Classification of EMG signals

B.Tech Minor Project

Submitted in partial fulfilment of the requirements

for the degree of B.Tech Computer Science and

Engineering

By

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APPROVAL SHEET

By the B.Tech Final Year Student

I hereby *declare* that the Major Project entitled **“Classification of EMG Signals”**, which is being submitted to the ***Amity University, Patna*** in partial fulfilment of the requirements for the award of the Degree of ***Bachelor of Technology*** in ***CSE*** is a *bonafide report of the Project work carried out by me*. The material contained in this thesis has not been submitted to any University or Institution for the award of any degree.

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Date: December 01, 2023

CERTIFICATE

This is to *certify* that the Research Thesis entitled **"Classification of EMG Signals"**, submittedby **Aman Kumar Singh** as the record of the research work carried out by them, is *accepted* as the *Research Thesis submission* in partial fulfillment of the requirements for the award of degree of ***Bachelor of Technology***.

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ABSTRACT

The use of electromyogram (EMG) signals to recognise hand and finger gestures has grown. The majority of research, however, have concentrated on wrist and whole-hand motions rather than individual finger (IF) movements, which are thought to be more difficult. In this paper, we use machine learning techniques to build EMG-based hand/finger gesture classifiers based on fixed electrode placement.

Various authors have published their papers that proposed different models for many hand andarm movements recognition. In which there are some prominent classification models such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Random Forest, Decision Tree etc.

The current study on EMG-based hand gesture categorization confronts obstacles such imprecise classification, poor robustness, and insufficient generalisation. In order to solve these issues, this article suggests using a convolutional neural network (CNN) deep learning model to categorise an EMG dataset made up of 8 types of hand motions.

10 volunteers who were consistently seated with their arms supported provided the EMG signals. According to the findings, K-Nearest Neighbor and convolutional neural networks both produced average classification accuracy rates of 81.60 percent and 83.2 percent, respectively (CNN). The investigation has revealed that the proposed approach, CNN, has categorized the data the most properly.

Finger movement identification is an important innovative interfacing method which has count-less possible applications. It can be used to create a new age in human computer interfacing (HCI) devices. It can also be applied to medical applications, such as in the development of a more advanced prosthetic hand. The current research for this purpose includes methods such as computer vision and detecting finger motion through mechanical vibrations from skin surface. They have the limitation of being restrictive, in terms of the degree of movement that the hand is allowed from a certain optimum position, as well as being susceptible to environmental factors. In this study the response at the flexor carpi radialis muscle of the forearm is plotted for a group of subjects to observe the qualitative responsiveness of the EMG to different types of finger movements. The results show that finger movement generates a corresponding response on the EMG electrodes. For the particular muscle being studied, the greatest individual digit amplitude response was observed for the ring finger (digitus annularis) across the subjects. In future studies, this research could be made more quantitative in nature by observing the frequency content of a variety of hand gestures across a sample of subjects.

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Contents

Chapter 1

Introduction

With the advancement of technology, people have attempted to create robots that can perform the same tasks as humans. People sometimes employ these robots to replace lost limbs, and they also use remote control to manipulate robot arms. EMG signals are now being used to move more robots.

Electromyograms (EMGs) have been used for many years to operate prosthetic hands and wrists. Theoretically, different movements may be controlled by using EMG data obtained from certain muscles connected to hand and finger gestures. However, due to the intricacy and delicacy of muscle activation for IF motions, individual finger (IF) gestures are thought to be harder to categorize than whole-hand and wrist gestures. The majority of finger gesture prediction algorithms are expensive and sophisticated since they rely on EMG inputs from several channels. Because of these factors, many earlier research concentrated on categorizing whole-hand or wrist gestures; however, more recent improvements in computing power and machine learning methods have made it possible to categorize IF motions with a small number of channels without sacrificing the accuracy orresponse time.

The amplitude of an EMG signal with a stochastic structure and a Gaussian distribution function ranges between 0 and 10mV (peak-to-peak) or 0 and 1.5mV. (RMS). Clinical diagnosis, assistive devices (prosthetic limbs), and electrical stimulation all employ EMG signals to provide information about muscle movements.

Movements related to muscle groups that are damaged or not-functioning can be classified if EMG data from robust muscle groups is processed using appropriate methods. Thus, control signalcan be generated to control an artificial limb. Hand opening and closing movements in the prosthesiscan be done with little knowledge of the control signal. The control signal will increase when thereis a lot of movement, the classification rate will decrease.

Studies on biological signals have provided interpretation of EMG signals and new methods for modeling and classifying hand movements. A control system must have accurate, intuitive control and acceptable response time to be successful. It is necessary for the control system to operate with almost 100% accuracy so that the user can perform the desired movement. The response time of the control system should be short enough for the user to understand. Experts have been working on prosthetic limb applications that have been able to respond more quickly and functionally. They focus on classifier success for rapid response time and functional prosthesis mechanics. It is aimed to develop algorithm that operate with fairly high accuracy and as short as possible. One of the advantages of myo-electrically controlled prostheses is taking advantage of the fact that even the disabled people who have lost some of their limbs can flex stump muscles voluntarily.

The basic concept of a prosthesis that can be controlled by muscle impulses dates back to the 1940s. Bottom-ley proposed that signals from the muscles in the amputed limb's residual region be perceived in prosthetic studies. Suzuki has also researched on controlling multifunctional prosthesis using small electrodes implanted in the body.

In this study, the data used features from EMG signals are extracted by statistical methods. Extracted features are classified by CNN. The highest accuracy is obtained average 83.2%.

Chapter 2

Related Works

According to [6], the author state that on the basis of the results, the classification accuracy was achieved an average 80.60% by using K-Nearest Neighbor, average 81.84% by using Linear Discriminant Analysis (LDA). As a result of the analysis, it has been detected that LDA has classified the most accurately.

A method for identifying finger movements using the wavelet transform of a multi-channel electromyography (EMG) data is provided in the publication [13]. The analysis of the surface EMG signal using the wavelet transform's many resolutions is the initial stage. The feature values are then imported into an artificial neural network (ANN) in order to recognise the finger motion.

According to [20] EMG signal carries valuable information regarding the nerve system. This study clearly points up the various types of EMG signal analysis techniques so that right methods can be applied during any clinical diagnosis, biomedical research, hardware implementations and end applications.

According to [12] Convolutional neural networks (CNN) is a recently emerging artificial neural network structure. Because it is using CNN in image and speech recognition to better test results, so this algorithm is widely spread and applied. CNN is the most commonly used fields of computer image recognition, but because of its constant innovation, has been applied to video analysis, drug analysis, natural language processing and other fields.

In this research paper [7] [14] [19] [21],researchers have developed a technique using wavelet transform to classlfy single motor unit (SMU) potentials and to decompose EMG signals into their constituent SMU potentials.Their technique is designed for decomposition of multi-unit EMG signals with serious waveform superimposition. Therefore, it is not suitable for on-line analysis. In general, the degree of human involvement depends on the number of active SMU potentials recorded in EMG signals.

In this paper [22], a hybrid CNN model is introduced for hand gesture classification using sEMG data. The proposed modelis a combination of Slow-Fusion and Inception models. There are two Inception modules in parallel at the beginning.First Inception module fed by the information of 4 electrodes and the second Inception module fed by the rest of the electrodes. To fed parallel CNN's with split data is the common behavior in Slow-Fusion architecture. Then the outputsof the inception models are fused throughout the network. The 3D input feature maps are constructed by STFT of allelectrodes time-series raw data. The experimental results demonstrate that the proposed method yields 83.97% accuracyand 0.027 standard deviation. Moreover, it was denoted that the introduced model is more successful than Slow-Fusionand Inception models using alone.

According to this paper [10], Results showed that among time domain features, the first derivative of time samples exhibit the best separability. Discrete Fourier transform coefficients offered the best separability among frequency domain features. However, neither morphological nor frequency domain techniques outperformed time domain features. Using principal component analysis slightly improved the results, but it is time consuming.

The purpose of this research [2] is to select the best features to have a high rate ofmotion classification for controlling an artificial hand. Here, 19 EMG signalfeatures have been taken into account. Some of the features suggested inthis study include combining wavelet transform with other signal processingtechniques. An assessment is performed with respect to three points of view: (i)classification of motions, (ii) noise tolerance and (iii) calculation complexity.The energy of wavelet coefficients of EMG signals in nine scales, and thecepstrum coefficients were found to produce the best features in these view.

According to this [17],Surface electromyography recordings of skeletal trunk muscles are commonly contaminated with spike shaped artifacts. This artifact originates from electrical heart activity, recorded by electrocardiography, commonly present in the surface electromyography signals recorded in heart proximity.Limitation are -Relatively higher fluctuations of the ECG signal during sEMG recording were not taken into account in this study.

According to papers [3],[4],[26] the EMG signal of finger gestures is more difficult to be analysed than the EMG signal from hand gestures that conducted in previous study. This is because the position of muscles that connect to certain finger are close each other. Once a certain finger was moved, the other muscle may also be moved. Therefore the accuracy result of classification of finger gestures especially for thumb finger is less than the classification accuracy of hand gestures.

[5] [1] states that the system determines the type of grasp a human subject is willing to use, and the required amount of force involved, with a high degree of accuracy. This represents a remarkable improvement with respect to the state-of-the-art of feed-forward control of dexterous mechanical hands, and opens up a scenario in which amputees will be able to control hand prostheses in a much finer way than it has so far been possible.

According to [23] [9] Artificial Neural Network provide 60.34% accuracy, Logistic Regression provide 60.00% accuracy, Random Forest provides 58.00% accuracy and Support Vector Machine provides 56.00% accuracy but our CNN model provides 83% accuracy which signifies CNN is the best model to classify the signals.

The result of this paper [8] [18] show that 1) it is possible to identify distinct areas of sEMG activity on the forearm for different fingers; 2) hand position influences sEMG activity level and spatial distribution.

According to [24] [11] Wavelet Transformation is best method for feature extraction and to classify EMG signals into normal, neurogenic or myopathic, multilayer perceptron neural networks (MLPNN), dynamic fuzzy neural network (DFNN) and adaptive neuro-fuzzy inference system (ANFIS) based classifiers were compared and it was found that ANFIS modelling is superior to the DFNN and MLPNN in at least three points: slightly higher recognition rate; insensitivity to overtraining; and consistent outputs demonstrating higher reliability.

For gesture recognition problem, this paper [15] proposes a gesture recognition method based on Convolutional neural networks. Convolution neural network in the processing of two-dimensional images, through the layer of convolution and down sampling operation, you can extract the image of the structural features.Experiments have showed that this method is effective and good prospects of convolutional neural networks in gesture recognition. The feature that CNN recognizes is usually a spectrogram.

Chapter 3

Background of EMG

An aggregate electrical signal collected from any organ and referred to as a "biomedical signal" denotes a physical variable of interest. The amplitude, frequency, and phase of this signal, which is often a function of time, can be used to describe it. The EMG signal is a type of biological signal that gauges the electrical currents produced by contracting muscles, which are a representation of neuromuscular processes. Muscle contraction and relaxation are always under the direction of the neurological system. In light of this, the EMG signal is a complex signal that is managed by the nervous system and is reliant on the anatomical and physiological characteristics of muscles.

The EMG signal picks up noise as it passes through various tissues. Additionally, the EMG detector gathers signals from many motor units simultaneously, especially if it is near the skin's surface, which might result in signal interaction. The ability to detect EMG signals using strong and sophisticated techniques is quickly becoming a crucial necessity in biomedical engineering. EMG signal analysis is mostly used for clinical diagnostics and biological applications, which is why there is interest in this field. One of the key application areas is the field of management and rehabilitation of motor disability. An important source of data for the diagnosis of neuromuscular disorders is the form and firing rate of Motor Unit Action Potentials (MUAPs) in EMG signals. The nature and features of the signal may be fully understood, and hardware implementations can be built for a variety of EMG signal-related applications, if suitable techniques and methodologies for EMG signal analysis are easily accessible. Up to this point, substantial research has been done in the field, leading to the development of improved algorithms, the improvement of current approaches, and the advancement of detecting techniques to lessen noise and obtain precise EMG signals. For prosthetic hand control, grip recognition, and human-machine interface, few hardware implementations have been made.

Artificial Intelligence (AI) and various mathematical methods have drawn a lot of interest. Wavelet transform, time-frequency techniques, Fourier transform, Wigner Ville Distribution (WVD), statistical measurements, and higher-order statistics are a few examples of mathematical models. Artificial neural networks (ANN), dynamic recurrent neural networks (DRNN), and fuzzy logic systems are examples of AI methods for signal recognition. The mapping of EMG signals to desired hand gestures has also been accomplished using evolvable silicon chips and genetic algorithms (GA). A non-stationary signal like an EMG is ideally suited to the wavelet transform. Using a time-frequency method with WVD in hardware would make it possible to create a real-time tool for biofeedback circumstances that can be utilized for training certain motor units. Due to the special qualities of HOS utilized, higher-order statistical (HOS) techniques may be employed to analyze the EMG signal. We have used CNN in our proposed classification method as Convolutional neural networks (CNN).

[12] are a kind of artificial neural network that has just recently become more well-known. Since this method employs CNN for picture and speech recognition to enhance test results, it is extensively utilised and put into practise. CNN is one of the most extensively used computer image recognition techniques, but because to its continual innovation, it has also been used in video analysis, drug analysis, natural language processing, and other fields. The most recent AlphaGo match on the network utilises the CNN algorithm, which gives a computer remarkable capacity to read and advance.

The convolution neural network technique, which is based on deep learning, has a local perception area, a hierarchical structure, a feature extraction and classification process, as well as other features that enable it to automatically learn the proper characteristics and classification, which has had a very positive practical impact in the area of image recognition. The characteristics of gesture images are all embodied in the differences of different gesture types and the spatial information of gestures.
In order to completely characterise the gesture images in this paper, skin colour modelling and convolution neural network are also employed. An image feature can maintain the spatial connection of the original signal and improve its properties while lowering noise with the aid of the convolution process. You may reduce the amount of data that has to be processed while preserving the invariance, displacement, scaling, and distortion characteristics of the original signal by employing the local correlation principle of the picture and subsampling. Experiments show that the strategy provides good recognition outcomes.

CNN doesn't like how conventional algorithms handle each input pixel. However, the neural network may observe the images by improving the continuity of picture information rather of seeing a point for each processing tiny pixel region. Convolution neural network improves picture knowledge concurrently. CNN's volume filter continually gathers picture data, but the data is never more than a tiny percentage of the total pixels in the image. separating edge information from an image group and edge information from the overall image of information.

Chapter 4

Data Set

The Datasets that we have gone through are-

4.1 UCI Machine learning repository(EMG data for gestures Data Set)

Relevant Paper with this databese is [16].

4.1.1 Data Set Information:

We utilised a PC with a Bluetooth receiver and a MYO Thalmic bracelet that was worn on the user's forearm to record patterns. Eight sensors evenly placed around the forearm are included inside the bracelet, which concurrently capture myo-graphic signals. The signals are sent to a PC through a Bluetooth link. We show 36 individuals' raw EMG data as they made a series of static hand gestures. Two series are performed by the subject, each consisting of six (or seven) fundamental motions. The duration of each motion was 3 seconds, with a 3 second break in between each gesture.
There are around 40000–50000 recordings in each column (30000 listed).

4.1.2 Description of raw data file :

There are 10 columns in each file: 1) Time: Time measured in milliseconds; 2-9) Channel: Eight EMG channels on the MYO-Thalmic wristband; 10) Class: The name given to the gestures: Unmarked data (0), a hand at rest (1), a hand clenched in a fist (2), a wrist stretched (4), radial deviations (5), ulnar deviations (6), and an extended palm (7)- (the gesture was not performed by all subjects).

4.2 UCI Machine learning repository(EMG dataset in Lower Limb Data Set)

4.2.1 Data Set Information:

Protocol:

There were 22 male patients, 11 of whom had previously had professionally identified knee problems. To examine the behaviour related to the knee muscle, they do three movements: walking, leg extension from a sitting posture, and bending of the leg upward. Four electrodes (Vastus Medialis, Semitendinosus, Biceps Femoris, and Rectus Femoris) and a knee goniometer were used in the acquisition procedure.

Instrumentation :
These data were collected directly to the computer's MWX8 internal storage with a microSD card and transmitted in Real-time Datalog software through a bluetooth adapter, with a 14-bit resolution and a sampling frequency of 1000Hz. Datalog equipment was used by Biometrics, consisting of 8 digital channels and 4 analogue channels, of which 4 were used for sampling and 1 for goniometry.

Data configuration:

The total number of electrodes is 4, corresponding to the time series one for each channel (1 to 4).Each series contains 5 shares or motion repetitions for each subject.

4.2.2 Attribute information :

Each data file contains 5 columns, organized as follows.
Segment Lower Limb
Channel Ch1 Ch2 Ch3 Ch4 Ch5
Muscle RF BF VM ST FX
Column 0 1 2 3 4

4.3 EMG data for gestures Data Set

4.3.1 Protocol:

With the aid of the programme nukleos, available on github at https://github.com/cyber- punk-me/, four motion classes were created from the MYO armband. Eight sensors on the skin surface of the MYO armband monitor the electrical activity generated by the muscles underneath. Classes for gestures were: rock (0), scissors (1), paper (2), and okay (3). Six 20-second recordings of each move were made. Every time, the motion was ready and in place when the recording began. The motion was still being held when the recording was interrupted. Each motion is maintained in place for a total of 120 seconds. They all took turns recording from the same right forearm for a brief period of time. Each recording for a particular class of gestures was combined into a.csv file with the associated name (0-3).

4.3.2 Attribute information :

There are 8 consecutive values from each of the 8 sensors in each dataset line. thus, EMG data in 64 columns. The action that was taken as a result of capturing the data is shown in the last column (classes 0-3) As a result, each line has the following format.

[8sensors][8sensors][8sensors][8sensors][8sensors][8sensors][8sensors][8sensors][GESTURE_CLASS]

A classifier given 64 numbers would predict a gesture class (0-3). Gesture classes were : rock - 0, scissors - 1, paper - 2, ok - 3. Rock, paper, scissors gestures are like in the game with the same name, and OK sign is index finger touching the thumb and the rest of the fingers spread. Gestures were selected pretty much randomly.

4.4 KAGGLE dataset

4.4.1 Data set description :

Then We finally decided and took dataset from kaggle, the data set contains data of 8 electrodes. The data is actually processed and the raw data is converted into 10 features for each of the electrode. The features are in the order
1.standard_deviation
2.root_mean_square
3.minimum
4.maximum
5.zero_crossings
6.average_amplitude_change
7.amplitude_first_burst
8.mean_absolute_value
9.wave_form_length
10.willison_amplitude
So the dataset contains 6,823 rows and 81 columns 80 columns is of features of 8 electrodes and the last column consists of labels such that-:
1 == index_finger
2 == middle_finger
3 == ring_finger
4 == little_finger
5 == thumb
6 == rest
7 == victory_gesture

Chapter 5

Traditional methods for decomposition of EMG Signals we read from the past literatures were:

The Fourier Transform

- The Fourier Transform provides frequency information of a signal that represents frequencies and their magnitude.
- It does not tell us when in time the frequencies exist. The transform is therefore, ideal for stationary signals.

The Short-Time Fourier Transform (STFT)

- The STFT was developed to overcome the poor time resolution of the Fourier Transform. It gives us a time-frequency representation of the signal.
- With STFT we can assume some portion of the non-stationary signal is stationary.
- We then take a Fourier Transform of each stationary portion along the signal and add them up.

Wavelet Transform Method

As the main advantages of wavelets is that -

- They offer a simultaneous localization in time and frequency domain.
- The second main advantage of wavelets is that, using fast wavelet transform, it is computationally very fast. Wavelets have the great advantage of being able to separate the fine details in a signal.

Then after analyzing all these two methods, we found Wavelet Transform Method to be the best suitable method.

Now we know how to fetch EMG Signals from the Human Body by using above methods, so we are now focusing on Finger Movement Detection and Neuro-Muscular Disease Detection.

1. **Finger Movement Detection Using SVM:**

   Aim for this classification using SVM was to use this Learning Model and get a data set which helps in Narcotic Tests. Since we know there are unwanted Hand movements in the case of person defected with Drug Addictions. So we can induce this Model along with other methods used by Narcotic Department to detect Person using Drugs.

   We used various SVM Models for this Classification like XGB, Random Forrest etc. and after analyzing we figured out that accuracy of XVG was around 90% and of Random Forest was 94%.

   So, we opted Random Forest Method for the Learning Model.

2. **Neuro-Muscular Disease Detection.**

   Aim is to making a SVM Model to detect Neuron-Muscular Diseases with better accuracy than previous algorithms. Since EMG is used for diagnostics of various Neuron-Muscular Diseases by Doctors. Also EMG Signal Analysis by Doctors is Time Consuming and Sometimes also inaccurate.

Current State of Project:

- Right now, i've trained SVM and classified Hand Movements EMG Signals.
- I am searching Data Sets of Neuron-Muscular Diseases. Since such data is highly classified and Research institutes don't easily share such data. Therefor i lagged behind in achieving this Aim to making a SVM Model to detect Neuron-Muscular Diseases with better accuracy than previous algorithms.

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