Y. Tian, and W. Chen, "Multi-pattern recognition of semg based on improved bp neural network algorithm," in *Control Conference (CCC), 2010 29th Chinese*. IEEE, 2010, pp. 2867–2872.

[23] H. Ling, Y. Bo, and Z. Lina, "Clustering analysis and recognition of the emgs," in *Intelligent Control and Information Processing (ICICIP), 2011 2nd International Conference on*, vol. 1. IEEE, 2011, pp. 243–246.

[24] H. Huang, T. Li, C. Bruschini, C. Enz, V. M. Koch, J. Justiz, and C. Antfolk, "Emg pattern recognition using decomposition techniques for constructing multiclass classifiers," in *Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on*. Ieee, 2016, pp. 1296–1301.

[25] C. Savur and F. Sahin, "Real-time american sign language recognition system using surface emg signal," in *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on*. IEEE, 2015, pp. 497–502.

[26] I. Mesa, A. Rubio, J. Diaz, J. Legarda, and B. Sedano, "Reducing the number of channels and signal-features for an accurate classification in an emg pattern recognition task." in *BIOSIGNALS*, 2012, pp. 38–48.

[27] R. J. Oweis, R. Rihani, and A. Alkhawaja, "Ann-based emg classification for myoelectric control," *International Journal of Medical Engineering and Informatics*, vol. 6, no. 4, pp. 365–380, 2014.

[28] M. Rossi, S. Benatti, E. Farella, and L. Benini, "Hybrid emg classifier based on hmm and svm for hand gesture recognition in prosthetics," in *Industrial Technology (ICIT), 2015 IEEE International Conference on*. IEEE, 2015, pp. 1700–1705.

[29] M. E. Benalcázar, A. G. Jaramillo, J. A. Zea, A. Páez, and V. H. Andaluz, "Hand gesture recognition using machine learning and the myo armband."