FEATURE SELECTION USING LEM ALGORITHM FOR THE CLASSIFICATION OF EMG SIGNALS

SELEÇÃO DE RECURSOS USANDO ALGORITMO LEM PARA A CLASSIFICAÇÃO DE SINAIS EMG

SELECCIÓN DE CARACTERÍSTICAS USANDO EL ALGORITMO LEM PARA LA CLASIFICACIÓN DE SEÑALES EMG

Juan Camilo Londoño Lopera
Juan Pablo González Alzate
Esteban Camilo Lage Cano
Mónica Ayde Vallejo Velasquez
Juan Fernando Ramírez Patiño

Facultad de Minas
Universidad Nacional de Colombia
Medellín, Colombia
jclondonol@unal.edu.co
jpgonzaleza@unal.edu.co
eclagec@unal.edu.co
mavallejov@unal.edu.co
jframirp@unal.edu.co

Fecha de Recepción: *16 de septiembre de 2019*
Fecha aprobación: *05 de marzo de 2020*

Abstract

In medical applications, the amputation of an arm or the lack of a limb of the body inspires the technological advances in the area of robotics for the creation of intelligent prosthesis replaces and recovers a percentage of the functionality of the absent limb of a person. One of the most important bases for the development of robotic limbs is the analysis and study of EMG signals (surface electromyographic signals). EMG signals provide information on the dynamics of a muscle in its different states and provide amplitude and frequency values that describes the movement, contraction and rest of a muscle. For an EMG signal, there are representative characteristics like the RMS value, Histogram, standard deviation, among other functions that allow characterizing a given signal in the time domain and frequency. The objective is to compare the most commonly used approaches and characteristics of EMG signals to differentiate between different signals that represent gestures or movements of the hand.

Keywords. Electromyography, classifier, gesture recognition, evolutionary algorithm, prosthesis, robotic hand.

Resumo

Nas aplicações médicas, a amputação de um braço ou a falta de um membro do corpo inspira os avanços tecnológicos na área da robótica para a criação de próteses inteligentes substitui e recupera uma porcentagem da funcionalidade do membro ausente de uma pessoa. Uma das bases mais importantes para o desenvolvimento de membros robóticos é a análise e estudo de sinais EMG (sinais eletromiográficos de superfície). Os sinais EMG fornecem informações sobre a dinâmica de um músculo em seus diferentes estados e fornecem valores de amplitude e frequência que descrevem o movimento, contração e descanso de um músculo. Para um sinal EMG, existem características representativas como o valor RMS, Histograma, desvio padrão, entre outras funções que permitem caracterizar um determinado sinal no domínio de tempo e frequência. O objetivo é comparar as abordagens e características mais utilizadas dos sinais EMG para diferenciar entre diferentes sinais que representam gestos ou movimentos da mão.

Palavras chaves: Eletromiografia, classificador, reconhecimento de gestos, algoritmo evolutivo, prótese, mão robótica.

Resumen

En las aplicaciones médicas, la amputación de un brazo o la ausencia de un miembro del cuerpo inspira los avances tecnológicos en el área de la robótica para la creación de prótesis inteligentes que sustituyen y recuperan un porcentaje de la funcionalidad del miembro ausente de una persona. Una de las bases más importantes para el desarrollo de las extremidades robóticas es el análisis y estudio de las señales EMG (señales electromiográficas de superficie). Las señales

EMG proporcionan información sobre la dinámica de un músculo en sus diferentes estados y proporcionan valores de amplitud y frecuencia que describen el movimiento, la contracción y el descanso de un músculo. Para una señal EMG, existen características representativas como el valor RMS, el Histograma, la desviación estándar, entre otras funciones que permiten caracterizar una señal dada en el dominio del tiempo y la frecuencia. El objetivo es comparar los enfoques y características más utilizados de las señales EMG para diferenciar entre las diferentes señales que representan gestos o movimientos de la mano.

Palavras chaves: Electromiografía, clasificador, reconocimiento de gestos, algoritmo evolutivo, prótesis, mano robótica.

Introducción

Currently, the robotic arms are used to facilitate and optimize some risk activities for the human being. A robotic arm is considered as a programmable mechanical arm able to approximate and simulate the movements of a human arm. These movements are interconnected through articulations (degrees of freedom), allowing rotational, transnational movements and linear displacements. Many of the applications of robotic arms are developed for the construction of prostheses as presented in [1] where they develop a system for predicting arm angles for the control of robotic prostheses. Also, in [2] they perform the control of a finger prosthesis. These works are focused on people with missing limbs. Typically, in this class of applications, it is necessary to acquire electromyographic signals as in [3], [4] and [5], here they use this type of signals for the recognition of gestures and control of robotic arms. This case focuses on the acquisition and processing of electromyographic signals (EMG). For this, it is necessary to locate different sensors around the arm measuring the neuromuscular functions.

Some applications were to relate EMG signals are for example the one shown in [6]. They focus on the discrimination between normal EMG (NOR), myopathy (MYO) and neuropathic (NEURO) signals, where they apply the support vector machine (SVM) and the probabilistic neural network (PNN) as feature classification methods. A similar development takes place in [7] where SVM, LDA and KNN methods are applied for the classification of 7 gestures to control a robotic army telemetry. In [8] they perform statistical analysis for the classification of EMS, finding the best and shortest features vector that describes the gesture. In [9] perform Hand Gesture Recognition Optimization based on EMG using preprocessing of supervised and unsupervised data in healthy subjects with transradial amputation. Nowadays, many works are carried out for the recognition of patterns in EMG signals using Deep Learning as those presented in [10] where through a method called Transfer Learning, they perform the classification offhand gestures. In [11] they use EMG signals in the time-frequency domain to identify normal and aggressive actions through convolutional neural networks (CNN).

In some cases, a combination of EMG signals and visual characteristics has been used as in [12], [13] and [14] who perform image acquisition using a camera to identify hand movements. In [15] they create a database for the analysis of individuals during learning injuries of other languages. Also, MG signals have been used for different tasks as in [16] they propose that they can serve as a biometric characteristic for the identification of people or diagnosis of diseases.

One of the main drawbacks of the work done with EMG signals [17] A large amount of data is required to correctly label and perform a good classification stage. For this reason, much work has been done to contribute to the scientific community of the data set related to EMG signals of arm movements and gestures, as mentioned in [18]. They describe in detail the main and largest Dataset publicly available to develop this type of application. The most used Dataset is presented in [19] so it is taken as a reference for this work.

In most of these works, it is observed that it is not easy to determine the characteristics that manage to clearly differentiate between EMG signals corresponding to different gestures. In this work the performance of the classifiers has not been improved, this to implement an evolutionary algorithm that improves performance, selecting the vector of features that best classify gestures. This document is organized as follows: In section II, the approach of the materials and the methods used for the acquisition, extraction, and selection of characteristics of the EMGs signals is described. Section III describes the analysis of the EMGs signals and the method of evaluation and selection of characteristics through a learning evolution model (LEM). Section IV shows the experiments and results. Finally, section V provides some comments and future projections of this work.

Materials and methods

Before implementing the feature selection system for the classification of gestures, it is necessary to define a series of methods necessary to carry out this process. This section describes the used Dataset, the characteristics extraction stages, some classification methods, and the evolutionary algorithm.

A. Dataset

The selection of the Dataset is one of the most important aspects when starting a pattern recognition work as mentioned in [20]. It is necessary to have a large amount of data with subjects of different ages and gender to achieve greater robustness in the classifiers. In [18] present a detailed description of the most used Dataset of EMGs signals. Based on this, it is decided to select the NinaPro Benchmark Dataset. NinaPro is for public use and was developed for non-invasive prostheses. It is currently the largest and most used publicly available.

NinaPro describes the distribution and acquisition protocols of EMG signals that include data from 78 people, where 11 people have amputation in the radial area of the arm. The 78 people were instructed to perform 4 sets of exercises while carrying out the EMG signals acquisition protocol. The first exercise contains 12 basic movements of the fingers, the second exercise contains 8 isometric and isotonic hand configurations and 9 basic movements of the wrist, the third exercise contains 23 grip movements and the last exercise 9 strength patterns and a position of rest. These exercises were carried out in a process with 3 seconds rest between exercises, and with a duration of 5 seconds per exercise. The data described above form a set of three different Dataset. During the development of this work, DB2 will be the main reference in the advance of the acquisition, extraction, and classification of the characteristics of a signal EMGs. It is composed as shown in Table 1.

Table 1. Dataset 2

Subjec ts	Movemen ts	Repetitio ns	Exercise 2	Senso rs
40	50	6	17 movemen ts	12

Table generated by the Authors.

In DB2, 12 sensors are used distributed along the arm in the following way, 8 sensors equally spaced in the forearm, 2 sensors located in the flexor digitorum superficialis muscle and the extensor digitorum superficialis muscle and finally, 2 sensors located in the muscles biceps and triceps brachii muscles. For this work, the analysis of the EMG signals obtained from the first 10 sensors, the 2 sensors located in the muscles biceps and triceps are not considered, as shown in Figure 1.

Fig. 1. Position of sensors used.

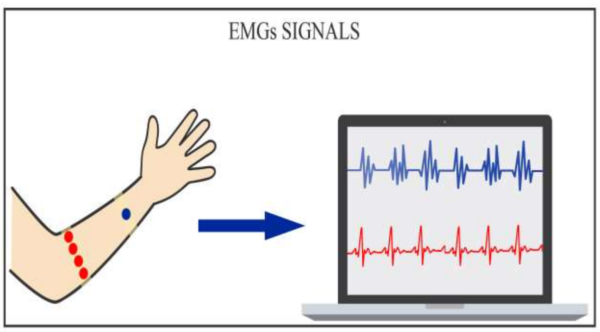

Figure generated by the Authors.

B. Feature extraction

The process of extraction of characteristics is carried out by separating the signals in 200ms windows. NinaPro was acquired with a sampling frequency of 2KHz, so the resulting window contains 400 data. For this work, the quantity of characteristics to extract is a key aspect. It is intended that the evolutionary algorithm define the best set of characteristics in such a way that a better performance is obtained. Feature extraction is performed in the time domain and in the frequency domain according to Table 2 and the Wavelet transforms with 7 levels db45.

With this, we obtain a set of 55 characteristics to be evaluated by the evolutionary algorithm.

Table 2. Features

Time domain	Frequency domain
Root mean squared value	Mean
Mean absolute deviation	Average
Mean absolute value	Median.
Interquartile range	Flnsmk2
Integrated Absolute Value	Flnsmk3
Slope sign change	Flnsmk4
Standard deviation	Flnsmk5
Variance	Total power
Zero crossing	Median power
Waveform length	Energy cd1 wavelet
Mean squared error	Energy cd2 wavelet
Autoregressive 5 coef	Energy cd3 wavelet
Maximum value	Energy cd4 wavelet
Permutation entropy	Energy cd5 wavelet
Multiscale Permutation Entropy	Energy cd6 wavelet
Histogram 20 bins	Energy cd7 wavelet

Table generated by the Authors.

C. Feature selection

There are several methods of feature selection that can be structured mainly in 2 groups:

1) Deterministic methods

- Karhunen Loeve expansion
- Fisher Linear Discriminants
- Principal component analysis (PCA)

2) Probabilistic methods

- Divergence method
- Bhattacharyya distance
- Mahalanobis distance

These mentioned methods are just some of those that have been developed to fulfill the task of selecting the best set of characteristics. Despite this, in some cases, these methods are not enough. Some researchers resort to the exhaustive search process. Therefore, the implementation of an evolutionary algorithm that takes care of this task is considered. Different sets of characteristics are taken as a population of evolution until reaching a result that generates greater performance. The LEM (Learnable Evolution Model) algorithm is established as an evolution method [21]. It presents a hybrid approach and has been highly generalized for optimization tasks. The general idea of LEM is to execute repeated stretches of evolution and serial learning. Each stage of evolution is based on prior learning, that is, information acquired from previous generations. This information is used to generate new evolved individuals to make up the new population. So that in each generation, a more appropriate set of characteristics is obtained for the classification stage.

D. Classifiers

Several tests are performed using characteristics like those selected in [19] to select the classifiers that show better behavior. The following classifiers are established.

- Classification ensemble model
- Classification decision tree
- KNN classification model
- Neural Network using a Generalized Linear Model

Methodology

The EMGs signals from DB2 are read and the windows are separated in each repetition of the gestures that will be classified. An analysis of the signals is presented to verify their dynamics and extract the windows that contain the most representative information. Subsequently, the extraction procedure of the characteristics mentioned in section II-B for the whole set of EMG signals is presented. The selection of the best set of characteristics is made through the LEM algorithm. Finally, the classification method is implemented.

A. EMGs signals

Figure 2 presents an EMGs signal extracted from the DB2 presented in the section ref dataset. The EMG signal represents the dynamics of one of the windows and one of the 8 isometric movements (gestures) of the hand. Each gesture is repeated 6 times by the subject, this signal is acquired from the sensor 10 located in the area of the extensor Digitorum Superficialis muscle of the arm.

The red signal represents the time where the repetition of each gesture is executed (constant signal different from zero) and the time where there are breaks (signal equal to zero) between repetitions of the movement. This Figure contains 6 repetitions of the signal EMGs representing the first gesture, for each of the EMGs signals, the repetitions 1, 3, 4 and 5 were used to train the classifiers and the repetitions 2, 5 were used for the evaluation of the classifiers.

Fig. 2. Signal EMG for the first gesture.

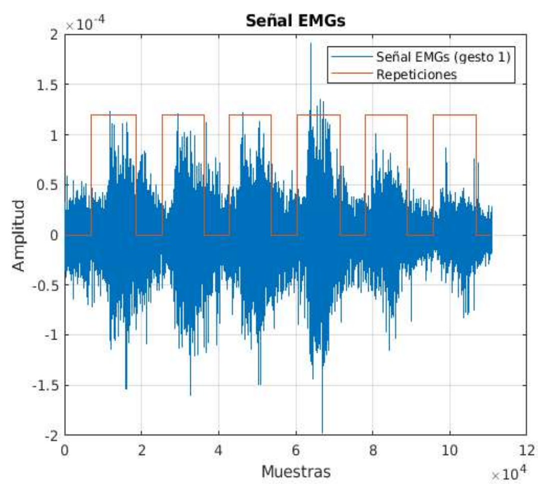

Figure generated by the Authors.

In general, most signals contained in DB2 have a similar dynamic to the EMGs signal presented in Figure 2. For the analysis of the EMG signals, the signals representing gestures 1, 2, 8, 9, 10, 12, 13 and 14 are taken into account, as shown in Figure 3. The resting times are not taken into account to perform the analysis of the samples where the signal represents each gesture.

Taking into account that the resulting windows are 400 data in each repetition of each signal EMGs. Each repetition is divided into 6 equal partitions, to analyze the 4 internal partitions where the most representative information of the treated gesture is found and thus carry out the process of extracting characteristics.

B. Classification

In this stage, the implementation of some classifiers that show good behavior in the distinction of several classes is carried out.

- Neural Network using a Generalized Linear Model
- Classification decision tree
- Ensemble of classification learners
- KNN classification model

During the tests, the classifier that presents the best results was the Neural Network using a Generalized Linear Model. For this reason, it was decided to select this as an evaluation function for individuals for the evolutionary algorithm.

Fig. 3. Gestures.

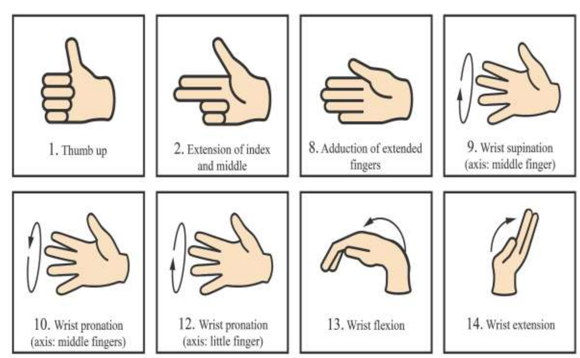

Figure generated by the Authors.

C. Feature selection with LEM

Although there are 55 characteristics for the classification of gestures, not all characteristics are useful for classifying some gestures. Taking them into account can result in at least a higher computational effort. In the worst case, the performance of the classifier worsens. To solve this problem, a model of evolution by LEM learning was used. In [22] this method has been generalized for optimization, the general idea is to execute repeated stretches of evolution and serial learning, where the new evolution is based on previous learning, that is, information acquired from previous populations. The algorithm uses KNN learning method in conjunction with LEM. An XOR is used as a crossing operator and no mutation operator, KNN is applied as a particular form of survival selection operator that judges an individual according to the neighbors' fitness values, in Figure 4 presents the pseudocode of the LEM algorithm.

The algorithm is encoded in binary form and starts generating a random population of 200 individuals that are constituted by 55 bits, where each bit is related to the use or omission of one of the features mentioned in the section II-B. This population is evaluated by a fitness function and is separated into 3 groups, one in which the best fitness values are contained (Group H), another in which is the worst (Group L), and another to replace children and new individuals.

The fitness function is a comparison between the gesture you want to make and the gesture that is predicted. This is done through a Dataset designed to test the performance of the algorithm, the number of correctly predicted gestures over the totals will be the fitness value for the individual. From the group of good individuals, the algorithm crosses two individuals from group H to generate a child.

The son is only part of the next generation if he fulfills that his closest neighbors belong to Group H. LEM is executed according to the learning gap, which corresponds to the number of generations that must pass to update group H. The algorithm performs this process of evolution for 5 generations.

Fig. 4. Pseudocode

Algorithm 1 pseudo-code for KNNGA

```
1: population size= 200; i=0 .
2: max generation number= 10 .
3: k=4, learning gap=1, threshold=0.4 .
4: generation number = 0 .
5: Initialize a new population with population size.
6: Evaluate current population .
7: repeat
8:    reproduce current population .
9:    if(generation number % learning gap== 0) then
10:   copy current population into learning population .
11:   calculate the H-group and L -group according to threshold .
12:   end if
13:   while(i < population size) do
14:       mutate a parent individual to generate a new child.
15:       calculate the k nearest neighbours for this child.
16:       if(the majority of this child's k neighbours are nearer to H-Group) then
17:          evaluate and place it into the next generation.
18:          j ++.
19:       else
20:          child is aborted.
21:       end if
22:       apply crossover on two parent individuals in the current population to generate two new children.
23:       for each of these two children, repeat steps 15-21.
24:   end while
25:   generationnumber ++.
26: until(generation number == max generation number)
```

Figure generated by the Authors.

Experiments and results

Different trials were carried out to test the extraction methods, classification and evolution of the features for each EMG signal. Considering that each sub-dataset of the signal contains 6 repetitions per gesture, 66% of the repetitions of each of the EMG signals contained in DB2 will be implemented for the training 34% of the repetitions of each of the signals for the evaluation.

First, a total of 14 random subjects are considered, where 2 gestures (gestures 2 and 10) made by each subject are evaluated. Subsequently, the variances in the performance and evolution of the classifiers mentioned in the section of characteristics corresponding to each EMG signal are analyzed for the first 10 sensors located along the arm, observing similar results to those presented in [15].

Table 3 shows the results of the first test of the performance calculations and the evolution of the selected characteristics for each signal, considering each sensor located along the arm. The total of characteristics selected by the LEM evolutionary algorithm is also presented. It is observed that the evolutionary algorithm manages to improve performance by approximately 15 %.

Table 3. First Test for 14 Subjects and 2 Gestures

Sensors	Performance %	Evolution %	Selected Features
1	53.13	70.78	29
2	57.13	68.96	27
3	68.61	74.68	23
4	55.56	69.30	29
5	62.66	71.59	26
6	64.03	75.72	27
7	50.40	67.12	27
8	51.32	70.10	22
9	50.63	77.32	25
10	52.12	67.12	24

Table generated by the Authors.

After performing the tests for each sensor and taking into account the 14 subjects and the 2 gestures treated (2 and 10), it was found that the performance of all the characteristics extracted from the EMGs signals captured by the sensor 9 is 50.63 %, this indicates that the sensor located in the Flexor Digitorum Superficialis muscle of the arm, has an acceptable response in which some characteristics mentioned in the section II-B are distinguished for the 2 gestures treated. When submitting this result to the LEM evolutionary algorithm, it is found that performance evolved by finding the 25 most representative characteristics of gestures 2 and 10 of the EMG signals captured by the sensor 9.

On the other hand, there is an increase in performance of 26.69 % on the part of the LEM algorithm, which results in a new evolution performance of 77.32 %. These results reveal the accuracy and rigor of the LEM algorithm by increasing performance by selecting the most representative characteristics for gestures.

Table 4 shows the results of the second test of performance calculations and the evolution of the selected characteristics for each signal, considering a total of 14 subjects and 4 different gestures made by each subject are evaluated.

Table 4. Second Test for 14 Subjects Variation of 4 Gestures

Sensors	Performance %	Evolution %	Selected Features
9	43.05	52.36	28
9	43.32	53.11	21
9	43.18	55.91	28
3	40.77	54.89	28

Table generated by the Authors.

For the second test, the same number of subjects are considered, but changes are made in 4 different gestures and a change in the indicator of the sensor to be analyzed. Initially, the performance of the sensor 9 is analyzed, in the first result obtained in Table IV the gestures 14, 12, 13 and 1 are taken into account when acquiring all the characteristics for each gesture made by the different 14 subjects, an initial performance of 43.05% is obtained. This result is submitted to the LEM algorithm, which results in an evolution performance of 52.36% for an amount of 28 selected characteristics, which indicates an increase of approximately 9.31% of the performance.

A change in the analysis of the gestures is made taking gestures 2, 8, 13 and 1 as a reference, so the second result obtained in Table IV shows that the performance for all the characteristics is 43.32 %. This result is submitted to the LEM algorithm, which results in an evolution performance of 53.11 % for an amount of 21 selected characteristics, which indicates an increase of approximately 9.8 % of the performance.

The third result obtained in Table IV is obtained by reference gestures 2, 9, 13 and 1, unlike the previous result a gesture 8 is changed by gesture 9. In this case, a performance of 43.18 % is obtained. This result is submitted to the LEM algorithm, which results in an evolution performance of 55.91 % for an amount of 28 selected characteristics, which indicates an increase of approximately 12.73 % of the performance.

Finally, the last result reflects the analysis of the sensor 3 in which the same number of subjects and the same gestures of the previous result were implemented. A performance of 40.77 % was obtained (lower than that of the previous results). However, when this result is processed by the LEM algorithm, an evolution performance of 54.89 % is obtained for an amount of 28 selected characteristics, which indicates an increase of 14.12 % (higher than that of the previous results).

Conclusions

The LEM algorithm proved to be an effective tool for identifying the most appropriate set of characteristics to define each gesture. Optimizing in all cases the performance of the classifier by 10 % in the worst case and the best case up to 26.69 %.

As future work, we want to improve the performance of the classifiers before making use of the LEM algorithm, performing a processing to the previous EMGs signals, in this way to achieve the best possible performance to implement and develop a robotic prosthesis, that makes successful form the movements desired by the subject and natural dynamics of an arm.

References

[1]. Antfolk, C. Cipriani, M. Controzzi, M. C. Carrozza, G. Lundborg, B. Rosen, and F. Sebelius, "Using EMG for real-time prediction of joint ´ angles to control a prosthetic hand equipped with a sensory feedback system," Journal of Medical and Biological Engineering, vol. 30, no. 6, pp. 399–406, 2010.

[2]. R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals," Expert Systems with Applications, vol. 39, no. 12, pp. 10 731–10 738, 2012.

[3]. A. Dellacasa Bellingegni, E. Gruppioni, G. Colazzo, A. Davalli, R. Sacchetti, E. Guglielmelli, and L. Zollo, "NLR, MLP, SVM, and LDA: A comparative analysis on EMG data from people with trans-radial amputation," Journal of NeuroEngineering and Rehabilitation, vol. 14, no. 1, pp. 1–16, 2017.

[4]. Y. Du, W. Jin, W. Wei, Y. Hu, and W. Geng, "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation," Sensors (Switzerland), vol. 17, no. 3, pp. 6–9, 2017.

[5]. V. K, P. LS, N. SN, and P. S, "Development of Surface-EMG Based Single Finger Movement Identification and Control for a Bionic Arm," Journal of Bioengineering & Biomedical Science, vol. 08, no. 01, pp. 1–5, 2018.

[6]. V. Kehri, R. Ingle, R. Awale, and S. Oimbe, "Techniques of EMG signal analysis and classification of neuromuscular diseases," vol. 137, pp. 485– 491, 2017.

[7]. H. F. Hassan, S. J. Abou-Loukh, and I. K. Ibraheem, "Teleoperated robotic arm movement using electromyography signal with wearable Myo armband," Journal of King Saud University - Engineering Sciences, no. xxxx, 2019. [Online]. Available: https://doi.org/10.1016/j.jksues.2019.05.001

[8]. A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," Expert Systems with Applications, vol. 39, no. 8, pp. 7420–7431, 6 2012.

[9]. F. Riillo, L. R. Quitadamo, F. Cavrini, E. Gruppioni, C. A. Pinto, N. C. Pasto, L. Sbernini, L. Albero, and G. Saggio, "Optimization ` of EMG-based hand gesture recognition: Supervised vs. unsupervised data preprocessing on healthy subjects and transradial amputees," Biomedical Signal Processing and Control, vol. 14, no. 1, pp. 117–125, 2014. [Online]. Available: http://dx.doi.org/10.1016/j.bspc.2014.07.007

[10]. U. Cotˆ e-Allard, C. L. Fall, A. Drouin, A. Campeau-Lecours, C. Gos- ´ selin, K. Glette, F. Laviolette, and B. Gosselin, "Deep Learning for Electromyographic Hand Gesture Signal Classification Using Transfer Learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 760–771, 2019.

[11]. P. Sattam and B. Abdulaziz, "Deep Learning of EMG Time – Frequency Representations for Identifying Normal and Aggressive Actions," vol. 18, no. 12, pp. 16–25, 2018.

[12]. F. Gomez-Donoso, S. Orts-Escolano, and M. Cazorla, "Largescale multiview 3D hand pose dataset," Image and Vision Computing, vol. 81, pp. 25–33, 2019. [Online]. Available: https://doi.org/10.1016/j.imavis.2018.12.001

[13]. R. Li, Z. Liu, and J. Tan, "A survey on 3D hand pose estimation: Cameras, methods, and datasets," Pattern Recognition, vol. 93, pp. 251– 272, 2019.

[14]. A. Carf`ı, F. Foglino, B. Bruno, and F. Mastrogiovanni, "A multi-sensor dataset of human-human handover," Data in Brief, vol. 22, pp. 109–117, 2019. [Online]. Available: https://doi.org/10.1016/j.dib.2018.11.110

[15]. S. Pizzolato, L. Tagliapietra, M. Cognolato, M. Reggiani, H. Muller, and ¨ M. Atzori, "Comparison of six electromyography acquisition setups on hand movement classification tasks," PLoS ONE, vol. 12, no. 10, pp. 1–17, 2017.

[16]. J. S. Kim and S. B. Pan, "A Study on EMG-based Biometrics," Journal of Internet Services and Information Security, vol. 2, no. May, pp. 19–31, 2017.
[17]. J. F.-s. L. B, A.-a. Samadani, and D. Kuli, "Segmentation by Data Point Classification Applied to Forearm Surface EMG," vol. 166, pp. 153–165, 2016. [Online]. Available: http://link.springer.com/10.1007/978-3-319- 33681-7
[18]. A. Phinyomark and E. Scheme, "EMG Pattern Recognition in the Era of Big Data and Deep Learning," Big Data and Cognitive Computing, vol. 2, no. 3, p. 21, 2018.
[19]. M. Atzori, A. Gijsberts, C. Castellini, B. Caputo, A. G. M. Hager, S. Elsig, G. Giatsidis, F. Bassetto, and H. Muller, "Electromyography ¨ data for non-invasive naturally-controlled robotic hand prostheses," Scientific Data, vol. 1, pp. 1–13, 2014.
[20]. J. E. Goez Mora, J. C. Londono Lopera, and D. A. Pati ˜ no Cortes, ˜ "Automatic Visual Classification of Parking Lot Spaces: A Comparison Between BoF and CNN Approaches," in Communications in Computer and Information Science, 2018, pp. 160–170. [Online]. Available: http://link.springer.com/10.1007/978-3-030-00350-014
[21].R. S. Michalski and L. Saitta, "Learnable Evolution Model: Evolutionary Processes Guided by Machine Learning," Machine Learning, vol. 38, no. 1, pp. 9–40, 2000. [Online]. Available: http://dx.doi.org/10.1023/A:1007677805582.
[22]. G. Sheri and D. W. Corne, "The simplest evolution/learning hybrid: LEM with KNN," in 2008 IEEE Cong.