Hand Movement Classification using EMG signals

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***Abstract*—With the rapid progress in the field of robotics it is now possible to design and produce prosthetic limbs which are dexterous and lightweight. Still, most of the disabled population is far from reaping these benefits. In this situation, EMG-controlled prosthetics are a viable solution. The system has to first pick up the signal, calculate the features and decode the required intention and perform the desired motion of the prosthetic. In order to achieve this, a pattern recognition-based system is an optimal solution. In this paper, the identification of basic hand movements for prosthetic hand control using s-EMG data is studied.**

Keywords—EMG, EMD, Bio-signals, Feature Extraction, Segmentation, k-NN, FFNN, MRMR

I. Introduction

Bio-Signals refer to physiological electrical signals emitted by biological beings that can be continuously measured and monitored. These bio-signals are captured by skin-mounted sensors or bio-sensors. Bio-signals are of various kinds. EMG is one such bio-signal. An electromyogram (EMG) signal is an electric signal from muscles that are controlled by the nervous system and are produced during muscle contraction. Electromyography signals are considered most useful in medical fields because the basic method for understanding the human body's behaviors under normal and pathological conditions is provided by a recording of sEMG signals.

The early myoelectric hands controlled via EMG signals were limited to "on" or "off" states depending on the amount of mean absolute value of signals. If the amount of mean absolute value of the EMG signal is more than a specified threshold value, the output is considered is as "on" and a simple activation would occur; otherwise, the output is "off" and no activation would happen. This technique causes prosthetic hands to perform limited movements, much less than the expected actions done by a human hand. Pattern recognition is one of the most promising approaches to classifying finger movements. Similarly, these sEMG signals play an important role in the movement of the robotic exoskeleton. Due to the capability of EMG signals, many researchers have concentrated on finding appropriate features and classifiers to achieve high accuracy. So, in this paper, EMG signals are used for the classification of basic hand movements. In this work, Empirical Mode Decomposition (EMD) is used for the decomposition of the signal, which improved the identification accuracy of a pattern recognition scheme but EMD has ambiguity so to synthesize and recompose the results of EMD, principal component analysis was also used and comparison is done. Results show that information carried by EMD-extracted time-frequency domain features can further increase classification accuracy. Various classification algorithms like k-NN, SVM, and Bagged Trees are used for classification. MRMR algorithm is used to find the most relevant features and the top 20 relevant features are used to classify and the comparison of accuracy is presented.

The rest of the paper is laid out as follows. Section II provides basic information regarding EMG. Section III deals with the methodology used. Section IV focuses on the various features extracted. Section V deals with the results obtained and the paper concludes with the Conclusion in Section VI.

II. Background

In this section, we provide an overview of EMG signals and some basic background regarding EMG signal generation and acquisition.

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 for intervention of the electrodes through one's muscles and skin. On the other hand, the Surface EMG is an approach where we don't need to intervene with the electrodes through the muscle, but just place them on the surface of the skin, but this approach lacks measurement specificity. The detection of EMG signals through surface electrodes on the skin surface has been clinically beneficial. Bipolar electrodes coupled with a differential amplifier are the most commonly employed measurement arrangement.

B. MUAP: Multiple muscle fibers are innervated by a single motoneuron, the firing of motoneuron results in the 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.

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 human musculature outside the context of a complex and interdependent system such as the human body is probably not fair. Without 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.

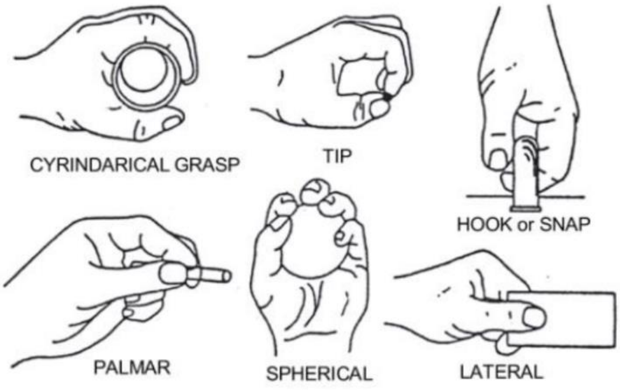

Figure 1: Various Grips

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 an overlap x. Next, the segment is decomposed using EMD, and Hilbert Transform is applied. These features extracted from EMG signals are used for classification and accuracy, precision, and other performance parameters are evaluated using different classifiers. 10-fold cross-validation is used in all the classifiers. The block diagram is given below.

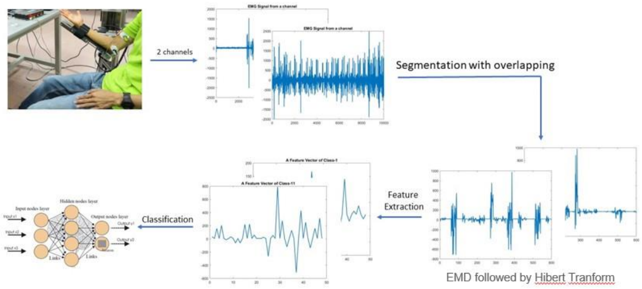

Figure 2: Block Diagram

IV. FEATURES

In this section, we discuss various features used Feature extraction is essential and plays a vital role when we are dealing with higher dimensions. The feature extraction stage is used frequently as it reduces the complex dimensionality of the raw signals. We have considered two different sets of features and then performed classification with each set at a time. The following are the features used in each set:

Set-1: Integrated Electromyogram (IEMG), Zero Crossings (ZC), Slope Sign Change (SSC), Waveform Length (WL), Willison Amplitude (WAMP), Variance, Skewness, Kurtosis.

Set-2: Root Mean Square (RMS), Simple Square Integrated (SSI), Difference Absolute Mean Value (DAMV), Second Order Moment, Difference Absolute Standard Deviation (DASD), along with Set-1 features.

A basic description of the features used is given below:

1. **IEMG:** It is the average value of the absolute values of the EMG signal. It is given by:

$$\mathrm{IEMG} = \frac{1}{N}\sum_{k=0}^{N}|x(k)|)$$

2. **RMS:** Root Mean square, is given by:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=0}^{N} x(n)^2}$$

3. **Variance:** It is the measure of the power density of the EMG signal, the variance is given by:

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} x(n)^2$$

4. **Second Order Moment:** The second order moment is given by:

$$\mathrm{SSM} = \sum_{n=1}^{N-1}\left(x(n+1) - x(n)\right)^2$$

5. **Waveform Length:** It is cumulative variation of the EMG that can indicate the degree of variation about the EMG signal. It is given by:

$$\mathrm{WL} = \sum_{n=1}^{N-1}|x(n+1) - x(n)|$$

6. **Simple Square Integrated:** It is expressed as the energy of the EMG signal as a useable feature. It is given by:

$$\mathrm{SSI} = \sum_{n=1}^{N} x(n)^2$$

7. **Difference Absolute Mean Value (DAMV):** The mean absolute difference is defined as the "average" or "mean", formally the expected value, of the absolute difference between two random variables X and Y independently and identically. It is given by:

$$\mathrm{DAMV} = \frac{1}{N-1}\sum_{n=0}^{N-1}|x(n+1) - x(n)|$$

8. **Difference Absolute Standard Deviation Value (DASD):**

The average deviation, or mean absolute deviation, is calculated similarly to standard deviation, but it uses absolute values instead of squares to circumvent the issue of negative differences between the data points and their means.

$$\text{DASDV} = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}\left(x(n+1)-x(n)\right)^2}$$

9. **Willison Amplitude (WAMP):** It is the number of counts for each change of the EMG signal amplitude between two adjacent samples that exceeded the threshold. It is given by:

$$\text{WAMP} = \sum_{n=1}^{N-1} f(|x(n+1)-x(n)|)$$

10. **Skewness:** The skewness of a distribution is given by:

$$s = \frac{E(x-\mu)}{\sigma^3}$$

11. **Kurtosis:** The Kurtosis of a distribution is given by*:*

$$k = \frac{E(x-\mu)^4}{\sigma^4}$$

12. **Zero Crossings (ZC):** ZC counts the times that the signal sign changes, ZC is given by:

$$f(x) = \begin{cases} 1, \ if, (x_k > 0 \ AND \ x_{k+1} < 0) \\ \quad OR \ (x_k < 0 \ AND \ x_{k+1} > 0) \\ 0, \ otherwise \end{cases}$$

13. **Slope Sign Change:** SSC counts the slope of the signal changes the sign. SSC is given by:

$$f(x) = \begin{cases} 1, \ \ if, (x_k < x_{k+1} \ AND \ x_k < x_{k-1}) \\ \quad OR \ (x_k > x_{k+1} \ AND \ x_k > x_{k-1}) \\ 0, \ otherwise \end{cases}$$

V. Implementation and Results

A. Dataset: The proposed model is applied to the dataset provided by Christos Sapsanis and Anthony Tzes, School of Electrical and Computer Engineering at the University of Patras in Greece. The number of instances and number of attributes of the dataset are 3000 and 2500 respectively. Two different databases are included in the folder, one with 5 healthy subjects (two males and three females) of similar age approximately (20 to 22-year-old) performing six grasps 30 times each, while the other database provided the data of 1 healthy subject(male,22-year-old) performing the six grasps for 100 times each for 3 consecutive days. The movements or the hand grasps that were asked to perform by subjects are Spherical, Tip, Palmar, Lateral, Cylindrical, and Hook as shown in Figure 1.

B. Feature Extraction: As the signal is of length 3,000 from two channels, the segmentation is done with a window length of 300 and with an overlap of 50. EMD is performed on each segment and first three IEMD signals are considered and Hilbert Transform is applied on each signal. The features are extracted from each signal and the feature vector is generated for each sample.

C. Classification: FFNNs are used to classify the hand activities of each subject individually and as a whole, by using a set of 64 features and 104 features. Again, Bagged Trees, SVM, and k-NN are used to classify the activities using 64 features, 104 features, PCA features, and MRMR-rated top 20 relevant features. An accuracy of 90.5% is achieved using FFNN.

D. Results: In this section, the results obtained are explained. All the codes and confusion matrixes, along with ROC curves are present in the link presented in the Appendix. A brief discussion of results obtained by using various sets of features and classifiers is presented below.

1. **FFNN:** Feed Forward Neural Networks with only one hidden layer containing 10 activation units are used to classify the hand movements using 64 features from Set-1 and also using 104 features from Set-2. Subject-wise classification analysis and overall classification are performed. The confusion matrixes of the overall subject's classification using 64 and 104 features respectively are presented in Figure 5 and Figure 6 respectively. A training accuracy of 80.7% and 74% is obtained. A decrease in accuracy is observed when using FFNN. But, the accuracy of the classification of individual subjects accuracy is almost always above 93%. FFNN has outperformed all the other classification algorithms using any set of features used in this paper.

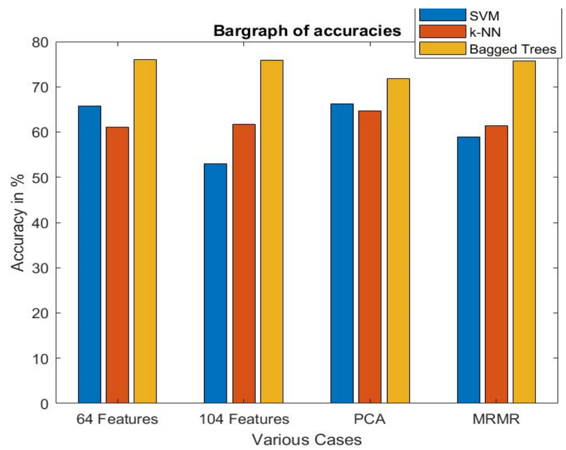

Figure 3: Accuracies of Classifiers using various Feature Space

2. **Classification using SVM, k-NN, and Bagged Trees:** PCA (Principal Component Analysis) is applied to obtain 10 new features and is used for classification. Later, the MRMR algorithm is used to score the 104 features based on their relevancy. The top 20 relevant features are used for classification. The subject's data is classified using the SVM, k-NN, and Bagged Trees classification algorithms. 64-feature, 104-feature, PCA features and MRMR based top-20 features are used separately to classify. The accuracies are shown using a bargraph in Figure 3. It can be observed that in all cases, Bagged Trees has performed better than SVM and Bagged Trees. An accuracy of 78.76% is obtained by using Bagged Trees. SVM has highest accuracy of 66.2% when using the 10 PCA features. K-NN have similar performance in all the four feature sets. It has highest accuracy of 64.67% using PCA features. The heatmap for all the accuracies is shown in Figure 8.

3. **Performance Metrices:** Various Performance metrices like accuracy, precision, recall, ROC curves , Confusion Matrix, and F1-Score are calculated for each classifier. The graphs for individual subjects and overall data using all classifiers and different feature sets are provided in the link. FFNN has the highest accuracy followed by Bagged Trees in almost all the cases, with a few exceptions.

4. **MRMR:** The Minimum Rendundancy Maximum Relevancy Algorithm is used to obtain the order of relevancy of the features used for classification. It is very quick, when compared to SFS and other algorithms. The MRMR algorithm provides scores for every feature and ranks according the score.

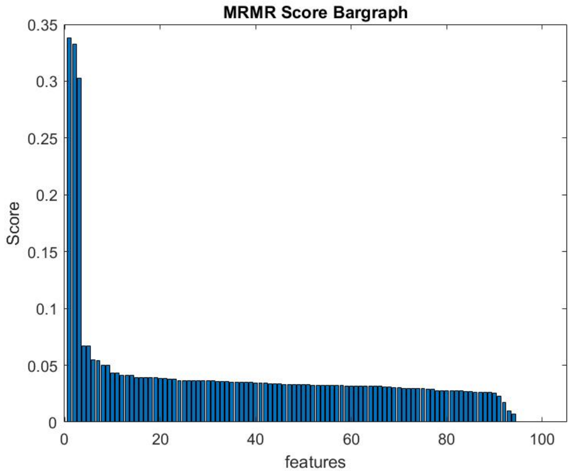

Figure 4: MRMR Scores

5. **PCA:** Principal Component Analysis is an algorithm used to reduce the dimensions of large feature-sized datasets. It reduces the computation complexity and created new features, which are more useful in improving the accuracy of the model.

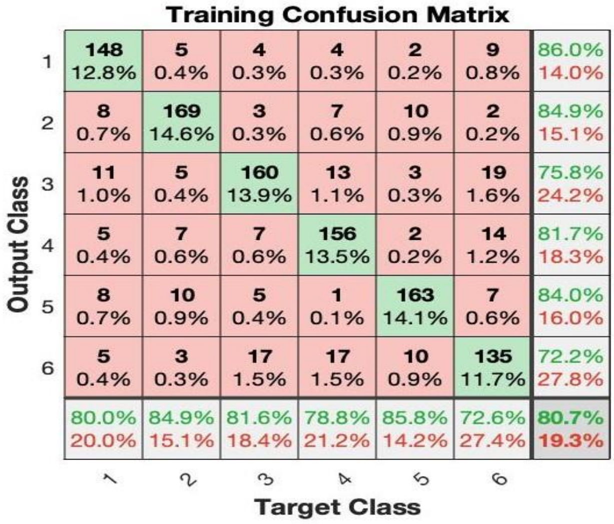

Figure 5: Confusion matrix using 64 Features and FFNN

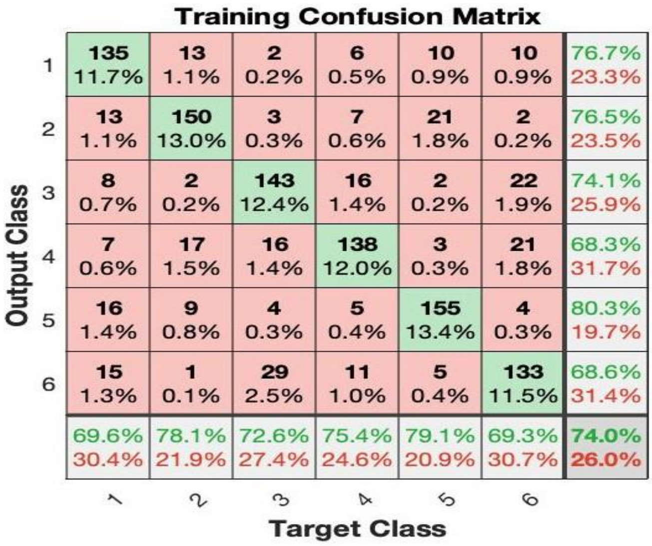

Figure 6: Confusion Matrix using 104 Features and FFNN

Figure 7: Confusion Matrix of Subject-1 using FFNN and 64 features

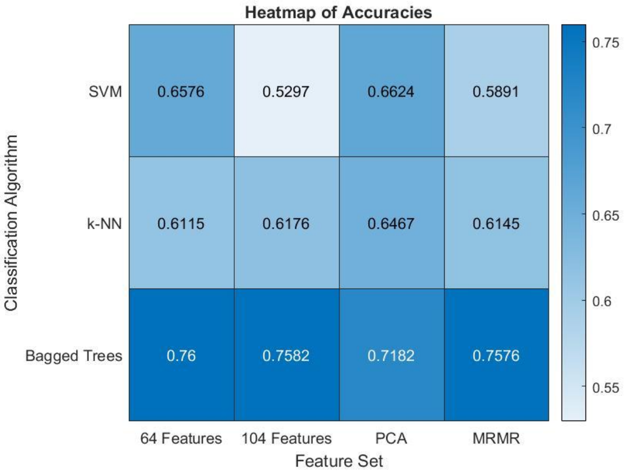

Figure 8: Heatmap of Accuracies

VI. CONCLUSION

In this paper, we have performed a classification of the basic hand movements with different methods and classifiers. Initially, the classification is performed using FFNN and the accuracy of each subject and overall accuracy using 64 features and 104 features is explored. An overall accuracy of 80.7% and 74% are observed for 64 and 104 features respectively. Apart from this, k-NN, SVM and Bagged Trees are used for classification. PCA and MRMR algorithms are used to obtain the most relevant features and classification is performed using the same classification algorithms.

VII. ACKNOWLEDGMENT

The graphs and figures presented in this paper were created using MATLAB, MATLAB Classification Learner app, and MATLAB Neural Net Pattern Recognition.

VIII. CONTRIBUTIONS

Surya Naidu: 40%
Vidya Sagar: 30%
Eswar Adapa: 30%

IX. APPENDIX

This appendix contains 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/1IoRKM7UiTJtoQjMkyEmEuQadgNlEig11?usp=share_link