Upper Prosthetic Design based on EMG: A Systematic Review

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Abstract. In the past few years, physical therapy plays a very important role during rehabilitation. Numerous efforts have been made to demonstrate the effectiveness of medical/clinical and human-machine interface (HMI) applications. The prevalent control methods are using electromyography (EMG) signals generated by muscle contractions to implement the prosthetic human body parts. This paper aims to provide and summarize ideas about recent researches in the field of Pattern Recognition (PR) based on EMG signals to save time and efforts for the readers working in this field. The first step starts by demonstrating a general overview of the various techniques to collect the database by taking into consideration the factors that affect the accuracy of the collected data. Hence, different types of filters are presented to process the signals and reduce the noise of the raw EMG signals. This research clarifies the features extraction methods using time-domain (TD), frequency domain (FD), and time-frequency domain (TFD) and which of these methods will be suitable to use for EMG signals. Finally, a group of studies is reviewed based on three classification methods i.e. artificial neural network (ANN), machine learning (ML), and deep learning (DL). Depending on these methods, the accuracy range can be specified for each classifier, also the factors which affect the accuracy percentage. Therefore, the researchers can avoid these issues that reduce accuracy.

Keywords: EMG; signal processing; HMI; physical therapy and feature extraction.

1. Introduction

Recently, the robotic has the effectiveness to increase the independence of the individuals living lifestyle with their disabilities. The objective is to improve the life quality that happens by empowering people to achieve a wide range of daily responsibilities within a few times. Humanoid robots can be prepared robotic limbs to make the physical actions of individuals as well as in the intelligent robotics industry. Nowadays, the most widely used is the robotic hands and arms, the robotic hands would have the ability to achieve the
main skills like the transfer from one place to another and grasp of objects in the same nonamputees individuals do. Therefore, depending on the object shapes, the human hand actions must be trained and applied to the designed robotics hand. The intuitive approach is creating an interface that brings the activity of the muscle and records it by using electromyography (EMG) sensors (Oskoei et al., 2007).

EMG signals are a way for estimating the electrical signal that relatives to skeletal muscle, the electrical signal consists of some motor unit action potentials (MUAPs). The MUAP contains muscle fibers stimulated by harmonizes and solo alpha motor (Rissanen et al., 2007). Currently, the prosthetic technique is used as an artificial part to resolve the problem of amputee’s parts. The appearance of the consumer-level 3D printers supports the prosthetics implementation. Thus, the develop prosthetics technique has gained popularity over traditional prosthetics which are expensive and unaffordable to many users (Amamcherla et al., 2018). The main challenge in the mechanical standpoint is how to mix many degrees of freedom (DOF). As a result, the increase in the DOF caused by decreasing in the gripping force that leads to an unstable system (Carrozza et al., 2002). Also, increasing in DOFs will lead to an increase in actuators number and high failure probability, so the prosthetic hand will need high maintenance and difficult manufacture (Choi et al., 2017).

This paper presents several problems that can happen in Pattern Recognition (PR), these problems start from the data collection passing through signal processing the feature extraction to end up with the required classification methods. These problems can be summarized as; myo armband position, number of electrodes that used to collect the data, the additive noise to the raw EMG signals, selecting the suitable features and how to reduce these features, and choosing the classifier depend on the a mounted of data. Each step in PR aims to solve these problems depending on the selected studies which used a different technique to reach the optimum solutions.

2. Electromyography Signal Processing

This part paper presents some essential information relevant to EMG signals. In addition, describing the methods that used for signal processing of raw EMG data, also presents the effectiveness and limitation of the environments and how it can be limited by understanding signals fundamental step and how to extract features that are related to pattern recognition (PR) to obtain a strong recognition system. Figure (1) shows a general overview of the EMG control signal.

2.1 Signal Overview

The innovation of electromyography signals has led to a countless application in clinical researches for motor unit employment, identification of neuromuscular disease, kinesiology, and motor unit disorders (C. J. J. I. T. o. B. E. De Luca, 1979). The EMG signals produce by the humanoid body in motor movement. The summing of the action potentials for the nerve cells will produce the EMG signals. The amplitude of these signals is very low and required suitable processing to give meaningful information (Prahm et al., 2017). The EMG signal is susceptible to the contamination that leads to the noise in the signals. For this reason, the authors proposed different methods to come over the noisy signals by using different types of filters (C. J. De Luca et al., 2010), other authors found a significant way to reduce the environmental noise by friction the surface of the skin with a rough conductive stick. Meanwhile, some authors work on the empirical mode decomposition (EMD) to cancel the noise of the signal (Huang et al., 1998), (X. Zhang et al., 2013).
2.2 Data Collection

The EMG (electromyography) electrode records the muscle movement. The principle of electrode based on muscle contraction that plays the role of electrical sparks to spread through the bone, tissue, and adjacent skin areas. This work depends on the data that have been collected from different types of sensors over the last ten years. There are different ways to recode EMG signal, Castiblanco, C., Parra, et al used Myo armband with 8 electrodes to detect the right forearm signals for 10 healthy persons (7 males, 3 females) (Castiblanco et al., 2016b).

Park, Ki-Hee, et al used three separate electrodes to record the data of prismatic four fingers grasp, tip pinch grasp, parallel extension grasp, power grasp, opening a bottle, and lateral grasp for 27 subjects (Park & Lee, 2016). Ibrahim and Al-Jumaily used MyoScanTM T9503M Sensors to collect the signals of ten different finger movements, each movement recorded in 5 sec (M. F. I. Ibrahim & A. A. Al-Jumaily, 2016). In (Tortora et al., 2019) the author used two Myo armband to record 5 degrees of freedom (DOF) for non-amputees subjects. Other authors used the UCI database that recorded to detect 10 normal actions and 10 aggressive actions for 3 males and 1 female (J. Zhang et al., 2019). M. U. Khan, et al used the insertion level of the needle to record EMG signals for 6 normal males and 4 females, also to record 6 males and 4 females have lateral sclerosis (ALS) (Khan et al., 2019).

If electrode liftoff or shift, the desired muscle action has to stay the same topographical map but that will cause shifting in the direction. Therefore, the detection and correction of the shifted electrode add more complexity to the recognition system. The increment in electrodes number leads to an increment in the probability of pattern recognition. Therefore, increasing the number of electrodes leads to add redundancy that requires more computational power to post-process the generated signals also will effect on regression/classification features (Simão et al., 2019).

2.3 Signal Filtering

First of all, the quality of digitalizing of raw EMG signals must be improved by amplification the signals usually between 500-2000 fold. The raw EMG signals use different approaches to preprocessing. Usually, the band-pass filters (BPF) within the approximate range 5-500 Hz, low pass filter (LPF) of around 500Hz, and high pass filter (HPF) started with 5Hz (sometimes higher) these types of filter has been used in EMG sensors. Also, to cancel the power line interference (PLI) the notch filter is used at frequencies 50/60 Hz. After that, the filtered signals convert into a digital form by using an analog to digital conversion (ADC) (L. Xu & Adler, 2004).

One of the selective studies on EMG signals for pattern recognition the author amplified the signal 1000 time and uses BPF of 10 – 500Hz band with a sampling frequency of 1000 Hz (Park, S, 1998). Some studies decreased the EMG signals noise by using HPF with a 500 Hz cutoff frequency and an LPF of 20 Hz cut-
off frequency to decrease gesture remains (Balbinot & Favieiro, 2013). Al-Angari, Haitham M., et al used the BPF with a range of 5-500 Hz (Al-Angari et al., 2016). The authors presented an effective control using 4 sensors placed upper limb to measure the following EMG signals; triceps-long head, extensor carpi radialis, biceps-short head, and flexor carpi radialis. The sampling frequency was 1000 Hz for the EMG signals, and this signal filtered using the BPF with a cut-off frequency of 90-450 (Riillo et al., 2014).

This study presents four raw signals with their filtered signal for three males and one female subjects ages from 25 to 30. The data signal is selected form the UCI Machine Learning Repository website. The data name is EMG Physical Action DataSet, the data was collected for ten normal actions i.e. waving, bowing, hand shaking, clapping, running, jumping, hugging, seating, standing, and walking. In this work the waving action for the right arm using bicep muscle is choosing for filtering process. This raw EMG signal has 10000 samples for each subject, the raw EMG signal is filtered to reduce the noise using first-order Butterworth LPF. Figure (2) shows the difference between the raw EMG signal and the filtered signal.

![Figure (2). The raw EMG signal and the filtered signal: (A)subject1, (B)subject2, (C)subject3, and (D)subject4](image-url)
A challenge of using electrode-based sensor systems that uses to record the EMG signal is how to reduce or avoid the external noise that affects signals detection. Reducing the noise will effect on the output signal, so rules must be applied to obtain good performance in the per-processing system:

- Skin preparation (shaving) to decrease the variance between the poles of the electrode (Piervirgili et al., 2014);
- cables arrangement for minimizing the coupling. (Merletti & Farina, 2016);
- Using differential amplifiers for common-mode rejection (Riillo et al., 2014).

This section pays little attention to the filtering stage, due to the importance of selecting the suitable pre-processing stage. Table 1 reviews some studies on filtering and suppression of PLI of EMG signal.

### Table 1. Summary on filtering and suppression of PLI of EMG signal.

| Authors                  | Filter type                  | Filter Range (Hz) | Sampling Frequency (kHz) | Comments                                                                 |
|--------------------------|------------------------------|-------------------|--------------------------|--------------------------------------------------------------------------|
| (Jamal et al., 2019)     | adaptive filter              | 40-250 Hz         | 1000 Hz                  | Used 6th order BPF, learning rate $\mu$ as 0.005, and 100 coefficients.  |
| (Wang et al., 2006)      | amplifier filters            | 5-1000 Hz         | 2400 Hz                  | Used AR coefficients                                                     |
| (Y. Paul et al., 2017)   | BPF + butterworth filter     | 15-500 Hz         | 500 Hz                   | Used notch filter at 50Hz.                                               |
| (Maurya et al., 2019)    | BPF + butterworth filter     | 5-500 Hz          | 2000 Hz,                 | Used Butterworth filter to remove PLI.                                   |
| (Li et al., 2017)        | BPF                          | 10-500 Hz         | 1024Hz                   | No comment                                                               |
| (Yang et al., 2019)      | Butterworth bandpass filter  | 20-500 Hz         | 2000 Hz                  | Used 4th order Butterworth and notch filter at 50 Hz.                    |
| (Qi et al., 2019)        | LPF                          | Cutoff of 950 Hz  | 2000 Hz                  | Used 3rd order Butterworth filter.                                       |
| (Benalcázar et al., 2017)| LPF + Butterworth filter     |                   |                          | Used 3rd order Butterworth filter.                                       |
| (A. Zhang et al., 2018)  | BPF                          | 20-50 Hz          | 1500 Hz                  | Used notch filter at 50Hz.                                               |
| (A. A. Adewuyi et al., 2015)| BPF                  | 30-350Hz          | 1000 Hz                  | Used 8th order Chebyshev filter.                                         |
| (Geng et al., 2016)      | HPF                          | 80 Hz             | 1024 Hz                  | Used 5th order Butterworth.                                             |
| (Amamcherla et al., 2018)| BPF                          | 20 - 450 Hz       |                          | Used 125ms as rectangular window of length and 25ms overlap.             |
| (P. Xu et al., 2018)     | BPF                          | 20-500Hz          | 2000 Hz                  | Used notch filter at 50Hz.                                               |
| (Young et al., 2012)     | HPF                          | 20 Hz             | 1000 Hz                  | Used 3rd Butterworth filter.                                             |
| (Roy et al., 2016)       | BPF                          | 2-16 Hz           |                          | Used 2nd order to minimize DC components                                 |
| (Bao, Zadi, et al., 2019)| HPF                          | 20 Hz             | 1024 Hz                  | Used 3rd order Butterworth filter.                                       |

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### 3. Feature Extraction of EMG

The traditional methods for extraction EMG features are frequency domain (FD) and time-domain (TD) analysis, which are commonly employed to analyze the data. Graupe, D. et al. were the first who employed the TD for feature extraction. Furthermore, Autoregression (AR) was applied to recognize several arm actions, in this work the accuracy reached 85% (Graupe et al., 1982). Han and other researchers had a classification accuracy reached 92% by extracting the mean absolute values (MAV) as a main the features of the hand actions, then the Bayesian model was applied as a classifier (Han et al., 2013). The RMS appeared to be the most important feature if it compared with Waveform Length (WL), ZC, MAV, SSC, and MAX that gave good information for the selection of the electrode (Kendell et al., 2012). Moreover, the integrated EMG (IEMG) feature used TD for the fixed exterior force to calculate the increasing in the signal power, the period, and the amplitude that produces a higher muscle fiber employment (Al-Mulla et al., 2011).
Only a few research had employed FD features in PR. FD depends on the spectrum analysis such as Fourier transform is employed for analyzing the data of EMG. Bilodeau found a relationship between the change caused by the thickness of the skin volume conductor and the increase in force, this relationship came from the analysis of the power spectrum density (PSD) of EMG signals (Bilodeau et al., 1995). Therefore, the PSD, median power frequency (MNP) and mean frequency (MNF) of the power spectrum is commonly applied to indicate the characterize EMG signals (Merletti et al., 1997). Researchers improved the median and mean in FD by taking the amplitude and calculate the median and mean for this amplitude instead of PSD. As a result, a new modified feature was obtained; modified median frequency (MMDF) and modified mean frequency (MMNF). After that, the MNP, MNF, bandwidth (BW), and normalized spectral moments (NSM) were extracted to identify muscle exhaustion for upper limbs (Rogers et al., 2013).

The researchers found a novel method that combined the characteristics of both TD and FD to present the wavelet transform. Thus, the time-frequency domain (TFD) analysis such as WT and short-time FT could be used to analyze the EMG signals. In (Patel & Gamit, 2016) the EMG features such as the RMS, MNF, and MNP are extracted with high accuracy by using continuous wavelet transform (CWT). In 2017 Fan extracted the EMG features using discrete wavelet transform (DWT) that have the strongest points of both TD and FD. After that, the DWT combined with a wavelet neural network (WNN), this work satisfies a high average ratio (Fan et al., 2017). The classifier performance affected by the EMG signal variations, to avoid this variation Abdullah et al, used the Wavelet Packet Decomposition (WPD) for feature extraction, the combination of Random Forest and WPD achieves better performance with high classification accuracy (Abdullah et al., 2017).

Surprisingly, the TFD is suffered from a high level of the resolution also complexity in the dimensionality of the feature vectors (Chowdhury, 2013). Therefore, efforts work to reduce the dimensionality and complexity of the vector that happened in TFD and preserving the discrimination capability (Rechy & Hu, 2015). Ibrahim and Al-Jumaily implemented a feature learning method that selects a subgroup from a large group of features, this method known as principal component analysis (PCA). The results of this study limiting the number of features gave a very closed accuracy result if it compared with the accuracy result without features reduction (M. Ibrahim & A. Al-Jumaily, 2016).

4. Classification Methods of EMG

The classifier takes the information extracted from the EMG signal to map several patterns and make matching between them. Therefore, the classifier is employed to recognized and extracted several features. After that, the gained result will be applied as control commands to the next stage of the controller. Many techniques are applied to classify the signals such as machine learning (ML) that contain the artificial neural networks (ANN), multilayer perceptron (MLP), support vector machines (SVM), linear discriminant analysis (LDA), K-nearest neighbor (KNN), and hidden Markov models (HMM).

Alkan and Ahmet made a comparison between the accuracy of LDA methods against an SVM, using the MAV as to classify upper arm movement, the results showed the accuracy of SVM is 99% better than the LDA model that achieved accuracy between 96% and 98% (Alkan & Güney, 2012). In 2015, (Gokgoz & Subasi, 2015) used the MAV, Standard deviation, Ratio of mean values and Average power to extract features from EMG signals. Then, the Random forest and the decision tree used to diagnose the neuromuscular disorder, the accuracy of the applied algorithm was 96.67%.

The fuzzy logic (FL) system is another technique that applied to classify the EMG signals, FL has the ability to control bio-signal (Ahmad, 2009). Therefore, the nonlinear dynamics methods were used on the EMG signals. The authors in (Chen et al., 2007) proposed a method that combining the multi-scale analysis and fuzzy entropy, the features extracted by the multi-scale fuzzy and the data classified by SVM the recognition rate was 97%.
In the past few years, the deep learning (DL) has emerged as a new technique, the main idea behind the DL is constructed from ML had numerous hidden layers that depend on taking a huge data such as a convolutional neural network (CNN) (LeCun, et al., 2015). In 2017 Cote-Allard presented a CNN using transfer learning (TL) techniques, the classifier was precise and robust for performing 6 DOF of the robotic arm. The CNN accuracy reached to 97.81% (Côté Allard et al., 2017). In 2019 the same authors presented a CNN classifier to train the raw EMG using CWT and Spectrograms, also the authors used the SampEn Pipeline, TD, Enhanced TD, and Nina Pro to extract features. For 17 participants the TL increased, and ConvNet achieved an accuracy of 98.31%. Moreover, when the NinaPro DB5 dataset had been used for 10 participants on a single Myo armband the average accuracy was 68.98% (Côté Allard et al., 2018). Table 2 reviews a list of studies that clarify several methods of feature extractions and classifications.

Table 2. Summary of some studies on feature extractions and classifications for EMG signal.

| Author                  | Features                                                                                      | Classification         | Accuracy                  |
|-------------------------|------------------------------------------------------------------------------------------------|------------------------|---------------------------|
| (L S et al., 2018)      | RMS and Integrated Absolute Value (IAV)                                                       | KNN and NBP            | 92-94%                    |
| (Kurniawan & Pamungkas, 2016) | RMS                                                                                                | ANN                    | 92.88%                    |
| (Y Paul et al. 2017)    | MAV, MAV2, MAV1, RMS, VAR, WL, DASDDV, SSI, Hjorth (Activity), AR, Hjorth (Complexity), and Hjorth (Mobility) | SVM and KNN            | Best accuracy achieved of 63% using DASDV and SVM |
| (Caesarendra et al., 2016) | MAV, IEMG, MAV2, MAV1, RMS, VAR, WL, DASDDV, SSI, Hjorth (Activity), AR, Hjorth (Complexity), and Hjorth (Mobility) | ANN                    | 85.70%                    |
| (Maurya et al., 2019)   | Approximate Entropy, Average Amplitude Change, IEMG, DASDDV, Kurtosis, MAV, Log detector, RMS, Variance, Simple Square, Skewness, Total power, Integral, Mean Power, and Mean frequency | KNN and SVM            | KNN of 99.7%, SVM of 99.6% |
| (McCool et al., 2014)   | ECG interference, PLI, motion artifact, additive white Gaussian noise (AWGN), and amplifier saturation: | SVM                    | 95.75%                    |
| (Chung & Benalcázar, 2019) | RMS                                                                                                | ANN                    | 85.08 ± 15.21%           |
| (Yang et al., 2019)     | RF                                                                                                | CNN                    | E-F was 0.888 ± 0.054, U-R was 0.803 ± 0.087, and S-P was 0.810 ± 0.048. |
| (Qi et al., 2019)       | CNN and TL                                                                                      | CNN                    | 95%, TL 96%               |
| (J. Zhang et al., 2019) | MAV, MAD, ZC, and SCS                                                                           | Deep Belief Network (DBN) | 99.79±0.29%              |
| (Park & Lee, 2016)      | CNN                                                                                                | CNN                    | Above 90%                 |
| (A. Zhang et al., 2018) | AR model with fifth order                                                                       | LDA, BPNN and SVM      | The LDA had the highest accuracy if it compared to BPNN with difference of 8.21%, p < 103, and SVM with difference 4.55%, p < 103. |
| (He et al., 2018)       | LSTM network and MLP.                                                                           | CNN                    | 66±6.04%                  |
| (A. Adewusi et al., 2015)| RMS, TD2, TD4, and TDAR                                                                          | sparse representation based classification (SRC) | The TDA-SVM of RMS-SRC accuracy range from 12.60% to 16.96%. When the training set was contaminated the accuracy range from 16.24% to 34.79%. |
5. Discussion

This study covers an important element that is lacked in the previous studies is the data sets. The published data is difficult to compare among different methodologies. The main challenges for the researchers are to get the identical set up for the data acquisition, due to the restricted existence of the measuring equipment’s and the EMG sensor's responsiveness, also taking into consideration the suitable place of the electrode (Jamal et al., 2019; Li et al., 2017; Maurya et al., 2019).

The current survey presents the most common PR approaches of EMG signals, that are involved in several applications, for instance the orthoses, the detection for neuromuscular disorders the rehabilitation devices, and the prostheses. The raw EMG signal contains unwanted signal sources. Therefore, filtering techniques are proposed to reduce the noise. Nevertheless, filtering processing can be reduced the noise level but that will affect the EMG signal quality. As a result, the researchers are focused on signal processing techniques to gain a simple, reliable, and accurately detects the signal. Hence, if the numbers of the electrode increase the numbers of control commands will increase too, so that will affect the computational time that classifier will take (Limem et al., 2016; Roy et al., 2018; Zhou et al., 2017).

The classification accuracy depends on the feature classifier combination. Therefore, the feature extraction of the time-domain and time-frequency domain is typically used. As noticed, from the previous studies frequency domain analysis is not promising, especially in isometric conditions. Therefore, the performance of time-frequency domain analysis using both ML and DL algorithms more than time-domain analysis to obtain high accuracies (Nazmi et al, 2016). However, the higher accuracies were gained using TD features with SVM and K-NN, correspondingly using the CNN with TL. Increasing the classification accuracies depend on a mixture of signal processing techniques and PR methods using the same contractions of the

| (Castiblanco et al., 2016a) | EMG, simple square, MAV, WL, variance, DASDV, average amplitude change, Willison amplitude, Myopulse percentage rate, MAVS, slope sign change, Cepstral coefficients, and AR. | SVM and k-means | SVM of 92%, K-mean1 of 55%, and K-mean2 of 75%. |
|----------------------------|--------------------------------------------------------------------------------|----------------|-----------------------------------------------|
| (P. Xu et al., 2018)       | RMS, maximum-slope and MF                                                     | BP and LVQ     | BP of 88.3% LVQ of 91% and LVQ of 86.0%       |
| (Young et al., 2012)       | MAV, ZC, number of slope sign changes, and WL                                | LDA            | single classification-95%                     |
| (Khan et al., 2019)        | mean, Kurtosis, Peak to Peak, Shape Factor, energy, jitter, ZC, Kurtosis, Spectral Kurtosis, Spectral Skewness, Spectral Flux, Spectral Centroid, Spectral Crest, Spectral Roll Off, Mel-Frequency Cepstral Coefficients, and Spectral Spread. | LR and SVM     | SVM of 94.1%, LR of 95.1%                     |
| (M. F. I. Ibrahim & A. A. Al-Jumailly, 2016) | Used Manhattan index 50 features are selected from PCA feature learning algorithm. | Quad SVM, Linear SVM, Fine Gauss SVM, Cubic SVM, Coarse Gauss SVM, and Medium Gauss SVM | Wavelet higher than 87%, the spectrogram of 82% |
| (Demir et al., 2019)       | AlexNet and VGG16                                                            | CNN            | 99.04%                                       |
| (Roy et al., 2018)         | VGG16                                                                        | CNN            | 93%                                          |
| (Bao, Zhang, et al., 2019) | MAV, RMS, VAR and 4th AR                                                     | CNN            | 90% for DOF1, 85.5% for DOF2, and 85.2% for DOF3 |
| (Narayan et al., 2019)     | 20 subsets of best features                                                  | 35 base classifiers | 100%                                      |
| (Jafarzadeh et al., 2019)  | Features reduction use PCA                                                   | CNN            | 91.26%                                      |
muscle (Demir et al., 2019; Qi et al., 2019). Hence, the combination of the method will increase the classification accuracies without using several muscle positions.

6. Conclusion

In this paper, the EMG signals are used for physical action recognition. To maintain an accurate pattern recognition some issues, have to be taken into consideration. First, to collect data correctly the position to the EMG sensors have to be fixed and the number of sensors is preferred to cover the muscles that give the required action. Second, overcome the noises interference that appeared with the raw signals using a band-pass filter (BPF). Third, using the time-domain analysis to extract features and avoid using frequency domain analysis. Lastly, the classifiers such as support vector machine and k-nearest neighbor show the highest accuracy in machine learning algorithm, and if the amount of data is large would be better to use deep learning. Therefore, obtaining high classification accuracy is required to train the prosthetic parts accurately.

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