Machine Learning and Signal Processing Based Analysis of EMG Signals for Daily Action Classification

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FEBRAURY, 2021

Declaration

I certify that this research work titled "*Machine learning and signal processing based analysis of EMG signals for daily action classification"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Abstract

Daily life of thousands of individuals around the globe suffers due to physical or mental disability related to limb movement. The quality of life for such individuals can be made better by use of assistive applications and systems. In such scenario, mapping of physical actions from movement to a computer aided application can lead the way for solution. Surface Electromyography (sEMG) presents a non-invasive mechanism through which we can translate the physical movement to signals for classification and use in applications. Keeping this in view, this study propose a machine learning based framework for classification of 20 physical actions. The framework looks into the various features from different modalities which contribution from time domain, frequency domain and inter channel statistics. Next, we conducted a comparative analysis of k-NN and SVM classifier using the feature set for multiple normal and aggressive activities. Effect of different combinations of feature set has also been recorded. Finally, the SVM classifier gives an accuracy of 100% for 10 normal actions and 1-NN for a subset of features gives an accuracy of 98.91% for 10 aggressive actions respectively. Additionally, we use both SVM and 1-NN to propose a hybrid approach to classify 20 physical actions. The hybrid classifier gives an accuracy of 98.97% respectively. These finding are useful for algorithm designer to choose the best approach keeping in mind the resources available for execution of an algorithm.

Key Words: *Segmentation, Feature extraction, Time domain, Frequency domain, Feature concatenation, Surface Electromyography, Support Vector Machine, K-Nearest Neighbor, Hybrid Classifier, Physical Activities*

Table of Contents

List of Figures

List of Table

CHAPTER 1: INTRODUCTION

In the modern day, physical disabilities present a major problem to the daily life. The main reason behind this is the various factors that contribute to these disabilities. These factors include gait disorder or limb impairment due to aging process [1], occupational injuries or trauma such as sports accidents which hinder the quality of life. Stroke is another major cause of limb disabilities in adults [2]. Most of these sufferers may require partial limb support or prosthetics limb to elevate their daily suffering. Apart from these factors, neurological disorders are also a leading cause of accidents [3]. Epilepsy, a major neurological illness, is caused by irregular nerve cell activity in the human brain [4, which effects almost 50 million of people around the globe [5]. This brings to light the immense need for a system that can categorize the physical signals for either prosthetic limb design or timely notification of epileptic attacks for injury prevention.

In this regard, a possible solution is to somehow sense the intended motion and take decisions accordingly. Surface Electromyography (sEMG) has been characterized as the best non-invasive performer for activity analysis [6]. Electromyography (EMG) refers to the electrical activity recordings, which are produced as a result of skeletal muscles. Figure 1. shows a side by side comparison of sEMG signals collected against normal and abnormal activities such as clapping and elbowing respectively. These signals represent the biomarkers for analysis of physical action or movement of humans. This make sEMG useful in the identification of muscular system's ailments, improvement in the interaction between human and computer, clinical and biomedical applications discussed in [3, 10]. These signals can be examined to detect medical anomalies [7, 8], emotion detection [9], prosthetic arms, hand and lower limbs control [10].

Various methods includes preprocessing, feature extraction, feature selection, signal classification of an EMG signal i-e; discrete wavelet transform, empirical mode decomposition, principal component analysis etc. have been recommended by different investigators to analyze EMG signal.

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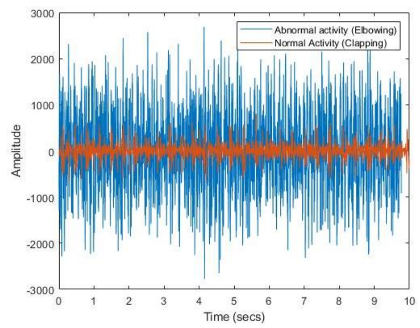


Figure 1-1: Raw sEMG for Normal and Aggressive activities signifying the difference

In this thesis, we investigate sEMG signals collected against 20 physical actions from a set of 5 subjects. The physical activities are divided into 2 sub-groups depending on the nature of action as aggressive or normal. We then investigate various signatures of the sEMG signals that can be used to differentiate between the 20 actions. Using these signatures we propose a new classification framework which can identify multiple physical actions using sEMG signals. In the proposed approach, a window of raw sEMG signal is initially pre-processed to enhance the variability between signals of normal and abnormal activates. The processed window is then forwarded to feature extractor where, among the well-known features for EMG, Time domain statistics, inter channel statistics (correlation and covariance) and frequency based signatures for classes are also calculated. The features from different modalities are then concatenated to make a feature vector which is then subjected to and is finally fed to a classification model that is comprises of optimized KNN and optimized SVM classifier to provide us with the output label of the signal. The proposed methodology results in high classification accuracy even with use of a simple classifier and lower number of features as compared to previous methods.

1.1 Motivation

Currently, Physical impairments become problematic in the world because of several reasons. For example, the getting old takes along difficulties such as abnormality in the way of walking and limb impairments leading to decrease the quality of life. Next various kinds of severe accidents like occupational based trauma and sport based injuries commonly make the individuals either fully or partially disabled. According to World Health Organization, around 15% of the population around the globe survives with various form of disability, of which 2–4% people experience major complications in working. This brings to light the immense need for a system that can categorize the physical signals for either prosthetic limb design or timely notification of epileptic attacks for injury prevention. In this regard, a possible solution is to somehow sense the intended motion and take decisions accordingly. Therefore, this effective technique might help the specialists in defining aggressive activities to observing patients. This can support in the field of healthcare to develop activity monitoring on EMG Signals.

1.2 Problem Statement

Physical activity recognition, which is a key component in developing an exoskeleton robot control system, prosthetic arm controls and to identify certain deformities of the musculoskeletal system. However, the challenge is aimed at making use of digital signal processing and machine learning in the identification of physical activities based on surface EMG signal. The aim of this study is to plan an effective algorithm for the classification of multi-class physical actions.

1.3 Aims and Objectives

Following are the objectives of this study as shown below:

- To use signal processing for processing of raw signals and noise removal
- To analyze EMG signals using signal processing techniques to extract useful features
- To use machine learning to develop a complete system intended for the investigation and classification of EMG signals

1.4 Structure of Thesis

The remaining research work is organized in the following manner:

Chapter 2 covers the analysis techniques regarding human muscles

Chapter 3 gives review of the up-to-the-minute algorithms proposed by researchers for detection of physical activity using EMG signals.

Chapter 4 consists of the proposed methodology in detail. It includes dataset explanation, feature extraction of EMG signals followed by their classification

Chapter 5 introduces the database used for assessment purpose. All the experimental results are discussed in detail with all desired figures and tables.

Chapter 6 concludes the thesis and reveals future scope of this research

CHAPTER 2: MUSCLES ANALYSIS TECHNIQUES

Human muscle is the tissue of the body which essentially has the capacity as a source of control. Muscles permit an individual to move, talk and chew. They control pulse, digestion, and breathing. Other apparently irrelevant capacities like temperature controls and vision too depends upon the muscular system of the human body. The muscular framework contains more than 600 muscles that work together to empower the total working of the body.

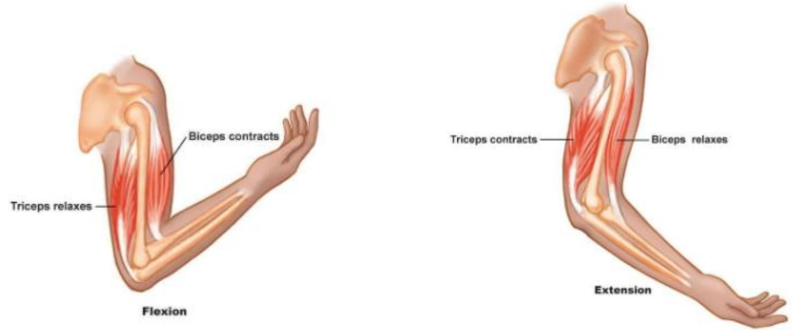
2.1 Types of muscles:

There are three types of muscles:

2.1.1 Skeletal muscle

Skeletal muscles are the muscles that are related to the skeletal development of the body and can be controlled deliberately. They are connected to bones, and contracting the muscles causes development of those bones. Some physical activities include running, standing, seating, walking etc. are the examples of use of these muscles. These muscles are regularly existing in sets, whereby one muscle is the essential mover and other act as the auxiliary mover. In addition, once you twist your arm, your biceps contracts whereas your triceps is relaxed. When your arm returns to the stretched situation it is the triceps that contracts and the biceps relax as shown in Figure 2.

Figure 2-1: Skeletal muscle, voluntary [11]



(a) Flexion of human arm (b) Extension of human arm

Figure 2-2: An example of skeletal muscle [12]

2.1.2 Smooth muscle

Smooth muscle lines the interior of blood vessels and organs, such as the stomach, and is additionally known as visceral muscle. It is the weakest kind of muscle but has a fundamental part in moving nutrition along the stomach related tract and retaining blood circulation through the blood vessels. Smooth muscle acts automatically and it contracts slowly and rhythmically.

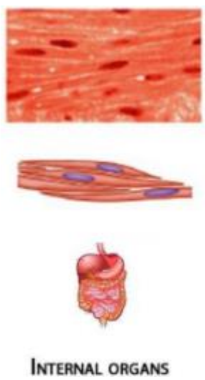


Figure 2-3: Smooth muscle, involuntary [11]

2.1.3 Cardiac muscle

This muscle is situated merely in the heart, it pumps blood everywhere in the human body. Cardiac muscle invigorates its own contractions that frame the pulse of human body. Signals from the nervous system regulates the level of contraction. This sort of muscle is strong and acts unwillingly.

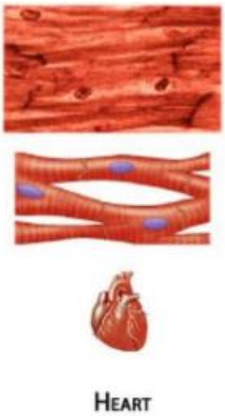


Figure 2-4: Cardiac muscle, involuntary [11]

2.2 Techniques to Analyze Muscles

Human muscles can be analyzed using different techniques:

2.2.1 Imaging techniques

Historically, imaging techniques include Magnetic Resonance Imaging and Computed tomography plays an important role to diagnose and monitor the diseases which are related to muscles such as myopathies and muscular dystrophies. Figure-6 shows the musculoskeletal MRI that protects the overall body which contain joints, bones, and soft tissues.

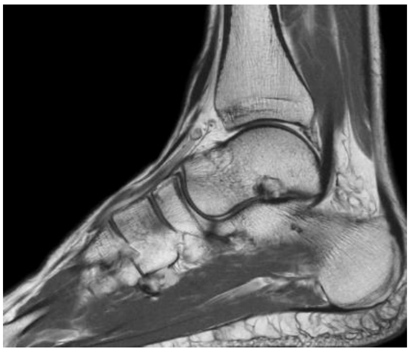


Figure 2-5: musculoskeletal MRI of sportsman foot [13]

2.2.2 Mechanomyography

Mechanomyography (MMG) has been mostly connected in clinical and experimental practice to examine the muscle characteristics including the functionality of muscle, prosthesis and/or switch control, signal processing, medical rehabilitation, and physiological workout. It is the technique which is used for evaluating and recording the mechanical signal from the muscle's surface when the muscle is contracted. In [14] the sensor was placed on the muscle. Figure-7 shows that the device's (which is utilized for measuring the acoustic waves created by contracting muscles strands) lodging is filled with fluid as the transmitting medium to convey the MMG signal powerfully.

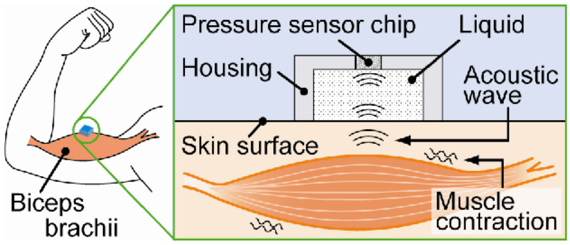


Figure 2-6: Conceptual view of Mechanomyogram [14]

2.2.3 Electromyography

Electromyography is a procedure that is used for measuring and recording the electrical action produced by skeletal muscles to recognize the variations between the nerves and muscles. It is implemented using a tool known as Electromyograph, to generate a record called an electromyogram. In qualitative analysis of EMG signal graphical examination of the record is concerned whereas amplitude, duration, frequency, power spectrum analysis takes place in the quantitative analysis of EMG signal. The EMG apparatus comprises of electrodes (can be skin electrodes or needle electrodes), an amplifier of high gain having 10-5000Hz which is attached to an oscilloscope and EMG is best prepared in an extraordinary constructed protected room to avoid intrusion. EMG is applicable in the clinical diagnosis of myopathies, neuromuscular disorders, human machine interaction, prosthesis control, kinesiology etc.

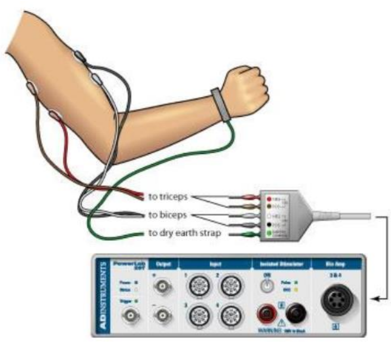


Figure 2-7: Electromyography

Electromyography is divided into two types:

2.2.3.1 Surface Electromyography

Surface EMG is a procedure in which electrodes are positioned on (not into) the skin spread over the surface of the muscle to identify the electrical movement of the muscle. It is also named as Intermuscular electromyography. It has various striking features like it does not include penetrating the skin and does not wounded. The main advantage of surface EMG is that it is quick, easy to apply and no medical supervision or certification is required. It is generally used only for superficial muscles.

Figure 2-8: Surface electromyography

2.2.3.2 Intramuscular Electromyography

Intramuscular EMG signals are identified with needles or cables injected into muscles. With regard to non-invasive methods, intramuscular electromyography has great discrimination for person's motor unit action potential (MUAP) and is therefore used to measure motor unit activity. The main advantage of intramuscular electromyography that it is extremely sensitive, access to deep musculature, little cross talk concern and record single muscle activity. On the other hand, it requires medical personnel and certification and detection area may not be representative of the entire muscle.

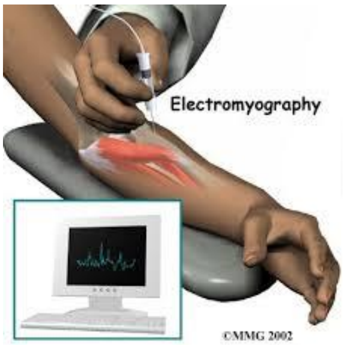


Figure 2-9: Intramuscular electromyography

2.3 Muscles diseases

2.3.1 Cerebral Palsy

Cerebral palsy is a brain damage causing decreased muscle control and usually occurs in young children. Characteristics contain muscle stiffness, involuntary activity, impaired speech and frequently paralysis. Figure 11 shows that the person suffering from cerebral palsy faces difficulty in using a mouse or keyboard.

Figure 2-10: This person affected with cerebral palsy [15]

2.3.2 Muscular Dystrophy

Muscular dystrophy is a hereditary disorder that causes dynamic feebleness and damage of muscle mass. In this illness, irregular genetic factor (mutations) interfere with the generation of proteins required to form healthy muscles. It can influence individuals at any age, but is most common in children. Assistive equipment include head wands, voice recognition software, mouth stick, adaptive keyboards etc.

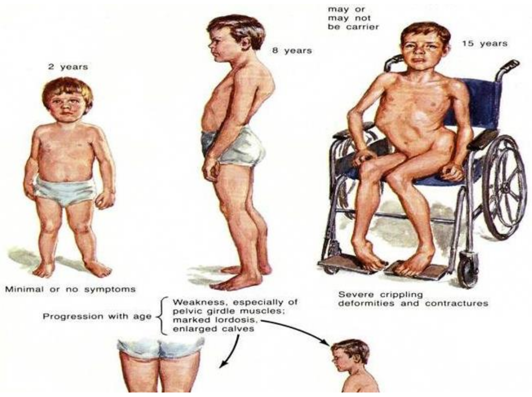


Figure 2-11: Progression of muscular dystrophy [16]

2.3.3 Multiple sclerosis

Multiple sclerosis is a possibly disabling syndrome of the human brain and spinal cord. It dissolves myelin (a layer of fatty tissue that encompasses nerve strands), blocking nerve fiber from conveying signals from the CNS to the muscles of the body. It impacts include tremors, feebleness, lack of feeling, slurred speech, unsteady walking, muscle tightness, disabled memory, and intermittent loss of motion.

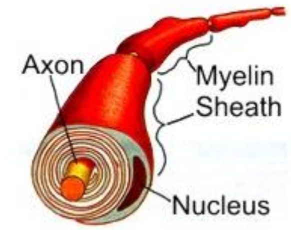


Figure 2-12: Multiple sclerosis [15]

2.3.4 Amyotrophic lateral sclerosis

Amyotrophic lateral sclerosis is a degenerative syndrome that stops neurons from sending impulses to the muscles. The muscle deteriorates over time, affecting ability in operating a mouse or keyboard and the situation may in the long run affects the muscles required for breathing, resulting in death. It symptoms include sluggishness in either movement or speech. Figure 14 differentiates between the normal nerve cell and the nerve cell that is affected with the ALS disease.

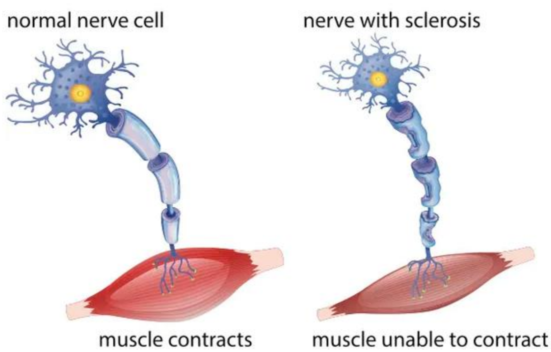


Figure 2-13: Amyotrophic lateral sclerosis [18]

2.3.5 Epilepsy

Epilepsy is a neuromuscular condition caused by the abnormal activity (abnormal firing of neurons) in the brain. Seizures take place when cluster of nerve cells in the brain signal unusually, which may temporarily change a person's awareness, movements or activities. There are numerous types of epilepsy (includes Nonappearance seizures, Tonic seizures, Clonic seizures, Tonic-clonic seizures, Myoclonic seizures, Atonic seizures etc.) which range in severity and each individual with epilepsy encounters it in an unexpected ways. Infectious diseases, Genetic influence, Head trauma, Pre-birth injury, Brain illnesses, developmental disorders are the various causes of epilepsy. Other risk factors include past head injuries, dementia, Brain infections, Stroke, seizures in childhood etc. Electroencephalogram (EEG) and different neurological imaging studies includes functional MRI, Magnetic Resonance Imaging, Positron emission tomography, Single-photon emission computerized tomography and Computed tomography are the tools used for the diagnosis of this ailment.

2.3.6 Parkinson's disease

This disease is a progressive brain clutter that leads to shivering, firmness, and trouble with walking, stability, and coordination. One strong possibility for Parkinson's is age. It causes wild tremors and/or unbending nature within the muscles. The condition considerably hinders keyboard and mouse use. Once in a while, the voice is affected as well, to the point that voice acknowledgement program is not an alternative. The analyst of King's College London suggests that changes in the brain serotonin (a substance which have various purposes in the brain including, cravings, disposition, cognition, prosperity and development) levels comes to begin with -and seem act as an early caution sign portrays in Figure 15

Figure 2-14: Brain scans shows a fall in serotonin (blue/black area) as Parkinson's growths [19]

CHAPTER 3: LITERATURE REVIEW

The recent years have gotten an improvement in the categorization of EMG Signals in the field of exoskeleton robot control, prosthesis control, human machine interaction, diagnosis of the muscular diseases etc. For this purpose, researchers have applied machine-learning techniques for solving different problems related to physical activities. This chapter reviews some of the valuable contributions that have been made to this field.

Surface electromyography is a procedure that studies or identifies the electrical activity produce by human muscles to be familiar with the variations between the nerves and muscles. sEMG signal is an electrical action generated when nervous and muscular actions are recorded from the surface of human body using electrodes, which can redirect the real-time working of neuromuscular framework. By the way, how to expertly exact features from EMG signals to recognize correct examination of proceedings is the main problem to get precision of rehabilitation therapy or treatment and production of EMG-controlled prostheses.

Akhundov et al. [31], evaluates the quality of surface EMG signal by performing comparison of five different classifiers. They used both supervised and unsupervised artificial neural networks. Supervised classifiers includes adaptive neuro fuzzy inference system and probabilistic neural network whereas, Convolutional neural network, Alex-Net and ResNet50 were used as unsupervised classifiers. In this study, feature extraction takes place using discrete wavelet transform (DWT) in order to get root mean square, variance, mean absolute value, power spectrum ratio for the supervised learning algorithms. For all three CNNs they take an envelope extraction of an EMG signal and then transformed it to an Image for further processing. In the end, it was concluded that unsupervised ANNs perform better classification accuracy as compared to supervised artificial neural networks. They got the accuracy more than 98% based on unsupervised ANNs.

Duan et al. [32], elaborates the gesture motion recognition, the collection of EMG data takes place for 10 different hand gestures using Myo arm band. They introduced multi task learning and multi label classification concepts to increase the generalization ability for motion recognition system. On comparing both CNN and SVM, CNN performs better classification accuracy of 94.06% than SVM, it reveals good translation invariance. Subsequently, the spectrogram images attained by assessing SEMG signals which is used as an image to Convolutional Neural Networks.

Sezgin et al. [20], describes that EMG signal was analyzed using bispectrum (higher order spectra). The binary class EMG dataset (normal action or aggressive action) was taken from UCI machine learning repository. First they analyzed EMG signals based on bispectrum and after that QPCs of each EMG segment was calculated. Next, the features of the analyzed EMG signals were put into learning machines classifier in order to classify the EMG signals as either belonging to normal activity or aggressive activity. The performance comparison was based on artificial neural networks, linear discriminant analysis, logistic regression, support vector machine, and an extreme learning machine classifiers. The train-test ratio for ELM was randomly selected as 50:50 from the features extracted using EMG data. But, ELM is more efficient and gives higher classification accuracy of 99.75% as compared to conventional learning machines.

Mishra et al. [21], demonstrates the improved EMD (empirical mode decomposition) method in which traditional EMD technique followed by median filter to remove the impulse noise from intrinsic mode functions. Amplitude modulation bandwidth, spectral band power, frequency modulation bandwidth, and first derivative of instantaneous frequency are the features extracted from improved IMFs for the classification of ALS affected EMG signals and Normal EMG signals.

Jana et al. [23], discussed the discrimination of aggressive actions from normal actions based on ANFIS (adaptive neuro-fuzzy inference system). In this work, discrete wavelet transform is used for the extraction of features from EMG signals. The EMG signals decomposed using DB-4 (Daubechies) wavelet with level 5 and extracts the coefficient approximation. Approximate coefficients from the signals were used as input to the Adaptive Neuro Fizzy Inference System to classify the physical activities. They used the training testing ratio as 70:30. The classification accuracy of proposed method using features was found to be 98% for binary class problem.

Alaskar et al. [22], presented a novel approach in which three convolutional neural networks are assessed using the two time-frequency illustrations. The spectrogram and scalograms images are produced from surface EMG signals as the input dataset of CNNs. From the analysis, it can be proven that EMG signal representation affects the performance of CNNs. Time-frequency images are used as the input dataset to the convolutional neural network in order to distinguish between normal and aggressive action. As a result, this algorithm achieved the accuracy of 94.61% for a binary class problem.

Classification of physical actions as normal and aggressive actions using bispectrum analysis of an EMG signal. QPCs (quadratic phase coupling) are extracted and fed into the developed artificial neural network and the acquired accuracy of 86.25% is described in [27].

Turlapaty et al. [24], proposed an improved classification framework for the classification of multi-classes. The EMG dataset has been taken from ML repository. The dataset is composed of 20 physical activities i-e 10 normal actions and 10 aggressive actions. The ten normal actions includes bowing, hand shaking, hugging, clapping, etc. whereas the ten aggressive actions includes elbowing, hammering, headering, slapping, etc. The classification framework includes probabilistic neural network and subspace KNN. The features are extracted from different modalities includes time domain, inter channel correlation, improved frequency moment based features, and local binary patterns. After that, sequential forward feature selection technique is used to lessen the dimensions. The classification is performed using multiple classifiers like subspace KNN, probabilistic neural network, cubic SVM, gaussian SVM, functional KNN, Bagged trees and LDA with the selected subset of features. But, subspace KNN gives highest accuracy of 93.91% for 20 physical actions.

Sukumar, et al. [25], performs identification of ten normal physical activities like bowing, clapping, walking, waving, jumping, etc. of sEMG signal based on variational mode decomposition for the analysis of musculoskeletal syndrome. VMD decomposes the signal into several modes. These modes are used for the extraction of statistical features like coefficient of variance, zero crossing rate, standard deviation, entropy, mean and negentropy. Next, the extracted features are put in to multi class least square support vector machine with RBF kernel for the discrimination of 10 normal activities and the system achieved an accuracy of 98.17% as compared to existing methods.

Subasi, et al. [27], proposed an EMG pattern recognition system for the exoskeleton robot control and rehabilitation purpose. In this study, multi-scale principal component analysis is used for the de-noising of various EMG signals. The discrete wavelet transform based statistical features includes mean absolute value, Mean power, Standard deviation and mean absolute ratio have been extracted. The extracted features are then fed into the SVM with gaussian kernel. The experimental results shows that the proposed system got an accuracy of 92.27% for 10 normal classes.

Sravani, et al. [29], discussed an extreme learning machine (ELM) classifier based on flexible analytic wavelet transform (FAWT) for the classification of multi-class problem. FAWT decomposes EMG signals into eight sub bands. The following features includes negentropy, mean absolute value, variance, modified mean absolute value, Tsallis entropy, simple square integral, waveform length, integrated EMG are extracted from each sub band. After that these features are fed into the ELM classifier for the identification of 10 normal activities and the proposed algorithm achieves an accuracy of 99.36%.

Demir et al. [28], discussed another approach in which time-frequency Image is utilize as an input to pre-trained convolutional neural networks. Deep feature extraction is performed using Alex Net and VGG-16 whereas SVM is used for the classification of EMG based Physical activities. The highest accuracy of 99.04% for 10 normal activities includes bowing, handshaking, clapping, standing, seating, waving, jumping, hugging and walking etc. is achieved by the deep feature concatenation of fully connected layers of both Alex Net and VGG-16.

Table 3-1: Literature review summary of features extraction and classification techniques

Year	Author	Methodology	No. of classes	accuracy
IEEE (2019)	Turla paty et al. [25]	EMG signal segmentation->Feature extraction->concatenation->feature selection->classification Feature extraction: TD Statistics, Inter channel correlation, Log spectral moments, Burg spectral features, LBP Features	20	PNN->93% sKNN-> 94%
IEEE (2018)	Sukumar et al. [26]	EMG Signal decomposition->feature extraction of modes->classification (MC-LS-SVM with RBF kernel) Feature extraction: Entropy, Coefficient of variation, Mean, Negentropy, Zero crossing rate, Standard deviation	10 normal	98.17%
2019	Saravani et al. [30]	FAWT->Feature extraction->ELM classifier Feature extraction: IEMG, MAV, MAV1, SSI, VAR, Negentropy, Tsallis entropy, Waveform length	10 normal	99.36%
IEEE (2017)	Sahenbegovic et al. [27]	Bispectrum analysis of EMG signal to extract non-linear interactions-> analyze QPCs in order to detect and distinguish signal non linearity->estimation of QPCs->ANN	2	86.25%
IEEE (2017)	Jana et al [24]	DWT->ANFIS	2	98%

2015	Anil kumar et al [22]	EMD->Feature extraction->classification(LS-SVM) Feature extraction: Mean frequency estimation, Singular values computation	2	99.03%
2019	Demir et al. [29]	Spectrogram->Feature extraction->Deep feature concatenation->classification(SVM) Feature extraction: Alex-net, VGG-16	2	99.04% 98.65%
2012	Sezgin et al [21]	Bispectrum analysis-> QPC->ELM classifier	2	99.75%

CHAPTER 4: METHODOLOGY

In our proposed methodology, we stated the problem of Multi-class classification of physical activities which is based on the information of C-channels of sEMG signals. The proposed methodology, in this regard, is divided into pre-processing of RAW sEMG signals, feature extraction, feature concatenation and classification into M-classes. The system level flow diagram representing the proposed strategy is presented in Figure 4-1.

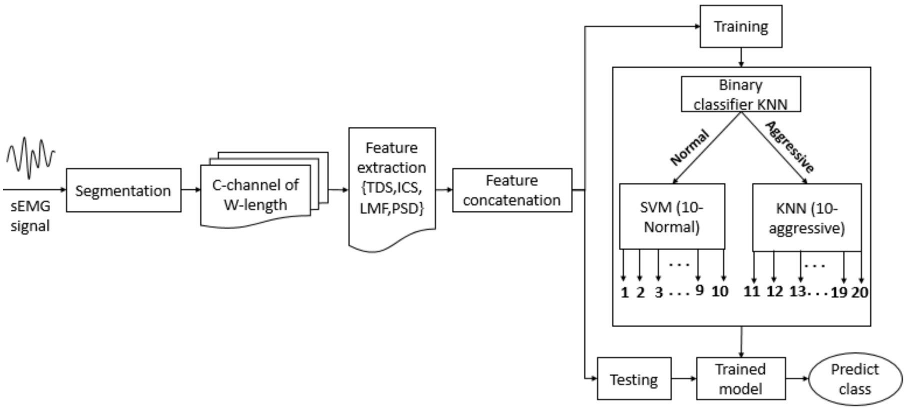


Figure 4-1: System flow diagram of proposed methodology

4.1 Dataset Information

This EMG data of Physical Activities has been taken from UCI machine learning repository [45]. The table 4-1 shows the class summary of this dataset. The details of dataset have been discussed in the results section.

Table 4-1: Class Information of UCI ML Dataset

Physical Activities	
Normal	Aggressive
Bowing	Elbowing
Handshaking	Front-kicking
Hugging	Hamering
Jumping	Headering
Running	Kneeing
Seating	Pulling
Standing	Punching

Walking	Pushing
Waving	Side-kicking
Clapping	Slapping

4.2 Data Preprocessing

4.2.1 Segmentation

The first step in our proposed methodology is to pre-process and segment out each channel of sEMG signal. In order to enhance the interclass variation between aggressive and normal actions W-length of windows has been taken. The length "W" of the window is controlled by the sampling frequency through which the concerned signal is acquired. Note that after segmentation now each C-channel sEMG signal is converted to Ns samples of length W having C-channels. Now feature extraction is performed on each of the sub-windows from every pattern.

Each signal is of approximately 10s with fs as 1kHz. The segmentation of signal is based on window (Rectangular) length of 1 second with an overlap of 25 milli seconds as shown in Figure 4-2.

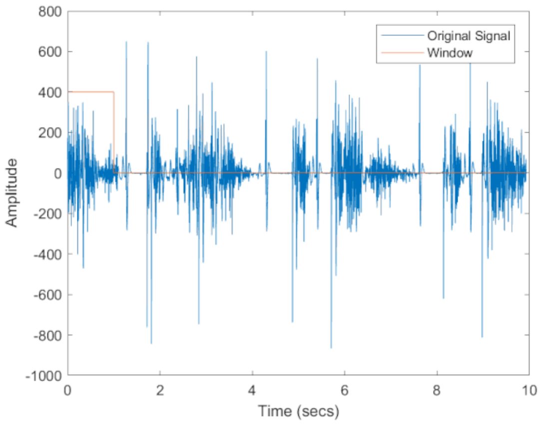


Figure 4-2: A segment of an EMG signal

For interclass variation (all aggressive and all normal) mean EMG signals are shown below.

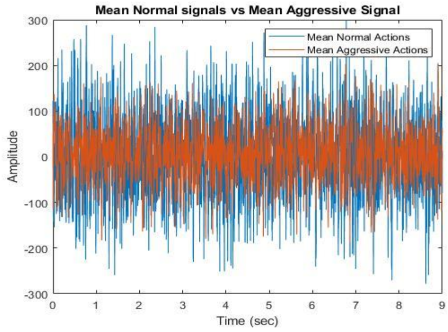


Figure 4-3: Mean Signal of Normal and Aggressive Action

4.3 Feature Extraction

The feature vector for our proposed methodology contains signatures from various modalities including Time Domain, Frequency Domain (Power spectral density and Log moment of Fourier spectra) and Inter-Channel Correlation and Covariance. In the subsections we elaborate on these features

4.3.1 Time Domain features

One of the most frequently used signatures is time domain analysis of an EMG signal. This modality shows that how a signal changes its parameters or shape with time as presented in the Figure 4-4.

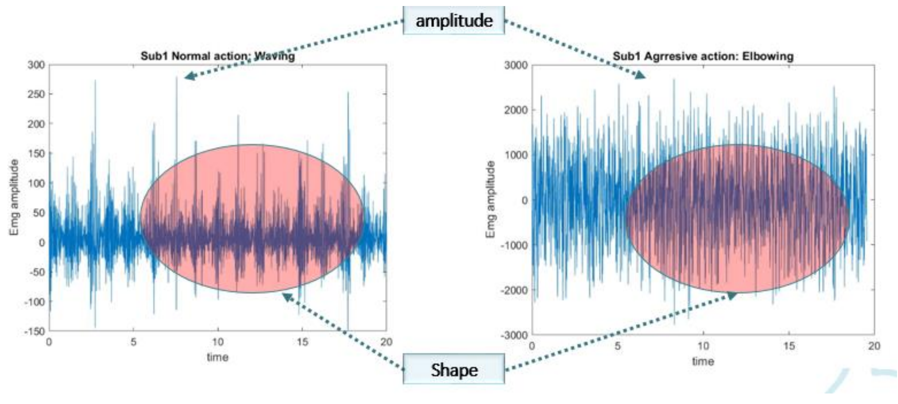


Figure 4-4: Time based analysis of an EMG signal

Following are the time domain features calculated for a surface EMG signal:

a. Amplitude

The maximum amplitude of the signal can be expressed as

$$\max\_\,amplitude = \max(|x_i|)^2$$

b. Root Mean Square

The RMS takes the square root of the mean power of an EMG signal for a certain period of time.

$$RMS = \sqrt{1/L\sum_{i=1}^{L}(x_i)^2}$$

Whereas, ‘L’ is the segment’s length and ‘x’ is the value of signal amplitude.

c. Variance

Variance of an EMG signal is used for evaluating the power of a signal, and it can be stated as

$$\text{var} = 1/L-1\left(\sum_{i=1}^{L}(x_i)^2\right)$$

d. Waveform length

Waveform length states the aggregated variation of the EMG that can point toward the level of variation related to the EMG signal [34].

$$WL = \sum_{k=1}^{N-1}(|x_{k+1}-x_k|)$$

e. Mean Absolute Value

This is one of the most common EMG feature, and it is defined as the mean of the integration of absolute value of EMG [34].

$$MAV = 1/N\left(\sum_{i=1}^{N}|xi|\right)$$

f. Simple Square Integral

It is termed as the integration of square values of the amplitude of an EMG signal [34].

$$SSI = \sum_{i=1}^{L}(x_i)^2$$

g. Zero Crossing

This counts the intervals that the signal changes its sign from positive to negative [29]. The two given contiguous sEMG amplitude samples xk and xk+1 the zero crossing can be calculated as ZC=∑ f(x)

$$f(x) = \begin{cases} 1, if, (x_k > 0 AND x_{k+1} < 0 OR (x_k < 0 AND x_{k+1} > 0, k = 1,2,3\cdots N-1)) \\ 0, otherwise \end{cases}$$

h. Slope Sign Change

This counts the intervals that the slope of the signal changes its signs [34]. Given three contiguous amplitude samples of an sEMG xk-1, xk, xk+1, the amount of slope sign varies is given by SSC=∑ f(x), where

$$f(x)=\begin{cases}1, if, \left(x_k < x_k AND x_k < x_{k-1} OR\left(x_k > x_k AND x_k > x_{k-1}\right), k=1,2,3\cdots N-1\right) \\ 0, otherwise\end{cases}$$

i. Willison Amplitude

It is the number of counts for each change of the amplitude of sEMG signal between two contiguous samples that go beyond a defined threshold [34].

$$WAMP=\sum_{k=1}^{N-1} f\left(\left|x_{k+1}-x_k\right|\right) \quad f(x)=\begin{cases}1, if, x > threshold \\ 0, otherwise\end{cases}$$

j. Integrated EMG

Integrated EMG (IEMG) is for the most part utilize as a pre-activation record for muscle action. It is the area under the curve of the EMG signal [34]. IEMG can be defined as the integration of the absolute values of the amplitude of an EMG.

$$IEMG=\sum_{i=1}^{N}\left(\left|x_i\right|\right)$$

k. Log detector

It is a characteristic of an EMG that is used for the estimation of the exerted force on muscles [34].

$$LD=\exp\left(1/L\sum\log\left(\left|x_i\right|\right)\right)$$

l. Myopulse percentage rate

This rate is the average of the output of Myopulse in which the absolute value of EMG signal go beyond the given threshold [34].

$$MYOP=1/L\left(\sum_{i=1}^{L} f\left(x_i\right)\right) \quad f(x)=\begin{cases}1, if, \left|x_i-x_{i+1}\right| >= T \\ 0, otherwise\end{cases}$$

Where, x is the wavelet's coefficient, L is the coefficient's length and T is the threshold value.

m. Difference absolute standard deviation value

It is another commonly used feature of an EMG signal [34].

$$DASDV=\sqrt{\sum_{i=1}^{L-1}\left(x_{i+1}-x_i\right)^2/(L-1)}$$

n. Enhanced Mean Absolute value

It is a feature that is used for the estimation of the exerted force [34].

$$EMAV = 1/L\sum\left|(x_i)^p\right| \quad p = \begin{cases} 0.75, if, i >= 0.2 AND i <= 0.8L \\ 0.50, otherwise \end{cases}$$

o. Enhanced Wavelength

In enhanced wavelength the parameter p is utilize to recognize the impact of sample present in the signal. A more prominent number of p is utilized for 20% to 80% of sections of enhanced mean absolute value and enhanced wavelength. This is because by support the information content at the intermediate region, more profitable data can be obtained. In this way, the worth of features can be enhanced. Besides, it is seen that EMAV and EWL were the extension of MAV and WL with some sort of changings, and hence no more extra computational time is required during assessment [34]

$$EWL = \sum_{i=2}^{L}\left(\left|x_i - x_{i-1}\right|^p\right) \quad p = \begin{cases} 0.75, if, i >= 0.2 and i <= 0.8L \\ 0, otherwise \end{cases}$$

Where, x is the coefficient of wavelet, T is the value of threshold and L is the coefficient's length.

p. Modified Mean Absolute Value

It is an expansion of mean absolute value feature by using the weight window function [34].

$$MMAV = 1/L\sum_{i=1}^{L} w_i\left|x_i\right| \quad w_i = \begin{cases} 1, if, 0.25L <= i <= 0.75L \\ 0.5, otherwise \end{cases}$$

q. Modified Mean Absolute Value 2

This is another expansion of mean absolute value feature by using the continuous weight window function [34].

$$MMAV2 = 1/L\sum_{i=1}^{L} w_i\left|x_i\right| \quad w_i = \begin{cases} 1, if, 0.25L <= i <= 0.75L \\ 4i/L, if, i < 0.25L \\ 4(i-L)/L, otherwise \end{cases}$$

Where, x is the coefficient of wavelet and L is the coefficient's length.

r. Maximum Fractal Length

This is a newly established technique for capturing low-level muscle activation. When the smallest scale is set to one, the definition of MFL takes a modified form of waveform length by combining the root mean square and logarithm functions [35]

$$MFL = \log\left(\sqrt{\sum_{n=1}^{N-1}\left(x(n+1) - x(n)\right)^2}\right)$$

s. Average Amplitude Change

Average amplitude change is the approximation of the waveform length feature, excluding the mean of wavelength [36].

$$AAC = 1/N\sum_{i=1}^{N-1}\left|x_{i+1} - x_i\right|$$

t. Kurtosis

This is a time domain based feature that defines the shape of a signal. It is the statistical technique that used to define the distribution and a characteristic that isolates the tendency of peak data [37].

u. Skewness

This is another one of the time domain feature of an EMG signal. It is expressed as the predisposition of data distribution. The data information is said to have a normal distribution when the position of the mean value, the median value and mode value on a line within the curve if these values are not found in one line within the bend, happens the skewness [37].

After calculating the above mentioned time domain features for each channel, all features are grouped to form a feature vector *f*(TDS). As the number of channels are eight so 8x21 will gives us the feature vector of length 168.

4.3.2 Inter Channel Statistics (Correlation and Covariance)

The figure 4-5, figure 4-6 presents some similar patterns between the channels of both aggressive and normal activities. In this way, the correlation and covariance between the channels has great impact on the variations between the classes.

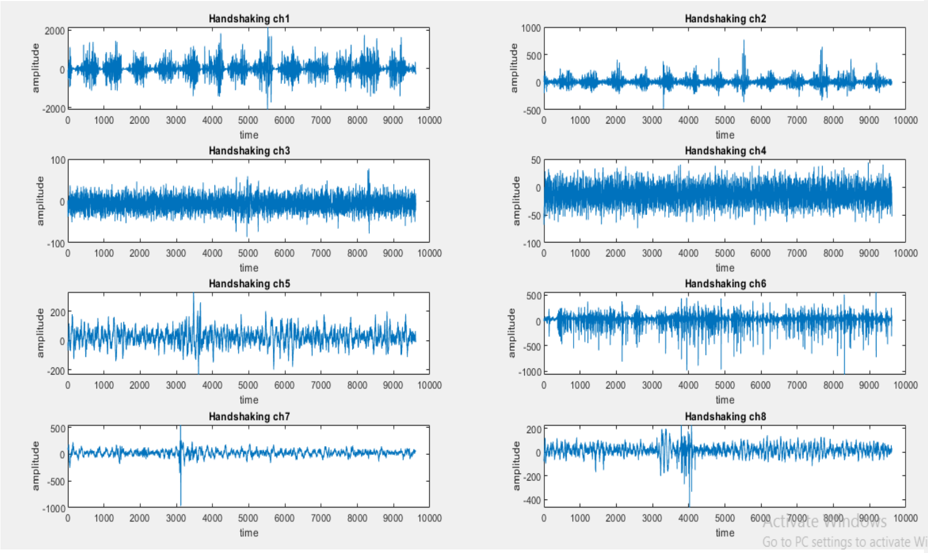


Figure 4-5: Channel visualization of a Normal activity

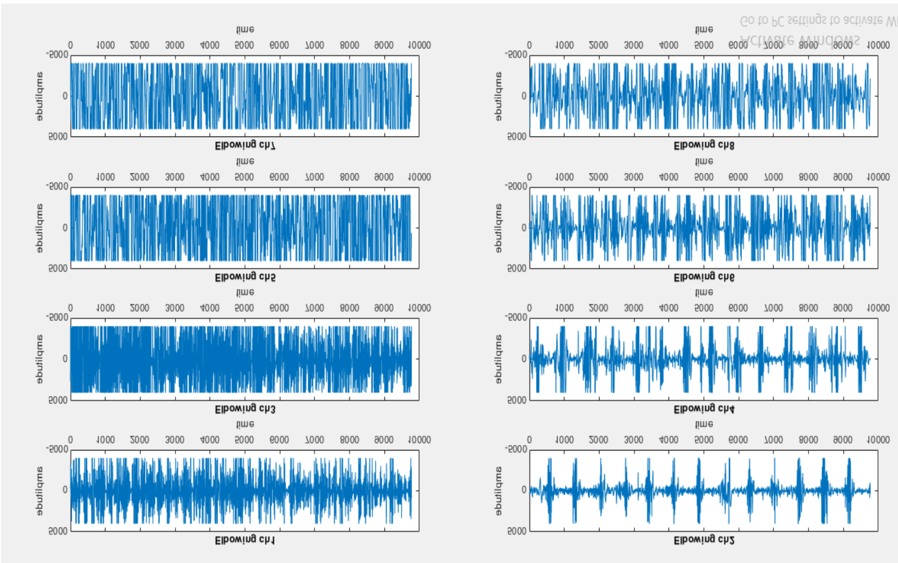


Figure 4-6: Channel visualization of an Aggressive activity

The subgroup of features based on maximum cross correlation and covariance [24] among the corresponding segments of two channels a and b of an EMG signal and is defined as

$$c^{a,b} = \max\left(C\{s_a(l), s_b(l)\}\right)$$

The above equation represents the maximum correlation between the segments of two channels s_a and s_b of an EMG signal and is shown in Figure 4-7. The Table 4-2, represents the pairing of different channels.

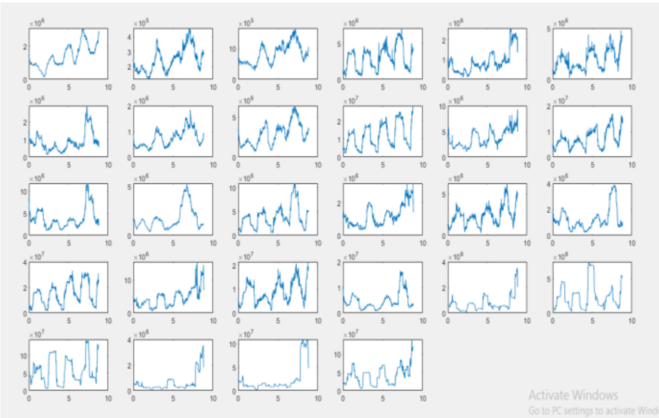


Figure 4-7: Graphical representation of Inter channel correlation

Table 4-2: Representation of channel-wise pairing

Channel-wise pairing						
(1,2)	(1,3)	(1,4)	(1,5)	(1,6)	(1,7)	(1,8)
(2,3)	(2,4)	(2,5)	(2,6)	(2,7)	(2,8)	
(3,4)	(3,5)	(3,6)	(3,7)	(3,8)		
(4,5)	(4,6)	(4,7)	(4,8)			
(5,6)	(5,7)	(5,8)				
(6,7)	(6,8)					
(7,8)						

As we have 8 channels so we can get 56 values after performing the maximum correlation and covariance between corresponding channels i.e. 28 values for the correlation and 28 values for the covariance between the channels then these features are assembled into feature vector *f*(ICS).

4.3.3 Logarithm of moments of Fourier spectrum

The frequency based moments and their ratios by taking their logarithms are calculated for the EMG segments based on [38]. Fourier transform of a segment of each channel of an EMG signal was computed and is shown in figure 4-8. After that, they took the square of the magnitude frequency spectrum. The *i*-th frequency based moment is defined as [39]

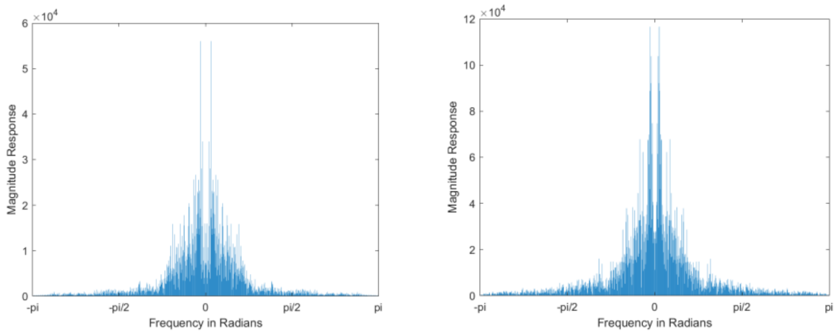
The total 17 log moment ratios were calculated for each channel described in the table 4-3. Hence, 17x8 gives us total 136 values of Log moment based features of each segment of each channel of an EMG activity.

Table 4-3: Log moment of Fourier spectra of each channel

LOG MOMENT RATIOS							
ch1	ch2	ch3	ch4	ch5	ch6	ch7	ch8
$fj(1)$	$fj(1)$	$fj(1)$	$fj(1)$	$fj(1)$	$fj(1)$	$fj(1)$	$fj(1)$
$fj(2)$	$fj(2)$	$fj(2)$	$fj(2)$	$fj(2)$	$fj(2)$	$fj(2)$	$fj(2)$
$fj(3)$	$fj(3)$	$fj(3)$	$fj(3)$	$fj(3)$	$fj(3)$	$fj(3)$	$fj(3)$
$fj(4)$	$fj(4)$	$fj(4)$	$fj(4)$	$fj(4)$	$fj(4)$	$fj(4)$	$fj(4)$
$fj(5)$	$fj(5)$	$fj(5)$	$fj(5)$	$fj(5)$	$fj(5)$	$fj(5)$	$fj(5)$
$fj(6)$	$fj(6)$	$fj(6)$	$fj(6)$	$fj(6)$	$fj(6)$	$fj(6)$	$fj(6)$
$fj(7)$	$fj(7)$	$fj(7)$	$fj(7)$	$fj(7)$	$fj(7)$	$fj(7)$	$fj(7)$
$fj(8)$	$fj(8)$	$fj(8)$	$fj(8)$	$fj(8)$	$fj(8)$	$fj(8)$	$fj(8)$
$fj(9)$	$fj(9)$	$fj(9)$	$fj(9)$	$fj(9)$	$fj(9)$	$fj(9)$	$fj(9)$
$fj(10)$	$fj(10)$	$fj(10)$	$fj(10)$	$fj(10)$	$fj(10)$	$fj(10)$	$fj(10)$
$fj(11)$	$fj(11)$	$fj(11)$	$fj(11)$	$fj(11)$	$fj(11)$	$fj(11)$	$fj(11)$
$fj(12)$	$fj(12)$	$fj(12)$	$fj(12)$	$fj(12)$	$fj(12)$	$fj(12)$	$fj(12)$
$fj(13)$	$fj(13)$	$fj(13)$	$fj(13)$	$fj(13)$	$fj(13)$	$fj(13)$	$fj(13)$
$fj(14)$	$fj(14)$	$fj(14)$	$fj(14)$	$fj(14)$	$fj(14)$	$fj(14)$	$fj(14)$
$fj(15)$	$fj(15)$	$fj(15)$	$fj(15)$	$fj(15)$	$fj(15)$	$fj(15)$	$fj(15)$
$fj(16)$	$fj(16)$	$fj(16)$	$fj(16)$	$fj(16)$	$fj(16)$	$fj(16)$	$fj(16)$

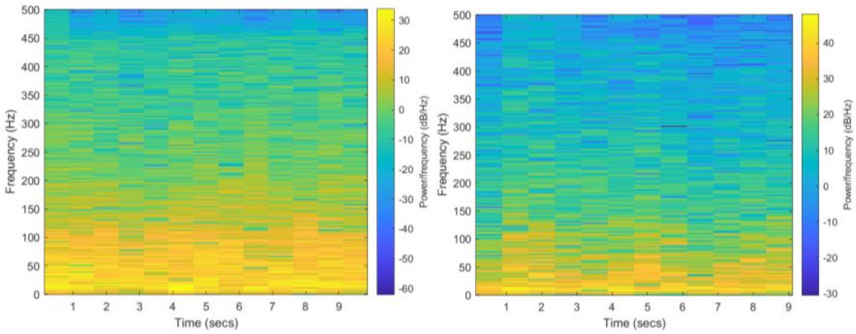
$fj(17)$	$fj(17)$	$fj(17)$	$fj(17)$	$fj(17)$	$fj(17)$	$fj(17)$	$fj(17)$

For the C channels, the features mentioned in above equations are combined into the feature vector *f*(LMF).



(a) (b)

Figure 4-8: Frequency based analysis of an EMG signal (a) FFT spectrum of clapping activity (b) FFT spectrum of slapping activity



(a) (b)

Figure 4-9: Spectrogram view of an EMG signal (a) STFT of clapping activity (b) STFT of slapping activity

4.3.4 Power Spectral Density (Burg's Algorithm)

The spectral band power signatures were proposed for the identification of an EMG signals in previous studies [40]. In the proposed technique, the spectral features were extracted. For each and every channel of an EMG signal, supposing a model order *4*, the model coefficient $\{ai\}$ are estimated using the Burg's estimation discussed in [41].

Finally, the spectral band power features are evaluated by splitting the spectrum into *Nb* bands and calculating the corresponding energy in those bands as shown in Figure 4-10.

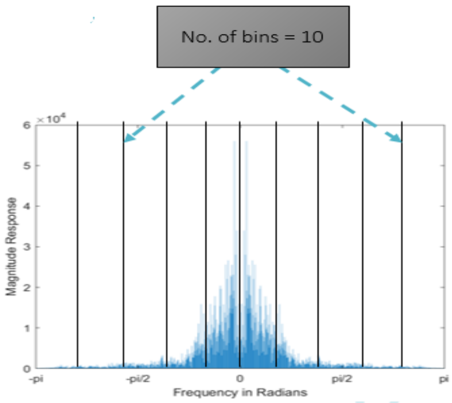


Figure 4-10: Division of frequency spectrum into N bins for calculating the energy response of each bin

And the feature vector created of these bins for all bands and channels. Hence the features extracted from above method are combined into feature vector *f*(PSD).

4.4 Feature Concatenation

After performing the extraction of features of the segment of each channel we need to concatenate the features from various modalities to make a single feature vector.

feature vector = [*f*(TDS), *f*(ICS), *f*(LMF), *f*(PSD)]

As a result, the length of concatenated feature vector will be of 440.

Table 4-4: Feature count from different modalities

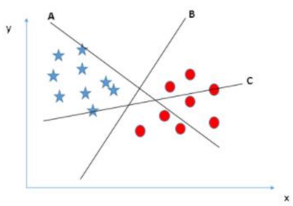
Feature characteristics	Count
***f*(TDS)**	168
***f*(ICS)**	56
***f*(LMF)**	136
***f*(PSD)**	80
Total features	*440*

4.5 Classification

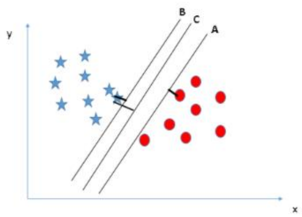
Classification of physical activities are performed by means of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM).

4.5.1 Support Vector Machine Classifier (SVM)

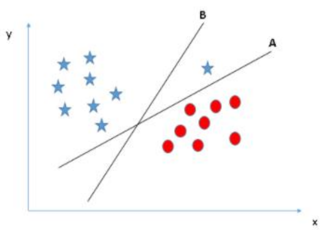
A support vector machine (SVM) is a supervised **machine learning** algorithm which is used for both regression and classification problems. SVM is a fast and reliable classification technique that performs well with a limited amount of data to analyze. Herein, each data sample is plotted as a point in an N-dimensional space whereas N indicates the number of dimensions. For the classification of data SVM finds the hyperplane that does not only separates the two classes but also maximizes the margin (i-e the distance between the margin and the closest data point of each class). Figure 4-11 shows how the algorithm identifies the best hyper-plane [42]. In Figure 4-11-(a), hyper-plane B is selected as the right hyper-plane as it divides the two classes better. In Figure 4-11-(b), all the hyper-planes (A, B and C) are separating the classes accurately. In this case the hyper-plane having the maximum margin from the closest data point will be selected, therefore, hyper-plane C will be preferred. In figure 4-11-(c), apparently, B may be a way better classifier but SVM selects the hyper-plane that classifies the classes precisely earlier to maximizing border. Later, the right hyper-plane is A, as it has no classification error. SVM can also ignore the outliers (noisy data points) and maximize the margin as shown in Figure 4-11-(d). Until now, we have only visualized the linear kernel but SVM can also solve a linearly non-separable problem using complex kernels e.g. radial basis function (RBF) kernel, polynomial of higher degree, Gaussian, Sigmoid, hyperbolic tangent, Laplace RBF etc. Figure 4-11-(e) shows a circular hyperplane for the data that is not linearly separable. For physical actions categorization, linear SVM is used to project ensemble features to a bigger dimensional space and then finding the best hyperplane.



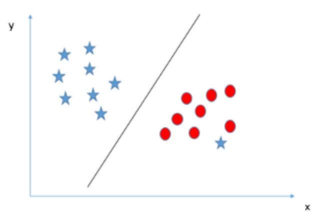
(a)



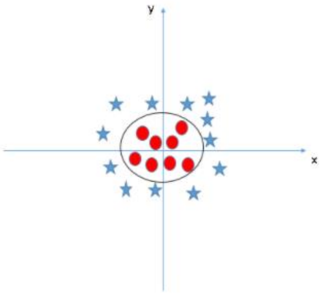
(b)



(c)



(d)



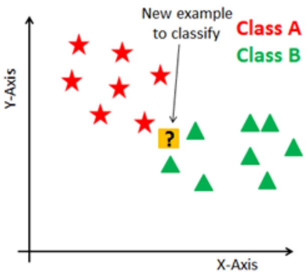
(e)

Figure 4-11: Hyper-plane examples for different data using SVM [42]

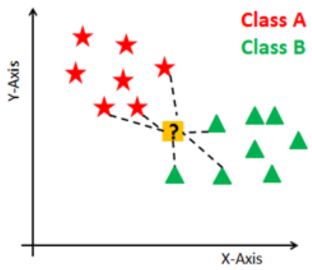
In order to classify the normal actions the SVM performs better classification as compared to KNN. The hyper parameters of SVM includes the 'Quadratic' kernel function, 'One vs. all' multi-class method and 5-fold cross validation is used in this study.

4.5.2 K- Nearest Neighbor Classifier (KNN)

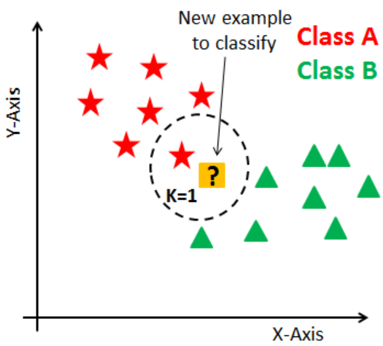
K-NN is one of the foremost simple and easy-to-implement supervised machine learning algorithm used for both classification and regression problems. It is widely used to recognize patterns, intrusion detection and data mining. According to this classifier the value of data point is determined by the data points around it or based on the majority voting principle. The mechanism of KNN is to find the distances (i-e, Euclidean, Manhattan, Minkowski, hamming etc.) between a new data point and all the neighbor examples in the training data, selecting the specified number neighbor examples (K) closest to the new data point, then votes for the most frequent label in classification problems. Figure 4-12-(a), represents the two class data and need to find k closest data point in order to classify new data point. Figure 4-12-(b) shows the calculation of distance of new data point with the k nearest data points. Figure 4-12-(c) indicates three nearest neighbors in which two data points are from triangle class and one data point is from star class. Hence new data point with be classify as triangle class because triangle class has maximum votes. For regression problems, KNN takes the mean of k nearest data points.



(a) Initial data



(b) Calculate Distance



(c) Finding neighbors and voting for labels

Figure 4-12: KNN Classification example [43]

In our proposed methodology, SVM and KNN are used for the classification of physical activities. The hyper parameters of KNN includes the value of K=1 whereas the distance metric is set as Manhattan distance which is also known as city block distance. It is the sum of absolute differences between points across all the dimensions. Following is the generalized formulae for an n-dimensional space:

$$Dm = \sum_{i=1}^{n} |pi - qi|$$

4.5.3 Hybrid Classifier for 20 class problem

In our proposed methodology, we ensemble both SVM and KNN classifier in hierarchical manner to classify the 20 different physical actions. First of all, we trained three different models using SVM and KNN classifiers. The Binary class model is trained using KNN which is based on 440 features, as it classifies the data into either normal or aggressive class. Another SVM based model uses the features from different modalities (i-e; 440 number of features) in order to classify the 10 normal actions. The KNN based model uses the subset of features (i-e

272 features from Inter channel correlation and covariance, Log moment of Fourier spectra and power spectral density domains) for the classification of 10 aggressive activities. The workflow of hybrid classifier is shown in figure 4-13.

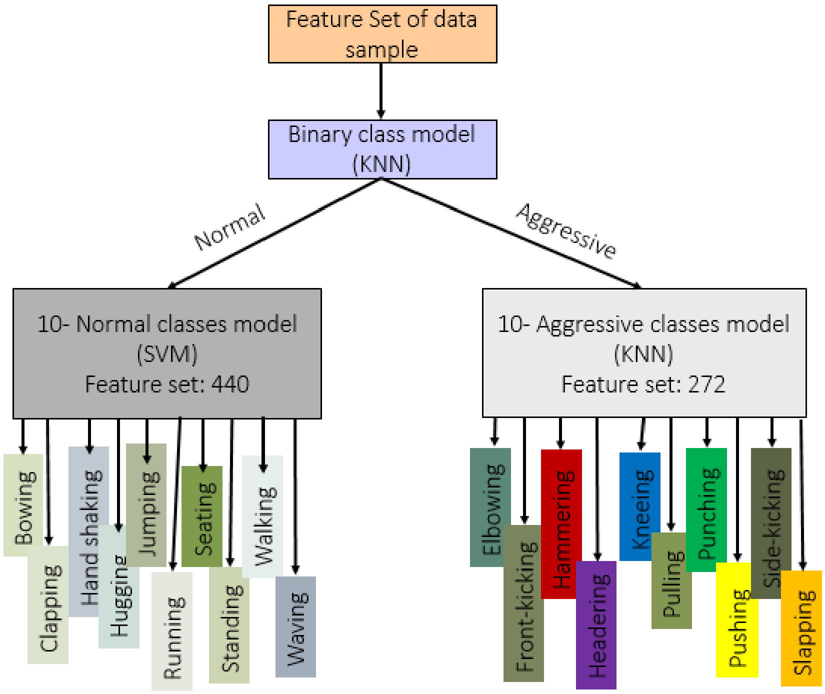


Figure 4-13: Multi Classification using Hybrid classifier

CHAPTER 5: EXPERIMENTAL RESULTS

In this chapter, the performance of the proposed hybrid classification algorithm is evaluated using MATLAB 2020a. We perform experimentation based on different subset of features and over all features using SVM and KNN classifiers separately. It is observed from the experimentation that SVM performs better for categorizing normal activities whereas KNN gives better classification results for aggressive activities. As a result, both SVM and KNN are ensemble to perform classification of 20 actions.

5.1 Dataset

The dataset of interest is taken from machine learning repository.

5.1.1 UCI Machine learning repository

This EMG data of Physical activities has been taken from UCI machine learning repository [45]. These EMG signals have been recorded using Delsys EMG apparatus on 4 subjects (3 males and 1 female) while they performed 20 different physical actions including 10 normal activities and 10 aggressive actions as mentioned in table 5-1. Each individual repeats the physical activity 15 times. There were eight EMG electrodes positioned on biceps and triceps, thighs and hamstrings. Each channel contains approximately 10,000 values.

Table 5-1: Summary of Physical Action Dataset

Data set description	
Subjects	(3 males, 1 female)
Number of electrodes	8 electrodes, 8 channels Ch1- right bicep Ch2- right triceps Ch3- left bicep Ch4- left triceps Ch5- right thigh Ch6- right hamstring Ch7- left thigh Ch8- left hamstring
Sampling frequency	1000Hz

Number of classes	10 Normal Actions 10 Aggressive Actions
Length of EMG signals	~ 10000 samples

5.2 Performance Measures

With the aim of, validate the performance of our proposed methodology we have computed various parameters from confusion matrix including precision, sensitivity, specificity, kappa coefficient, false positive rate, f-measure etc. The details of these parameters is discussed in the next subsections as follows:

5.2.1 Confusion Matrix

Confusion Matrix is an easiest way for measuring the performance of a classifier whereas the output can be of two or more classes. It is basically a table that gives the information of "actual class" vs. "predicted/ class". It contains the following parameters called as "True positive (TP)", "True Negative (TN)", "False positive (FP)", " False Negative (FN)" as shown in Figure below

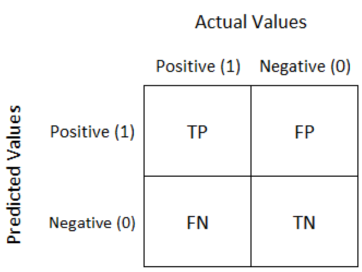


Figure 5-1: Confusion Matrix [44]

TP specifies the number of samples the classifier predicted positive were actually positive
TN specifies the number of samples the classifier predicted negative were actually negative
FP specifies the number of samples the classifier predicted positive were actually negative
FN specifies the number of samples the classifier predicted negative were actually positive

5.2.2 Sensitivity

Sensitivity is known as the true positive recognition rate: (i-e, the number of samples the classification model predicted were positive that were actually positive). Mathematically, it can be calculated as follows

$$sensitivity = \frac{TP}{TP + FN}$$

It is also termed as recall.

5.2.3 Specificity

Specificity is known as the true negative recognition rate: (i-e, the number of observations the model predicted were negative that were actually negative). Mathematically, it can be calculated as follows

$$specificity = \frac{TN}{TN + FP}$$

5.2.4 Miss classification rate

Miss classification rate is defined as the overall, how often is the classifier incorrect. It is also known as false positive rate (FPR). Mathematically, it can be calculated as

$$MCR = \frac{FP + FN}{TP + TN + FP + FN}$$

5.2.5 Precision

Precision is defined as the when a positive value is predicted, how often is the prediction correct. Mathematically, it can be calculated as

$$Precision = \frac{TP}{TP + FP}$$

5.2.6 F measure

F measure is the harmonic mean of precision or recall

$$F\beta = \frac{(1 + \beta 2)(precision)(recall)}{(\beta 2)(precision + recall)}$$

$\boldsymbol{\beta}$ is commonly 0.5,1 or 2

5.2.7 Cohen's Kappa

Cohen's Kappa coefficient calculates the dependability of two raters that are rating the same thing, adjusted for how frequently that the raters may agree by chance. The range of this coefficient is between 0-1. It is used for measuring both multi-class and imbalanced class problems.

$$\kappa = \frac{Po - Pe}{1 - Pe}$$

According to above equation, P_o is the likelihood of agreement whereas P_e shows the likelihood of random agreement.

5.3 Result and Discussion

This section details with the experimental structure and analysis of the proposed methodology for classification of 10 aggressive actions and 10 normal actions individually and as a combined 20 class problem. The first step in our proposed demands the segmentation of signal into *2* seconds segments having 25% overlap. Thus each activity can be subdivided to get a healthy sample space, having *600-900* segments which depends on signal length. The segment from this sample space is subjected to feature extractor, which extracts a feature vector of length 440 as discussed in section 4.4. Finally, the feature vector is fed to KNN, SVM and hybrid classifier for analysis. Furthermore, to perform evaluation at feature level, we have used each modality and their combination to calculate the accuracy for KNN and SVM classifiers to choose the best available feature subset.

5.3.1 Classification Results

The classification accuracy of different physical actions using simple K-Nearest neighbor. KNN calculates accuracy for all 440 features, which are composed up of various modalities includes time domain features (TDS), Inter channel correlation and covariance (ICS), Log moment of Fourier spectra (LMF) and power spectral density (PSD) whereas the value of k is from 1 to 10 for the different values of k as shown in Table 5-2. In Table 5-2 bold values shows that when the value of k is equal to 1 than KNN gives the maximum accuracy for 10 normal actions which is equal to 97.929%, for 10 aggressive actions accuracy is equal to 87.780% and for 20 classes the accuracy is 92.710%. It concludes that we should keep the value of 'k' equal to one in order to achieve the highest classification accuracy.

Table 5-2: KNN based classification of physical actions considering all features

All features (Channel wise)	**10 Normal actions**	**10 Aggressive actions**	**All 20 classes**
K=1	97.929	87.780	92.710
K=2	96.894	86.965	90.759
K=3	97.515	85.132	91.375
K=4	96.687	86.558	91.170
K=5	96.066	85.336	90.143

K=6	96.480	86.150	90.246
K=7	95.652	84.317	89.630
K=8	96.273	84.521	88.193
K=9	94.824	84.114	87.577
K=10	93.581	83.095	86.659

The classification accuracy of different physical actions using K-Nearest neighbor. This time the value of k=1 for different subsets of features is shown in Table 5-3. In Table 5-3 the subset of ICS, LMF, PSD feature vector, a combination of features from time domain statistics, inter channel correlation and covariance and power spectral density, gives the maximum classification accuracy of 98.136% for 10 different normal activities. The same subset gives the accuracy of 89.613% for 10 different aggressive activities whereas by considering all features from TDS, LMF, ICS and PSD of each channel we achieve maximum classification accuracy of 92.710% for 20 different activities.

Table 5-3: 1-NN based classification for physical activities with different set of features

Subset of features	**10 normal**	**10 aggressive**	**All 20 classes**
All features (Channel wise except TDS(Mean wise))	97.722	89.409	92.710
ICS+LMF(Channel Wise)	97.515	85.743	90.759
ICS+LMF+PSD	98.136	89.613	91.991
ICS+PSD	97.929	85.132	91.478
LMF+PSD	97.722	86.558	91.478
TDS+ICS	96.273	86.761	90.965
TDS+ICS+LMF	97.722	88.798	91.273
TDS+ICS+LMF (TDS Mean Wise)	97.308	86.558	92.094
TDS+ICS(TDS Mean Wise)	85.921	80.040	79.979
TDS+ICS+PSD	96.687	86.965	91.375
TDS+ICS+PSD(TDS Mean Wise)	92.132	85.539	88.090
TDS+LMF	96.894	85.336	89.835
TDS+LMF(TDS Mean Wise)	97.101	87.169	89.322
TDS+LMF+PSD	97.722	86.965	87.782
TDS+LMF+PSD(TDS Mean Wise)	96.687	87.780	89.014
TDS+PSD	95.445	83.095	89.219
TDS+PSD(TDS Mean Wise)	90.062	78.615	83.059

The classification accuracy of different physical actions using linear kernel of Support vector machines (SVM) and based on different features of subset is shown in Table 5-4. Table 5-4 shows that by taking the all features of each channel for the classification of 10 normal actions achieves a maximum accuracy of 99.585% for 10 normal activities whereas for the classification of 10 aggressive activities KNN performed better as compared to SVM as it gives the accuracy of 86.761%. For the classification of 20 different classes, first takes mean of all eight channel and then extract 21 Time domain features and concatenate it to the features extracted from ICS, LMF and PSD channel wise. It achieves an accuracy of 92.299%.

Table 5-4: SVM based classification of physical actions for different set of features

	10 Normal	**10 Aggressive**	**All 20 classes**
All features(CW)	99.585	86.761	91.067
All features(TDS MW)	98.757	84.725	92.299
ICS+LMF(Channel Wise)	98.343	79.633	89.630
ICS+LMF+PSD	98.964	84.317	91.478
ICS+PSD	96.066	83.299	87.577
LMF+PSD	98.136	75.967	87.371
TDS+ICS	98.343	81.466	91.273
TDS+ICS+LMF	99.378	85.743	91.683
TDS+ICS+LMF (TDS Mean Wise)	97.308	82.892	89.527
TDS+ICS(TDS Mean Wise)	91.304	67.006	77.310
TDS+ICS+PSD	98.343	86.150	91.170
TDS+ICS+PSD(TDS Mean Wise)	96.066	82.077	88.193
TDS+LMF	98.550	82.484	89.014
TDS+LMF(TDS Mean Wise)	98.136	76.171	85.318
TDS+LMF+PSD	98.343	84.114	90.759
TDS+LMF+PSD(TDS Mean Wise)	98.550	79.226	88.706
TDS+PSD	98.136	82.688	89.014
TDS+PSD(TDS Mean Wise)	96.066	74.338	84.702

The classification accuracy for physical actions using SVM’s polynomial kernel of order 2 based on different subsets of features is shown in Table 5-5. Polynomial kernel gives minimum accuracy for 10 normal activities, 10 aggressive activities and 20 classes for different feature subsets as compared to 1-NN and SVM with linear kernel as shown in above tables.

Table 5-5: Polynomial SVM based classification with different set of features

	10 Normal	10 Aggressive	All 20 classes
All features(CW)	96.273	86.558	88.501
All features(TDS MW)	96.480	87.169	89.014
ICS+LMF	97.101	84.725	88.398
ICS+LMF+PSD	96.480	85.743	89.014
ICS+PSD	90.890	83.706	82.751
LMF+PSD	94.409	82.484	88.295
TDS+ICS	97.101	86.965	88.603
TDS+ICS+LMF	96.687	86.354	88.809
TDS+ICS+LMF (TDS Mean Wise)	96.687	83.706	88.911
TDS+ICS(TDS Mean Wise)	90.476	73.727	79.568
TDS+ICS+PSD	96.894	85.743	88.603
TDS+ICS+PSD(TDS Mean Wise)	94.616	84.114	86.960
TDS+LMF	96.273	83.706	87.474
TDS+LMF(TDS Mean Wise)	96.066	82.077	87.679
TDS+LMF+PSD	96.687	83.910	87.885
TDS+LMF+PSD(TDS Mean Wise)	96.273	82.892	88.295
TDS+PSD	96.480	81.059	86.447
TDS+PSD(TDS Mean Wise)	92.546	74.541	82.956

On the basis of above experimentations, it is observed that 1-NN performs better classification for aggressive actions as compared to SVM whereas the SVM gives better classification results for normal activities as compared to KNN. In order to perform classification of 20 class problem, SVM and KNN are ensemble to form a hybrid classifier which is already discussed in section 4.5.3.

5.3.1.1 Confusion matrix (Binary class):

The confusion matrix is obtained by performing 80:20 split on 974 observations of binary class (Normal and Aggressive) using KNN classifier (whereas the value of K=1) with 5-fold cross validation on considering features from all modalities. The resultant model has been trained on 780 samples whereas has been tested on 194 samples. Hence, the model gives us the average testing accuracy of 100% as shown below.

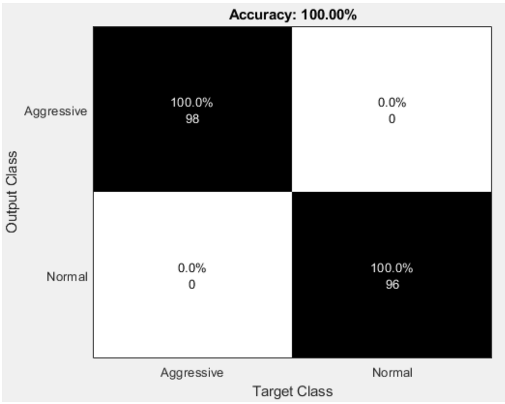


Figure 5-2: Confusion Matrix of binary class using 1-NN

5.3.1.2 Confusion matrix (10 Normal classes):

The confusion matrix is obtained by performing 80:20 split on 483 observations of 10 normal physical activities using SVM classifier with 5-fold cross validation on considering features from all modalities. The resultant model has been trained on 393 samples whereas has been tested on 90 samples. Hence, the model gives us the average testing accuracy of 98.89% as shown below.

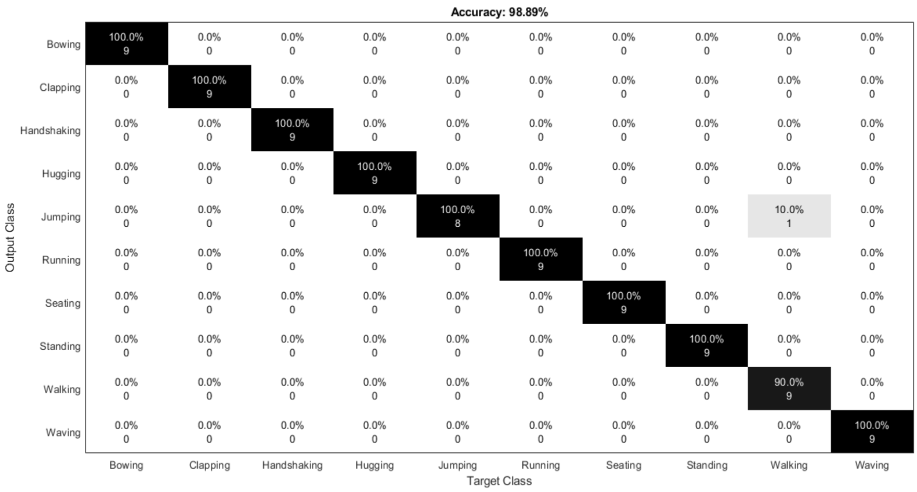


Figure 5-3: Confusion Matrix of 10 normal actions using SVM

Now, the classification of 10 normal activities performed with the same above mentioned parameters but using optimized SVM it improves the average accuracy up to 100%.

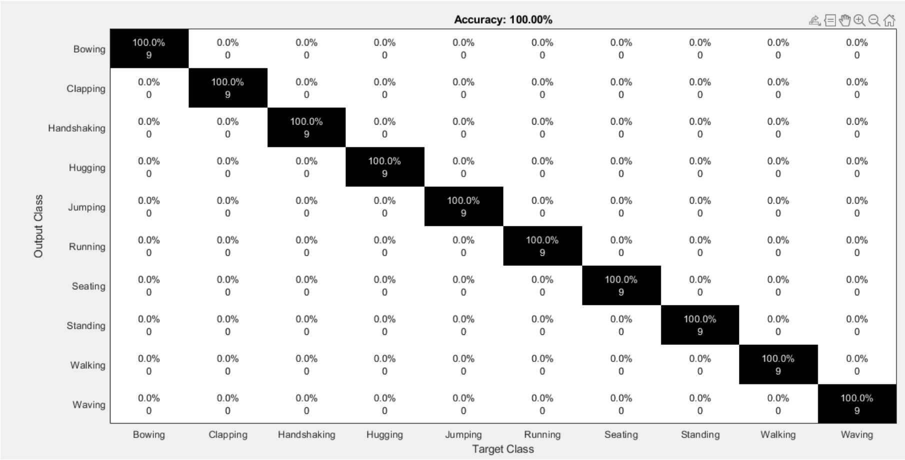


Figure 5-4: Confusion Matrix for 10 Normal activities using optimized SVM

5.3.1.3 Confusion matrix (10 Aggressive classes):

The confusion matrix is obtained by performing 80:20 split on 491 observations of 10 Aggressive actions using KNN classifier (whereas the value of K=1) with 5-fold cross validation on considering the subset of features from the modalities include Inter channel statistics, Log moment of Fourier spectra and Power spectral density. In this classification, Time domain features are not considered. The resultant model has been trained on 399 samples whereas has been tested on 92 samples. Hence, the model gives us the average testing accuracy of 84.78% as shown below.

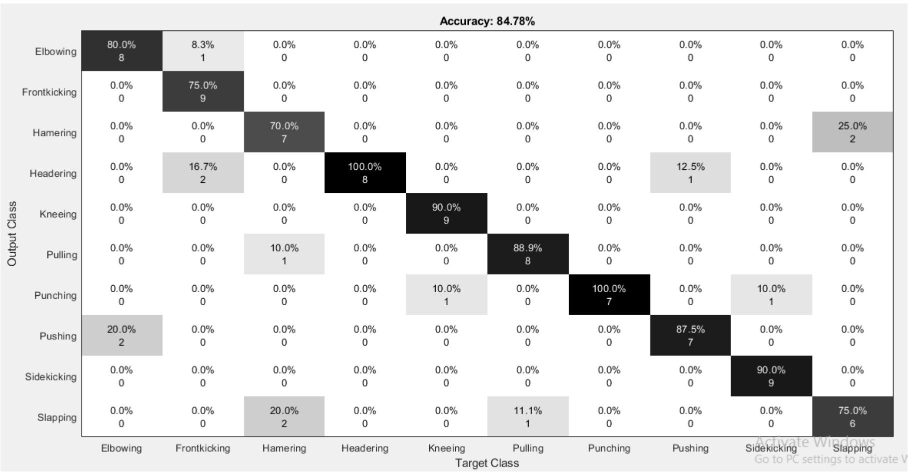


Figure 5-5: Confusion Matrix of 10 aggressive activities using 1-NN

Now, the classification of 10 aggressive activities performed with the same above mentioned parameters but using optimized KNN it improves the average accuracy up to 97.771% by running the script 20 times.

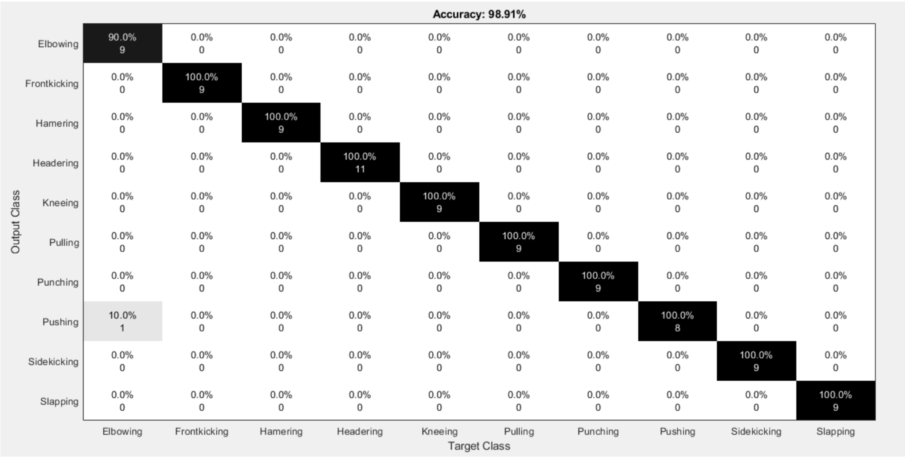


Figure 5-6: Confusion matrix of 10 aggressive activities using optimized KNN

The summary of performance parameters of binary, 10 normal actions and 10 aggressive actions is discussed in the following Table 5-6.

Table 5-6: Classification results statistics for different classes

Class	Testing acc.	Training acc.	Sen	Spec	Precision	FPR	F1-score	kappa
10 normal	0.9889	99.5%	0.9889	0.9988	0.9900	0.0012	0.9889	0.9383
10 aggressive	0.8478	100%	0.8505	0.9831	0.8564	0.0169	0.8466	0.1546
2 class	1.00	100%	1.00	1.00	1.00	0	1.00	1

5.3.1.4 Confusion matrix (20 classes) Hybrid model:

The confusion matrix is obtained by testing 194 observations of 2 class using KNN classifier (whereas the value of K=1) with 5-fold cross validation on considering the features from all different modalities. As a result, optimized KNN classify the samples into either normal class or aggressive class. The samples classified as Normal are fed into the optimized SVM classifier (trained using all features) whereas the samples classified as aggressive are fed into the optimized KNN classifier which are trained on the subset of features from the modalities include ICS, LMF and PSD. Hence the 20 class classification is performed by training two different classifiers in hierarchy. The model gives us the average testing accuracy of 99.015% as shown below.

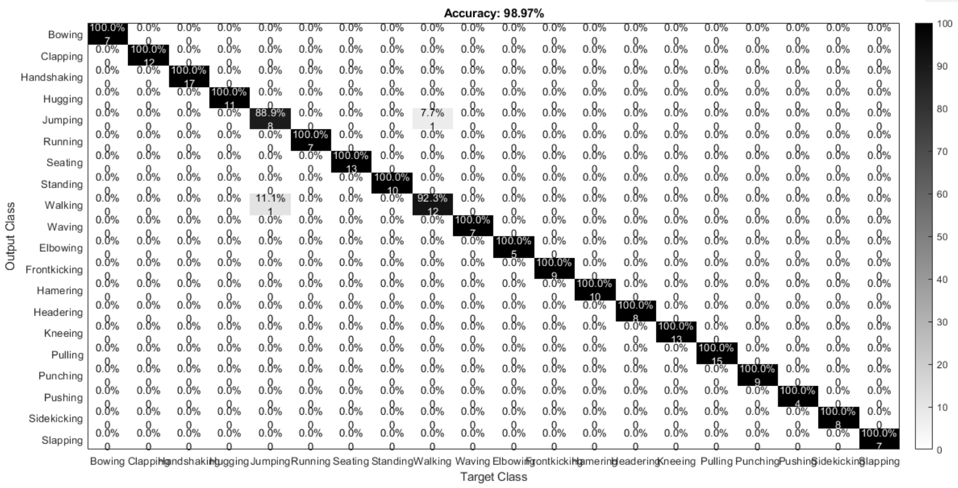


Figure 5-7: Confusion matrix of 20 physical actions using hybrid classifier

The following Table 5-7 represents the performance parameters of multi-class classification problem. The average accuracy is taken by running the script 20 times.

Table 5-7: Parameter calculations for 20 class

Class	Avg acc.	Sen	Spec	precision	FPR	F1-score	kappa
20 class	98.97%	0.9906	0.9995	0.9906	5.4651e-04	0.9906	0.8915

The performance comparison of our proposed method with the latest research work is shown in Table 5-8, Table 5-9 and Table 5-10. The obtained features from different modalities for each segment gives a good response to the classification of 20 physical actions of sEMG. It provides robustness to the variation between classes. This result shows that the hybridization of SVM and KNN models provides better performance for automatic identification of surface EMG signals.

This table shows that by increasing the feature set from different modalities in our proposed framework improves the accuracy of 20 EMG based physical actions from 93.91% to 98.97%.

Table 5-8: Performance comparison of Hybrid classifier with for 20 class

Author	Method and classifier	Accuracy. (%) 20-class

Turla paty et al, 2019 [24]	Feature extraction (time domain, Inter channel correlation, LMF, PSD, LBP), feature selection (SFS), PNN and sKNN classifier	93.91%
Proposed methodology	Segmentation, Feature extraction(Time domain, Inter channel correlation and covariance, LMF, PSD), SVM and KNN classifier	**98.97%**

According to below mentioned table, optimized SVM gives better accuracy as compared to previous research works along with feature set from different modalities

Table 5-9: Performance comparison of optimized SVM model for the classification of 10 Normal class

Author	**Model and classifier**	**Accuracy (%) 10-class normal**
Sukumar et al, 2018 [25]	Variational mode decomposition (VMD), feature extraction (Coefficient of variation, Zero crossing rate, Entropy, Standard deviation, Mean, Negentropy,), Multi-Class Least Square SVM with RBF Kernel.	98.17%
Demir et al, 2019 [28]	Time frequency image(STFT), deep feature extraction(CNN (Alexnet and Vgg-16), SVM classifier and Transfer learning	Alexnet->99.04% VGG-16->98.65%
Sravani et al, 2020 [29]	Flexible analytic wavelet transform (FAWT), feature extraction (IEMG, absolute mean, modified absolute mean, SSI, Variance, Negentropy, Tsallis_entropy, Waveform length), Extreme Learning Machine classifier	99.36%
Proposed methodology	Segmentation, Feature extraction(Time domain, Inter channel correlation and covariance, LMF, PSD), SVM	**100%**

Our proposed binary class model, split the EMG signal into either aggressive or normal activity using 440 set of features. The binary class model gives the maximum accuracy of 100%

Table 5-10: Performance comparison of KNN model for the binary classification

Author	**Model and Classifier**	**Accuracy (%) 2 class**

A. Swetapadma et al. [23]. 2017	DWT->ANFIS	98%
H. Alaskar et al. [22] 2018	Time-frequency representation->CNN	94.61%
A.Kumar et al. [7] 2015	EMD->Feature extraction->LS-SVM	99.03%
Proposed methodology	Segmentation, Feature extraction(Time domain, Inter channel correlation and covariance, LMF, PSD), SVM	**100%**

CHAPTER 6: CONCLUSION & FUTURE WORK

6.1 Conclusion

In this study, we have proposed a multi class classification framework based on SVM and KNN to classify the physical activities utilizing the features extracted from eight channels of the surface EMG data. A set of 440 features were extracted from various modalities including the time domain, frequency domain moments and the inter channel cross correlation and covariance, the mean band power of power spectral density estimates using Burg's calculation. The results show that the SVM performs better for the classification of ten normal classes whereas KNN improves the accuracy for the ten aggressive classes. In case of 20 class classification, adopting hybrid approach by combining SVM with KNN models improves the accuracy especially if the dataset is low. The classification results of proposed method shows better performance in terms of accuracy as compared to other existing methods

6.2 Contribution

The suggested method can be beneficial for the diagnosis of musculoskeletal disorders by using physical activity recognition of surface EMG signals in clinical application.
Review & comparison of our proposed methodology with the literature and physical activity recognition systems.

6.3 Future Work

The future plans for this research domain have two significant directions. The primary is to investigate deep learning methods or convolutional neural networks to increase the classification accuracy. A second direction is to conduct actual experiments to acquire the EMG estimations for various applications includes an orthotic exoskeleton for an upper limb control, rehabilitation, robot control, and prosthetic arm control need distinguishing physical activity of sEMG signals. Finally, the overall goal is to find the best combination of learning algorithms and control techniques for upper limb exoskeletons.

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