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EMG based Gesture Recognition using Machine Learning

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***Abstract*—Gesture recognition basically involves the usage of hardware equipments and software development tools where human movements are captured and Human Computer Interaction are improved. Gesture recogntion can be employed in various applications like gaming technology, virtual reality, in the domain of medicine, sign language interpretation, home automation etc. This work basically focuses on EMG based gesture recogntion taken in real time using Myoband. The Myoband is worn on the forearm and electrical impulses are measured for five gestures namely Rest, Fist, Wavein, Waveout and Fingerspread. These signals undergo a signal processing technique called Wavelet decompostion where the signals are fragmented into wavelet coefficients that are localised in time domain as well as in frequency domain. These coefficients make up the dataset and are classified using Support Vector Machines. When a user poses for a particular gesture, the model would recognises it and labels accordingly.**

Keywords*—*Gesture recognition, Electromyography, Signal Processing, Discrete Wavelet Transform, Wavelet Coefficients, Classification, Support Vector Machines.

I. INTRODUCTION

Electromyography (EMG) is a procedure which records the electrical activity due to the contraction and relaxation of muscles in human body. A muscle can be viewed as a collection of overlapping motor neurons [3]. These motor neurons inturn are a collection of fibres or muscular cells. To each of these fibre end lies a tendon attached to it. Each muscle at rest produces an electric potential difference of approximately -80 mV between its extracellular and intracellular environments. Some other motor neurons either have a connection with spinal cord and other neurons called neuromusular junction have a connection with fibres [3].

A motor unit can be defined as a single motor neuron and the associate muscle fibres which stimulate the neuron. The impulse called action potential generated reaches the muscles from the neuron. All the nerves contact the muscle at a point called neuromuscular junction. Once the action potential is dispatched over the neuromuscular junction, it is induced or triggered all over the muscle fibres of that corresponding motor unit. The addition of all these impulse response is called the motor unit action potential [19].

EMG signals can be measured in two ways: Intramuscular EMG and Surface EMG. Intramuscular EMG uses needle electrodes and it should be placed at the thickest part of our forehand muscle, the ”longitudinal midline” [19]. Placing the needle electrode on muscles is difficult and one should be careful while measuring signals using Intramuscular techniques [19]. Surface EMG uses non invasive sensors into the muscle. This work basically uses surface EMG: i.e the non-commercial surface sensor called Myoband.

There are a wide range of applications developed that uses the concept of gesture recognition. In medical applications, EMGs can be utilized to monitor what is occurring physiologically with respect to the nerves and muscles in realtime and to control medical devices like X-ray display, Magnetic Resonance Imaging etc [2][8]. In areas of engineering, applications of EMG plays a vital role in development of prostheses, rehabilitation devices, human- machine interaction systems etc [3]. This project focuses on hand gesture recognition where the gesture performed using hand is measured in real time. Hand gesture recognition are widely used in applications like sign language interpretation, human machine interfaces, virtual and augmented reality etc [3][7].

Gesture recognition mainly involves Data acquisition, Signal processing and Classification. Here data is acquired using the non-commerical surface sensor Myoband. Signal Processing is basically performed to obtain useful information or to extract features that are needed for recognising each gesture. Classification determines to which class the features extracted from EMG belongs to where techniques like Support Vector Machines, Artificial Neural Network, K-means clustering, Decision Trees etc can be used for this purpose.

II. LITERATURE SURVEY

Altin et al (2017) designed a wearable joystick which uses EMG signals to control a drone. A comparison of classification methods like Support Vector Machines, K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA) etc are also performed in this work. The paper also focuses on numerous feature extraction techniques like Mean absolute deviation, Mode, Entropy etc. From the experiment, it is claimed that LDA yielded the best result in terms of classification ratio and KNN is the best classifier [4].

Benalczar et al (2017) performed a recognition that uses signals measured from the non-commercial sensor worn on forearm called Myo Armband. Here machine learning algorithms namely k-nearest neighbour and dynamic time warping algorithms for classification are also discused. An accuracy rate of 86% is achieved [3].

Devi et al (2016) proposed a survey on Signal Acquisition and methods for Feature Extractions which involves the study of Wavelet Transform, Principal Component Analysis and Fast Fourier Transform. It is being concluded that Wavelet Transform is the best one among the three approaches [5].

Karlik (2014) gave a detailed comparison about various Machine Learning alogorithms like Artificial Neural Network, Fuzzy Systems, Naive Bayes, Linear Discriminant Analysis, Gaussian Mixture Model, Fuzzy Clustering Neural Network, K-Nearest Neighbour algorithm and Support Vector Machines. It also discussed Feature Extraction techniques like Time-Series Modelling (Autoregressive Modelling, Moving Average model) and Wavelet Transformation which includes Discrete Wavelet Transform and Packet Transform. These techniques figured out the EMG characteristics for myo electic control of human arm prosthesis. It is found that Fuzzy Clustering Neural Network is better in terms of obtain EMG characteristics when compared to other machine learning algorithms and Discrete Wavelet Transform showed more accuracy for feature extraction [9].

Duque et al (2014) proposed a detailed study that uses Discrete Wavelet Transform and K-nn classification for diagnosis of Neuromuscular disorders where the EMG signal is used to determine the neuromuscular disorders. Techniques like Fuzzy Entropy, Discrete Wavelet Transform , Stochastic Relevance Analysis are used here and classification is performed using K-nearest neighbour on a dataset of 25 samples taken from patients aged between the years 19 and 63. The data is categorized into 3 labels: normal, myopathy and amyotrophic lateral sclerosis [10].

Eldin et al (2013) performed a research based on gesture recognition that uses EMG signals and Artificial Neural Network algorithm for classification. For each movement made by the muscle, the corresponding EMG pattern generated is recorded and then the features extracted from the signal is given as input to Neural Network. The network was trained for about 170 set of data for different hand gestures and it is claimed that the algorithm Levenberg-Marquardt with 10 hidden neurons proves to be the the best classification which takes mininum time for training [12].

Ahsan et al (2011) proposed a paper which uses EMG signal for recognition of gestures using Artificial Neural Network (ANN). It mentions a detailed study about EMG signals and building a human-computer interface to aid aged or disable people. Signal is acquired from people aged between 25 and 30 years and features like Mean Absolute Value, Zero Crossing, Root Mean Square etc are extracted for four gestures namely left, right, up and down. For classification, Artificial Neural Network with back-propogation is used. A dataset of 204 samples is taken and a hidden layer of 10 neurons produced the best result with a success rate of 88.4% [13].

Sueaseenak et al (2010) presented a paper which gives a detailed description about the feature extraction from EMG signals that is based on Wavelet Transform. EMG signals are acquired using a programmable system on chip(PSOC) microcontroller from the forearm muscles. Then wavelet transform is applied where Daubechies Wavelet decomposed at different levels were used. Features like Root Mean Square, Standard Deviation, Centroid of Frequency were used here. And its claimed that RMS exhibits better perfomance in terms of extracting the EMG signals.Finally it is been concluded that this can be used to control Mechanical arm and will exhibit more efficiency [14].

Khorrami et al (2010) performed a detailed study focusing on feature extraction methods like DWT, CWT and DCT that can be used to classify EMG arrhythmias .The classification techniques used here are Multi Layer Perceptron and Support Vector Machines . Here feature extraction technique is used as a combination with classification methods and is concluded that determining the best feature extraction technique depends on the training time and the performance achieved during training and testing [15].

Kim et al (2008) proposed a paper which uses EMG signals to perform Hand Gesture Recognition. This paper focused on approaches like k-nearest neighbour and Naive Bayes which is implemented as a decision tree. The experiment was performed for gestures like press, circular, left and right. For each gesture 20 training samples and 20 testing samples were considered. The accuracy achieved was about 91% [16].

III. DESIGN OF GESTURE RECOGNITION SYSTEM

The basic design of this work has 3 stages:

- Signal Acquisition
- Signal Processing
- Classification

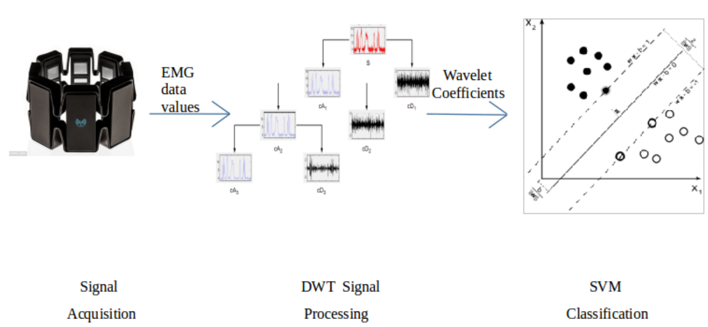

Fig. 1: Design of Gesture Recognition System

A. *Signal Acquisition*

Signal Acquisition is the process of obtaining the signal from muscles. Signals are acquired using non-invasive method i.e using the non-commercial surface sensor called Myoband. Myo armband has 8 sensors which is in the form of a bracelet. It is compact, convenient and light weight to use. These 8 sensors acquires the data from forearm and the signal is sampled at a rate of 200Hz and the data is generated as Bluetooth packets which gets transmitted via Bluetooth dongle connected to PC. The Bluetooth packet generated has EMG data values and IMU data values (Inertial Measurement Unit). But IMU data is not taken into account in this work.

B. Signal Processing

The raw signal obtained from Myoband has many artifacts and it needed to be processed. These artifacts can deterioate the quality of the signal and it can be caused due to factors like artifact motion, inherent noise in electrical equipment, inherent instability of signal etc and they have to be removed [1]. Signals like EMG are non-periodic in nature i.e it doesnt exhibit a repetitive pattern over time and most of the important information that is not seen in time-domain(time vs amplitude) can be seen only in frequency domain (frequency vs amplitude) [25]. So the signal undergoes a processing technique called Discrete Wavelet Transfom (DWT) where in the data from each sensor gets denoised and converted from time domain to frequency domain. As a result of this, wavelet coefficients are produced which is the input i.e a feature for classification technique. Thus a dataset is build out of these coefficients for each gesture performed with the required labels.

C. Classification

For classification, Support Vector Machine is deployed since it works well with dataset of few numbers. SVM uses a hyperplane that acts a decision boundary seperating the data from one another. The type of classification used here is multiclass using the linear kernel. There are five classes namely Rest, Fist, Wavein, Waveout and Fingerspread. Here in this work, SVM works on a dataset of 335 samples where 80% of data is used for training and remaning 20% of data is used for testing. Finally when a user performs a particular gesture, a live prediction is performed for the corresponding gesture shown.

IV. TECHNIQUES USED FOR GESTURE RECOGNITION

A. Discrete Wavelet Transform (DWT)

Wavelet Transform is an efficient and extensively used method to extract the required important features from the signal. Wavelet Transformation are of two types: Continuous Wavelet Transform and Discrete Wavelet Transform. Wavelet Transform fragments a signal or a mother wave into a set of basis functions or daughter waves called wavelets [6] .
Discrete Wavelet Transform splits a signal into multiple wavelets called sinusoidal basis function where each decomposed wavelets are of different frequencies [20]. When the signal are decomposed into sinusiodal basic functions which are of different frequencies, the information contained in the signal isnt lost. In the DWT, the coefficients are generated at each levels and successive levels decomposition is performed by passing approximate coefficients through a series of low pass and high pass filters [9].

Some of the properties of Discrete Wavelet Transform are [18]:

- Wavelet functions are localised in space.
- Wavelet function are dialated, translated and scaled versions of a common mother wavelet.
- Each wavelet function set forms an orthogonal set of basis function.

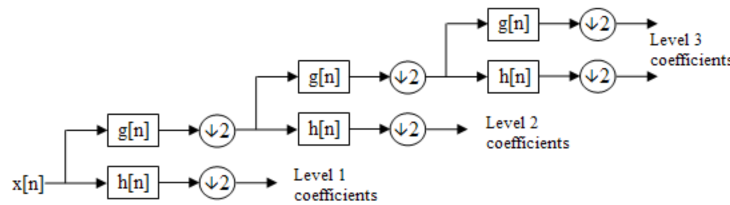

Fig. 2: Discrete Wavelet Transform [26]

To perform Discrete Wavelet Transform, the signal passes through a series of filters. When the samples passes through a low pass filter with impulse response, it results a convolution of the two:

$$y[n] = \sum_{k=-\infty}^{\infty} x[k] * g[n-k] \tag{1}$$

where n is the number of levels

In figure 2, x[n] denotes the EMG signal. Each level of decomposition has two filters g[n] and h[n] where g[n] denotes the Low Pass Filter and h[n] denotes the High Pass Filter. Filtering a signal implies that a convolution operation is performed on the signal with the impulse response associated with the filter [23]. The low pass filters on decomposition produce approximate coefficients whereas high pass filters on decomposition produce detailed coefficients at each level. At each level 't', the EMG signal is downsampled by "2", since half of the samples are redundant and it reduces the sampling rate of the signal. After passing through low pass filter, half of the samples are discarded without information loss. Thus the resolution of signal gets halved but the scale remains unchanged.
There isnt any criteria in choosing a wavelet.Different types of wavelets like Haar, Coiflets, Morlet, Mexican Hat, Symlets exist. Here Daubechies wave denotes as db1 is used since it is an efficient wavelet and proved to give better result than other wavelets [11]. Daubechies wave belongs to orthogonal wavelet family which elucidate Discrete Wavelet Transform [20]. These waves are continuous in nature [17]. In this work, DWT is implemented using PyWavelets, which is a free python module to compute Discrete Wavelet Transform.

B. Support Vector Machine (SVM)

Support Vector Machines belongs to the class of supervised learning models. It can be used for both classification and regression of data. When training samples (A combination of input feature with an expected output) is given, SVM algorithm defines or constructs a model such that a new sample could be classified to either of the classes. SVM uses a seperating hyperplane that actually serves as the decision boundary which actually seperates the tuples of one class from other.

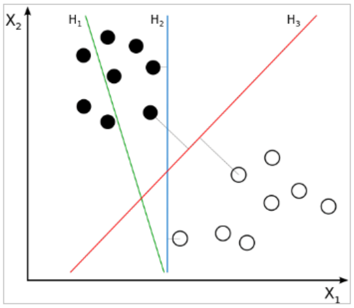

Fig. 3: Support vector machine on a classification [21]

In figure 3, the black dots and white dots are the two classes and the hyperplanes are denoted as H1 ,H2 and H3. The hyperplane that acts as the best seperator between the data point is H3. Support Vector Machine are widely used in a variety of applications like pattern recogntion, email spam categorization,fraud detection,image and text classification etc. Certain extensions like Soft Margin Classification, Non linear Classification and Multiclass SVM makes it robust and efficient.

The decision function for SVM [26] can be defined as :

$$sgn\,(\sum_{i=1}^{n} y_i\, \alpha_i\, K(x_i, x) + b) \tag{2}$$

where $K(x_i, x)$ is the kernel, y_i is the label, α_i is the weight of support vector in feature space, b is the bias

SVM can be viewed as a model which has a seperating hyperplane that acts as a "decision boundary", capable of dividing the samples by introducing a clear distance between the data as wide as possible. When a new sample is encountered then it is mapped to this space and prediction is performed based on the side of the hyperplane the sample falls [21].
Support Vector Machines are proficient in handling both linear and non-linear data.For non-linear data classification, the concept of kernel trick is used where the input data or the features are mapped to higher dimensional feature space, seperated and then brought to lower dimension space. Kernels like Gaussian Radial Basis Function, Hyperbolic Tangent, Polynomial, Sigmoid etc are used.
Linear kernel is used in this project for classification since the data has a large number of features and the data is linearly seperable. Moreover training SVM with linear kernel is faster than with another kernel [25]. Kernel is the parameter which defines the distance between the new data and the support vectors [22]. The summation of all the dot product computed between the input and each support vector is the resembleness measure used for linear SVM because the distance is a linear combination of the inputs [22].

V. EXPERIMENT AND RESULTS

The Myoband has to the synchronized first before it can be used for custom gesture input. This synchronization is performed by wearing the band on the appropriate forearm and doing a waveout. The most striking feature of the Myoband is that custom caliberation is available to the user so that users choice of gestures could be used. Here the gestures considered are Rest, Fist, Wavein, Waveout and Finger Spread. Dependences like PyoConnect, Numpy, PyWavelets, Scikit learn and Pygame window has to be installed. The data is recorded using a Sliding window approach. The window size is set as 50ms. When a set of samples are generated for a particular gesture, the window size gets modified such that new window size takes the samples from half the preceeding size onwards . For example let the size of the window be 100ms and the data is recorded between 0 ms and 100ms. Then the window size is resetted such that it takes the sample from 50ms to 150ms. This procedure goes on and it is performed for each gesture which is recorded about 2 seconds. These raw EMG signals are displayed using Pygame Window tool.

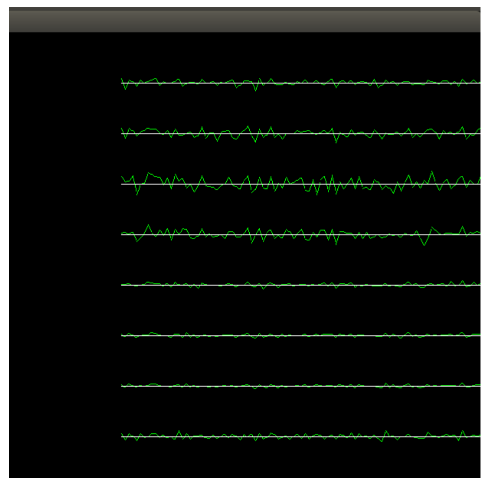

Fig. 4: Raw EMG signal for the gesture WAVEOUT

Since the data is generated as Bluetooth packets, the payload field of the packet is unpacked which are integers and is given as input to the discrete wavelet transform for converting the EMG data into wavelet coeffients. Myoband has 8 sensors and each of these sensors generated about 7 coefficients. The maximum level of decomposition is five and the data is decomposed at level 3 since the wavelet can be recreated back using the coefficients. A total of 56 coefficients are generated for each sample. Each of the coefficients generated from the sensors forms the dataset and is saved as a .csv file. These coefficients are the input features for classification purpose. In addition to these 56 features, label name with label number is also provided per gesture: Rest-0, Fist -1, Wavein- 2,Waveout-3, Fingerspread-4.

Scikit learn (Sklearn) which is an open source tool for data mining is used here for implementing classification. Implementation of SVM from Sklearn is an implementation based on libsvm. The dataset is first loaded and the labels are seperated from the coefficients. Then the data and the coefficients are splitted for training and testing purpose. The

	AP	AQ	AR	AS	AT	AU	AV	AW	AX	AY
1	41c	42c	43c	44c	45c	46c	47c	48c	49c	50c
2	-1.06066	-2.82843	-1.76777	-1.41421	-0.35355	0	-1.41421	-0.35355	-2.82843	2.82843
3	-1.76777	-1.41421	-0.70711	-1.41421	0	-1.41421	0.70711	0.35355	-2.82843	3.18198
4	-1.76777	-2.82843	-0.70711	1.06066	-0.70711	-1.06066	-1.06066	-1.76777	-1.41421	2.82843
5	-1.06066	-1.41421	-1.76777	-1.06066	-1.41421	-1.76777	-3.18198	-0.70711	0	2.12132
6	-1.76777	-2.82843	-2.12132	-3.18198	-0.35355	-1.41421	-2.82843	-1.06066	-2.82843	2.47487
7	0	-1.41421	-1.76777	-2.12132	-1.76777	-2.47487	0	-1.06066	0	4.24264
8	-1.41421	-2.82843	-2.47487	0.35355	-1.41421	0.70711	-2.47487	-1.76777	-1.41421	1.76777
9	-1.06066	-1.41421	0.35355	-2.82843	-1.76777	-1.06066	-0.35355	-0.70711	-1.41421	3.18198
10	-2.12132	-4.24264	-0.70711	-0.70711	-0.70711	-2.12132	0	-2.12132	-1.41421	3.53553
11	-2.12132	-2.82843	-1.41421	-1.06066	-2.12132	-0.35355	0	-2.12132	-1.41421	3.53553
12	-1.41421	0	-0.35355	-0.70711	-1.76777	-2.82843	-1.76777	0.35355	-1.41421	1.06066
13	-3.88909	-2.82843	-3.18198	-1.06066	0.35355	-0.70711	-1.76777	-1.06066	-1.41421	2.47487
14	-2.12132	-2.82843	-0.70711	-1.41421	-0.70711	-2.82843	0.70711	-0.70711	-1.41421	2.82843
15	-1.76777	0	-2.12132	0	0	-2.82843	-2.47487	-2.12132	-1.41421	3.53553
16	-3.53553	-5.65685	1.06066	0.35355	-1.41421	-3.53553	-2.12132	-1.76777	-8.48528	7.42462
17	0	-1.41421	-3.88909	-2.82843	-4.24264	-1.76777	0.70711	-1.06066	2.82843	4.94975
18	-0.70711	-2.82843	-1.06066	-1.06066	-1.06066	2.82843	-1.76777	-2.12132	2.82843	11.31371
19	-1.41421	0	0	-0.35355	-1.76777	-1.76777	-1.06066	-2.47487	-4.24264	8.13173
20	0.35355	-1.41421	-2.47487	-1.41421	-1.76777	-0.70711	-2.12132	2.12132	-9.89949	9.54594
21	0.70711	-4.24264	2.12132	-3.88909	0.35355	0	-3.53553	-0.70711	8.48528	9.54594
22	-1.06066	-4.24264	-1.41421	-1.76777	0.35355	-3.53553	1.76777	-2.82843	-12.72792	3.53553
23	0.70711	-1.41421	-4.94975	-1.41421	-1.76777	-2.12132	1.06066	-3.18198	-1.41421	5.3033
24	-0.70711	-2.82843	-0.70711	2.12132	-5.65685	0	1.41421	0.70711	1.41421	2.12132
25	-2.47487	1.41421	-0.70711	1.06066	1.06066	-0.35355	-3.88909	0.35355	-5.65685	12.37437
26	-3.18198	-4.24264	1.41421	-4.94975	-2.47487	0.70711	-1.76777	-2.82843	-7.07107	12.72792
27	1.41421	-2.82843	0.35355	-1.41421	-3.88909	-3.88909	2.47487	2.82843	1.41421	8.13173
28	1.41421	0	-4.24264	3.53553	3.53553	-0.70711	-4.94975	-0.70711	-4.24264	9.19239
29	-2.47487	0	-1.06066	-4.94975	0	-0.70711	-3.53553	2.82843	1.41421	8.48528
30	-2.12132	-2.82843	0	-1.76777	1.06066	-3.18198	2.12132	-0.70711	5.65685	10.6066
31	-3.88909	-2.82843	-4.94975	2.12132	0.70711	-6.36396	3.88909	-3.53553	4.24264	8.48528
32	-2.82843	-1.41421	-7.07107	4.24264	-3.53553	-3.53553	4.94975	-3.53553	-4.24264	6.36396

Fig. 5: Dataset with wavelet coefficients

data is splitted such that 80% is used for training and the remaining 20% is used for testing.

Total no of data	Training data	Testing data
335	268	67

Fig. 6: Training and Testing data

Figure 5 is the dataset in .csv format where each column represents the coefficients generated by each sensors for different gestures. It is with this dataset the SVM model with linear kernel is built by splitting data for training and testing purpose. Thus the accuracy obtained is 83%.

VI. CONCLUSION

This work focuses on gesture recognition which uses EMG signal taken from muscles of human body. These signals which are complex in nature are handled using the signal processing technique called Discrete Wavelet Transform and the advantage of this technique is that it performs a lossless decomposition which retains all the frequency components contained in the signal. The coefficients generated are classified using the supevised classification technique called Support Vector Machines which works well with data in different dimensions and a dataset with fewer samples. An accuracy of 83% is achieved for a dataset with 335 samples containing different gestures.

VII. APPLICATION

EMG signal with the concepts of Signal Processing using Discrete Wavelet Transform and Classification using Support Vector Machines can be deployed as an industrial application called Workers Safety problem where the Myoband can be used to measure the strain experienced by the workers in lifting up heavy goods thereby determining if the worker is prone to danger or not.

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