Classification and Feature Extraction of sEMG signals

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***Abstract*— Exoskeleton and wearable robots are playing an important role in people's lives with limb disability and other physical disabilities. The exoskeleton can help people with disabilities by helping them recover faster. One of the most appreciated and successful method is to use sEMG signals, extracting them from the subjects and understanding the information/pattern from these signals, which in turn act as feedback to the robot. This process starts by extracting the sEMG signals from the muscles of the subjects, the study of these signals should be able to communicate the actual intentions of the brain and then this information can then be carried to the exoskeleton/robot. The primary goal here is to understand/decode the information/pattern involved with the signal. For this task we are using many pattern recognition techniques. So, this paper deals with the classification and feature extraction of 20 different activities of the daily life (ADL) by using suitable machine learning algorithms. The k-NN classifier has achieved an accuracy of 94.1% for two classes.**

Keywords— sEMG, k-NN, MUAP, feature extraction

I. Introduction

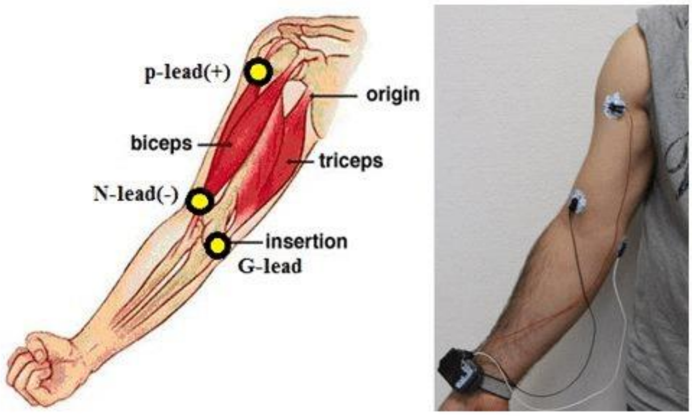
Bio-signal analysis has become an integral part of diagnosis of one's physiological, pathophysiological states, hence playing a vital role in one's health monitoring and diagnosis. Bio-signal analysis involves extracting the data from the subject, preprocessing the signals and finally extracting the pattern/information associated with the data. Electromyography is one such bio-signal which can be continuously monitored and measured.

Electromyography is the collection the electric signals produced during the contraction of the muscles. There are 2 types of EMG, sEMG and iEMG, Surface EMG also known as sEMG is a technique used for the collection of the EMG signals from the surface of the body. Whereas in intramuscular electromyography, we insert electrodes inside the muscles and then collect the signals corresponding to the muscle. sEMG is widely being used in analysis of many daily life activities.

One of the major problems today is physical disabilities; people suffering from physical disabilities. The majority of disorders can be cured or can be fixed. Although they really don't have a limb, but the brain still sends signals to the end of the limb. This motivation has started the research and production of prosthetics using EMG. This could be a very useful solution for people with disabilities. sEMG plays a vital role here by sensing the myoelectric signal from the muscles. Further we can extract the pattern / information from the study of these signals.

II. Background

A. *EMG:* Electrical activities of the skeletal muscles can be recorded by surface electrodes or needle electrodes (intramuscular EMG). The needle electrodes provide a detailed composition of the EMG signals and help in many medical activities but are not acquired easily as there is a need of intervention of the electrode's thorough one's muscles and skin. On the other hand, the Surface EMG is an approach where we don't need to intervene the electrodes through the muscle, but just place on the surface of the skin, but this approach lacks the measurement specificity [3]. The detection of EMG signals through surface electrodes on the skin surface have been clinically beneficial. Bipolar electrodes coupled with a differential amplifier is the most commonly employed measurement arrangement.

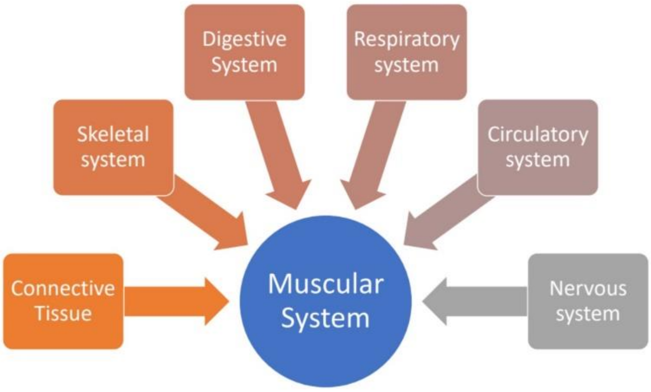


Bipolar Electrodes on the Surface of the hand

B. *MUAP:* Multiple muscle fibers are innervated by a single motoneuron, the firing of a motoneuron results in discharge of many muscle fibers. The summed activity of all these muscle fibers culminates in the generation of a motor unit action potential or MUAP.[4]

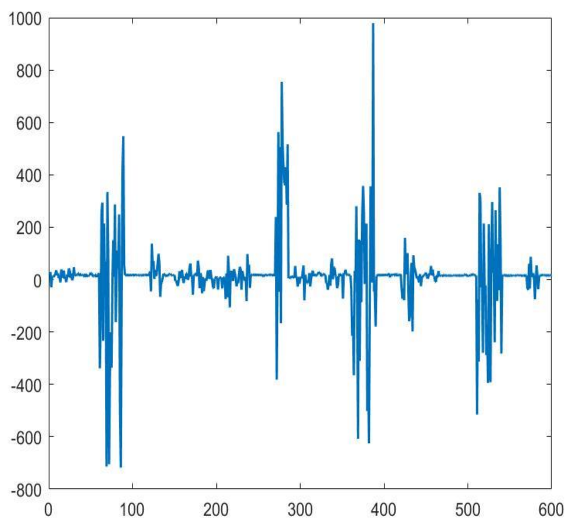
C. *Muscle Structures:* The salient anatomical features that affect the EMG signal include variations in muscle fiber length and fiber type composition, muscle partitioning, and variations in the distribution of sensory receptors.

To consider the human musculature outside the context of a complex and interdependent system such as the human body is probably not fair [4]. Without the connective tissue providing the "sacks" for the muscle fibers, the muscles would neither be organized into meaningful directions of pull, nor would they be anchored to the bones, and their actions would not produce movement of the body. Without a digestive system, there would be no glucose available for the body to burn. Without the lungs, there would be no oxygen to fan the flames of cellular respiration and produce the gasoline for the muscle—adenosine triphosphate (ATP). Without a circulatory system, these vital substances would not find their way to each and every cell, nor would the waste products of muscular metabolism (lactic acid) be carried away. Finally, without the nervous system, the muscle cells would not know when to fire or how to orchestrate their firings with other muscle cells.



III. Methodology

Consider a dataset A with data from S subjects and C classes and each performed for N trials. There are n channels, each corresponding to an electrode. First, segment the data without any overlapping into segment length L [1]. Next, the segment is again broken down into 3 patterns and the mean and variance are calculated for each one of the patterns. These are the features extracted from the EMG signal and are the inputs given to the classifier. The accuracy of the classifier is calculated by performing a 10-fold cross-validation.



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IV. Features

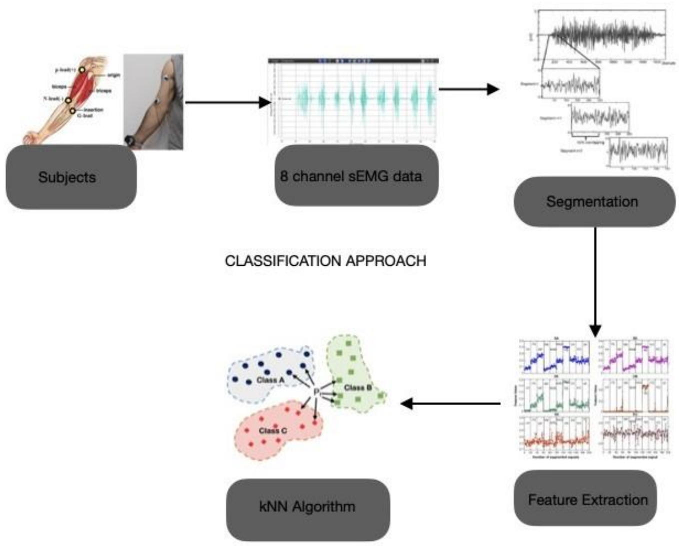
A. Mean: The first set of features is extracted from the samples of each pattern [1]. The mean of a pattern is given by,

$$\mu = \frac{1}{P}\sum_{l=1}^{P} s_i(l)$$

B. Variance: The next set of features is extracted from the samples of each pattern. The variance of a pattern is given by,

$$\sigma^2 = \frac{1}{P}\sum_{l=1}^{P} \left(s_j(l) - \mu\right)^2$$

Where, P is the length of the pattern.



Classification and Feature Extraction Approach

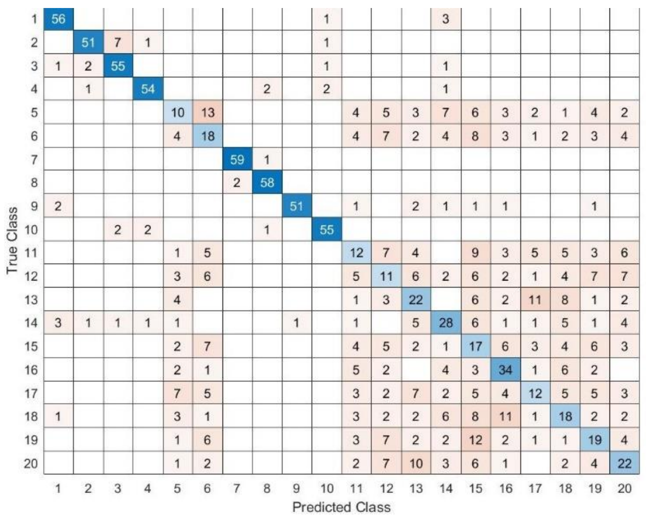
V. Implementation And Results

A. Dataset: The dataset used is from the UCI Machine Learning repository [2]. Data is extracted from 4 subjects, three male and one female. 8 Delsys electrodes are used to record the signal. 20 daily life activities of which 10 were normal and the rest were aggressive activities were performed by the subjects. The list of activities is shown in Table- I. Each activity is repeated 15 times. Each activity consists of 10,000 values from a single channel. Hence, the dimensions of the data for each activity per subject are 10,000 x 8. The sample size of the total dataset is 4 x 20 x 15 = 1200.

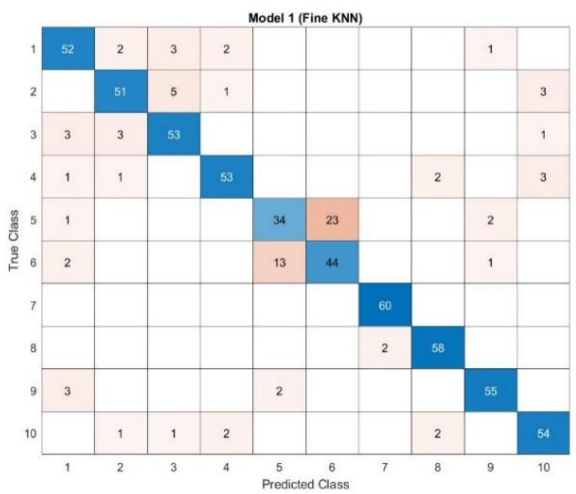
B. *Feature Extraction:* The length of the signal is 10,000 from each electrode and T=15, the segment length is approximately 10,000/15 = 666. This segment is again boken down into 3 patterns of length 666/3 = 222. The Feature vector is generated by the mean and variance of each pattern for every sample. So, for one segment the number of features is 3x 2 x 8= 48. The dimensions of the feature vector are 1200 x 48. A feature vector of Bowing activity is shown in the Figure.

C. *Classification:* The generated feature vector along with the targets are given as input to the classifier. The k-NN classifier is used for the classification. Ten possible combinations of classes for 2 to 19 classes are selected and their average accuracies are calculated. Average accuracy for two classes is 91.4 % and for all 20 classes is 54.4%.

Confusion Matrix of all 20 classes



Confusion Matrix of Normal Activities



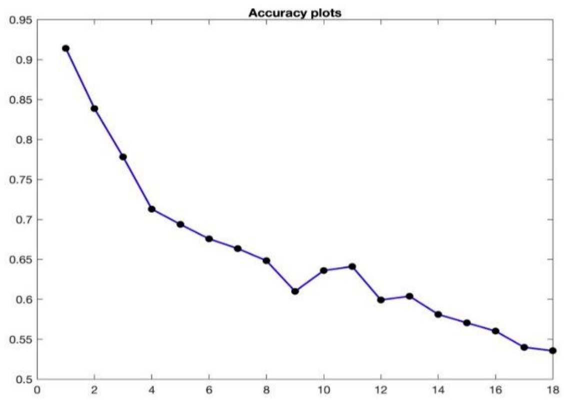
D. *Results*: The mean classification accuracies of the classes are shown in Figure(Covariance Matrix). The accuracy of classification has degraded with the number of classes being considered. The average classification is calculated as the mean of accuracies of ten different combinations of classes for all two to nineteen. The confusion matrix for 20 classes is given in Figure.There is a lot of mis classification in aggresssive activities.This has reduced the accuracy to 54.4%. The classification error is mainly due to the misclassification of class 5 as class 6 and vice versa. The accuracy of Normal activity classification using kNN is found to be 83.33%.

VI. Conclusion

In this paper, we dealt with the Classification and Feature Extraction of EMG signals of 20 classes categorized as Normal and Aggressive using the k-NN classifier. 48 features are extracted and used as input for the classifier. The performance of the model reduced as the number of classes kept increasing and the mean accuracy decreased with the increase in the number of classes. The future plans for this paper are to add new features using frequency spectra feature like log moments of Fourier Spectra [1], Wavelet analysis.

VII. Acknowledgment

The graphs and figures presented in this paper were created using MATLAB and MATLAB Classification Learner app.

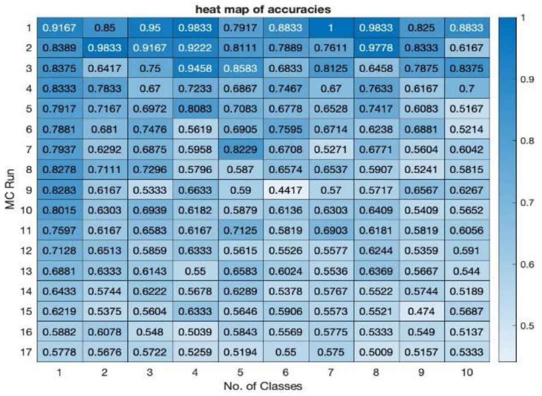


Mean Accuracies plot

TABLE I

Physical Action Categories and Class Labels

Label	Normal	Label	Aggressive
1	Bowing	11	Elbowing
2	Clapping	12	Frontkicking
3	Handshaking	13	Hammering
4	Hugging	14	Headering
5	Jumping	15	Kneeing
6	Running	16	Pulling
7	Seating	17	Punching
8	Standing	18	Pushing
9	Walking	19	Side-kicking
10	Waving	20	Slapping



VIII. APPENDIX

This appendix consists of the code that is used to classify the data and generate the plots in MATLAB. The code is written in MATLAB and it is a .mlx file.

Link:

https://drive.google.com/drive/folders/1SrOnfQLb2Kh1_ozT9Zxy2CQTMaK9umX9?usp=share_link

References

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