Feature analysis for Intention Decoding in EMG Signals

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Abstract

Prosthesis implants had been adored around the globe for amputee. The further advanced hand prostheses using electromyography signals getting common. The immense importance assisting biomedical domain the robotic applications are immersing. Command to our muscles generated by our mind are equivalent to EMG signals in electrical terms, therefore configuration of these signals reckon in the muscle activities. The aim of this study is synthesis of EMG signals produced during hand movement and analysis of the data by adopting different methods. To get the best results these signals are needed to be preprocessed to reduce the noise and unwanted signals inferred while recording data, as data can be collected by installing electrodes on patient's hand. NinaPro shared the data of previous the researchers of various streams on numerous hand movements, which simplifies the prosthesis implants to accomplish better movements. Intention of this thesis is to dive deep into the analysis of this available data set for its different classes, strategy to be followed is the processing of the EMG signals and then formation of window segmentation facilitating for smooth management of data for further steps. Moreover, to extract features which is the task to be achieved in a way to get a control on the hand prosthesis in frequency domain. Furthermore, the classifiers Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) applied on the extracted features and highest of 85.31% accuracy achieved with conventional classifier KNN. However ANN from deep learning gave far better results than the machine learning techniques.

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CHAPTER 1: INTRODUCTION

The research work in this dissertation has been presented sequentially the most of electromechanical applications now a days being used for automation of systems. Prosthesis implants are modernly being used in biomedical applications. These implants are customized for amputees to assist them nearly natural humans maneuver. This can be accomplished using EMG electromyography study in our study case.

Measuring the signals that are being generated by muscle activity. The contraction of muscle and relaxation produces pulses known as electromyography (EMG). The electrical signals generated by brain are transmitted to the muscles. EMG is able to sense if these signals fail to be sent properly or muscle fails to function properly. This situation needs an external source to stimulate the muscles.

An electromyogram (EMG) processes the electrical activity of muscles when they're at rest and when they're being used. Several studies were carried to measure these electrical signals. There are the nerves which control the muscles in the body with electrical signals called impulses. These impulses make the muscles to react in a certain way and cause some movement in arms and legs. The proposed solution is based on these EMG signals, which will extract features from the data, already collected from 27 intact subjects which is being taken from Nina Pro database, which contains the data of 52 hand movements with 10 iterations. The pre and post processing of the available and formulated data for classification of signals corresponding movement oriented using machine learning techniques. The purpose of this whole study is to assist amputees especially those who comes under the category of transracial amputee. Therefore, an effort is done to propose a user-adaptive decoding method for robust movement intention decoding in EMG signals.

1.1 Overview

From past few decades researchers has progressed to measure the signal generate by the brain, muscle and other activities of human being. And the signals measured from human body are categorized as electrical signals, as there is a potential difference lies in the cells of the human body. Researchers always try to do some innovative things by bringing progression in to the world of technology, however working on the different electrical signals of the body is beneficial in to the daily life of amputees. Very renowned electrical signals are ECG, EMG and EEG which are assisting mankind to recover their losses.

Towards hand prosthesis EMG signal got great attention for the advancement in the assistance of amputees. To assist the amputees' researchers are working hard to bring development in this technology, as it has become possible for the disabled to live near to the natural life. EMG signals are useful in the field of biology or in other words for the betterment of human life, as it gives the record of brain signals so many diseases related to brain can also be cured using this signal.

The purpose of this research is to extract features from the EMG data and classify these features using different classifiers to achieve the movements with better accuracy. However, a lot of work has been done in this field but the signal based technology will always be needing an effort to bring transmutation, as noise and other factors that affecting the quality of signals are always cause interruption in fetching real information.

The effort towards the achievement of proficient control in the world of prosthesis has immensely improved the standard of life for the amputees. Most of the robust systems of the hand prosthesis are subjected to EMG signals nowadays. Commonly used prosthesis include opening and closing of hand movements only, however these movements can be increased and can be achieved an advancement in its model by using different techniques in programming of control systems.

1.1 Background

Briefed earlier that extensive work and research have been made in field of interest (EMG Prosthesis), in order to develop better algorithms with innovative methodologies. The researchers has defined the prosthesis signals as biomedical signal. Biomedical signal means collective electronic signal that are acquired from any human organ with some physical variable of interest. This can be a function, or a polynomial; simply a mathematical term related to time variance.

The electrical signals generated by the brain to the muscle for its contraction and relaxation is being measured by the biomedical signal known as electromyography (EMG) signals. As the activities of the muscles i.e relaxation or contraction are being controlled by the nervous system of the body, therefore the EMG signal is investigated as a complex signal. Analysis of EMG signal is difficult somehow due to the noise pass off while oncoming through various tissues, however when the sensing element for EMG signal is mounted on the surface of the amputee produces fundamental interaction of different signals generated from various motors hub used at a time. In the field of clinical diagnosis, biomedical and bio robotics, EMG signal has got immense importance for its manipulation to assist amputees.

EMG is majorly associated to myoelectric activity as it is a control of prosthesis which can be explained as an artificial limb that is being externally hopped-up that can be controlled using the electrical signals which are produced by our muscle activity, moreover myoelectric components are also accessible which entails hand, wrist and elbow parts. There are two main issues occur while obtaining and recording EMG signals which effects the accuracy of the signal. One of which is the signal to noise ratio which can be explained as a proportion of the EMG signals contain energy to the noise signal having energy. And the other vital issue is deformation/ distortion in the signal i.e. the components used must have coherence in frequency. Data obtained in the raw form contains much more valuable information but in a useless form, to make its useful we need to calibrate the data obtained. There are so many methods accomplished in the world of EMG for the signal-processing to get the real and Fidel EMG signal from the raw EMG data. And there are the features of EMG signals which entails detailed and accurate data considering as an expeditious about the muscle motility. There are loads of features earned as a dependable EMG data, as researchers experimented these features for all of the channels and discovered that choice of designated features from different channels gives the desired performance in a far better way.

To classify the features further to get closer towards the desired accurate performance, many researchers has worked on various classifiers including Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), K-Nearest Neighbour (KNN), Support Vector Machine

(SVM), Quadratic Discriminant Analysis (QDA) etc. And deduced results nearly with same accuracy for both the types of subjects I.e. amputees and intact respectively. It is important to evaluate that which classifier which is classifying different movements in a better way. According to research almost linear and non-linear both the classifiers are working efficiently to classify, however LDA considered to be used more often, reason is great accuracy of classification and with fast computations [1].

Performance of the controller related to the hand movement needs to ascertain in order to go for the classification of low-level prosthesis which entails finger movements, wrist movement, grasping and other activities. Researchers have also worked on joint angles with respect to EMG signals in order to get acquire about the modulation of amplitude, as if there is any change occur in the joint angles correspondingly it will bring alteration in the features of EMG signals [2]. To remain unaffected with the occurrence in the joint angle, adjust the position of electrodes accordingly for the better perception of EMG signals, however activity perform with elevation in the joint angle cause change in the symmetry and posture of muscle fibres.

Researchers are working immensely in the field of prosthesis to bring innovation, advancement and execution of myoelectric activities, working eagerly to apply different classifiers for the classification of features and electrically driven prosthesis for amputees. Pattern recognition is always very helpful for prosthesis and here it helps the amputees to get back to life by reviving their grasping ability using these EMG signals for pattern recognition. It is workable for upper and lower limb prosthesis in the medical field. The intention of this research is to get control on hand movements including its eight classes of movements using different classifiers to get the best myoelectric control with great accuracy.

1.1.1 Scope

Recently, most effort toward advancing the practical myoelectric interfaces has revealed a gap between research findings and clinically viable implementation. This gap is mainly due to inter-user variability as myoelectric interfaces have to ensure stable performances across different users in daily life. Therefore, the purpose is to enhance stability and accuracy which will enable a prosthetic hand to perform its movement efficiently.

According to research the loss of hand and leg is more common than the loss of other parts, therefore this research will lead to help people with the revival of their important body part to feel complete. Bio-robotics world has flourished a lot and discovered a lot of different and new things for the amputees like very thin wires and needles are available for the detection of EMG signals, however the proposed work is focused on the utility of sensor. The reason behind the selection of the said electronics is comfortable instalment on the surface of skin and its calibration which give good results.

There are different techniques are available to make it happen, however in this research I have focused on classifiers from different streamline, like linear and non-linear. I have used Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN).

1.1.2 Motivation

Classification of EMG signals will facilitate the amputee to execute his hand and attain movements precisely, it will enable an amputee to get back to the life and perform his routine tasks again. Assistance to amputees is a great contribution to the nation because the proportion of amputees due to war is prominent and our soldiers are the considerable asset of our nation, and this EMG signal classification will enable these disables. It will boost our robotics industry and will give support to our artificial limb centers, furthermore it is a great motivation for our youth to do something innovative in their educational field along with the assistance to man-kind.

Proposed work has got immense advantages as it will assist amputees, will help people to get out of the devastation of being paralyzed. There will be a contribution to the bio-robotics industry and medical sciences as well. Utilizing EMG signal minimize the concept of artificiality, as the electrical signal of body will be used for assistance and classification of these signals will help to get the accurate and desired movements.

1.1.3 Problem Statement

The purpose of this research is to find out a conventional classifier which can give a better result from the available data set for different movements of hand. EMG signals are computationally efficient but after all these are signals and signals always get interrupted by noise and loose the desired information with the superposition of noise signals. To get the signal with its real information, try to keep them free from radio waves as their frequency can also cause disturbance in the modulation of EMG signals. Frequencies of power lines and other components used for the detection and measurement of data can also get interfaced with the desired data of EMG.

To develop a good quality signal, there are few more things to cater as well, which includes quality of electrode; its placement and execution. Moreover, resistance caused by the skin on which sensor has to be mounted is also act as a hindrance. As explained earlier that EMG signal produced by the activity of a muscle either relaxation or contraction, still it gives different amplitude for the same movements of muscles of an amputee. Therefore, it is always very difficult to deal with the EMG data to get an accurate and robust desired output.

1.1.3 Objectives

Subsequent are the intense objectives of this research work.

1. Extraction of Features from intention decoding of EMG data set taken from readily available database Ninapro.
2. Evaluate and compare the extracted features on the basis of accuracy.
3. Implementation of different classifiers including Linear Discriminant Analysis (LDA), Support Vector System (SVM), K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN).
4. Comparison of classifiers on the basis of their accuracy.

CHAPTER 2: LITERATURE REVIEW

The hand prosthesis using control of electromyography EMG is specified for clinics but the degrees of freedom are finite. The number of movement that a subject can perform also become limited. The movement can be increased refining control features and sequences. The advanced mechatronics techniques have enabled prosthesis to next level using EMG signals. The advent of modern signal processing and machine learning techniques has boosted accuracy and performance of the porotypes [3].

In scientific literature it can be seen that practically techniques from pattern recognition is started to be applied [4].To record the command of activity generated by the brain of amputee who does not possess the full arm or hand, many electrodes are in use. However to classify the movements which an amputee wish to perform can be achieve by using different pattern recognition or machine learning techniques. Mostly the classification accuracy obtained from different classifiers are less than 80% [5], and the maximum number of accuracy achieved is the 90% for the 10 movements [6]. Although according to literature quite high results are obtained i.e. accuracies with great percentage but still this area require lots of improvement in many ways. People worked on it with very low number of subjects and the classification accuracy is never enough of high with the large number of movements to be applicable in real life to circumvent misclassification. Furthermore, most of the time the data is not available openly to get access and get comparison of result after the application of different classifiers. With the disparity of present condition, in many areas there are the databases and benchmarks available openly and has been used by most of the researchers for the comparison and improvement of the techniques [7-9]. From literature we can see that researchers are working immensely on the gesture recognition for the engineering of feature extraction [1-120]. People are working on different techniques of classifiers from machine learning, deep learning and computer vision but with the ultimate goal to attain the maximum robustness [13].

To monitor the health, one can wear different available sensing devices helping to monitor continuously with respect to time that allows to gather data of physical activity empowering different human assistive applications [14]. Myoelectric control is the method for the detection, processing, acquisition, classification, including all the related parameters processed for the myoelectric signals, however inauguration towards this advancement has already been started fifty years ago with the available controlling components of that time which were calibrated to perform in accordance to function designed as per the setting of striking threshold value [15-16]. Effort towards the assistance of man-kind is always a focus of researchers, therefore a lot of encroachment has been brought in the field of prosthesis with the great number of movements so precisely that even fingers can move, reflecting the improved perspective of beginning.

The utilization of static (relentless state) and dynamic (transient) periods of EMG flag at the same time empower framework's improvement [17-18]. Varieties in stance cause undesirable impacts which can be decreased by using different static hand stances for example (five, five and three [19-21]) for preparing. Likewise, handling the classifier for dynamic movements likewise encourage EMG acknowledgment control keeping in view the reliance of some hand developments upon the other body stances. Concentrates identified with the utilization of mix of static (four hand developments) and dynamic movements (three hand stances) for seven unique developments 8 uncovered that the arrangement rate is really impacted via preparing the classifier in one stance and seeing in the other [22]. The order blunder was examined to be limited if data is gathered from different hand conditions.

Accordingly latest freely accessible database named NinaPro (Non-Intrusive Versatile Prosthetics) database depends on the information of 52 upper appendage developments rehashed commonly for quite a while length gathered from 27 flawless subjects. It comprises of EMG data of increasingly number of subjects when contrasted with different datasets and furthermore utilizes information got from sound subjects to guarantee more precision [23]. The machine produced for the prostheses reason underpins human-PC connection which might be interfaced with other wise frameworks and robots utilized for restoration reason.

Scientists have researched that in perspective on ongoing headways in apply autonomy, availability and ease of use of precisely useful prostheses isn't an issue these days. Be that as it may, its constrained use and functionality is a direct result of the less progressed myoelectric control as they have vigorous equipment for prosthetic purposes. Specialists need a sharp center not just around extricating right and solid data from EMG flag yet in addition improve the characterization techniques to accomplish better control results. Albeit a great deal of accomplishment has been accomplished in this examination work yet it is as yet indistinct that which method is practically progressively material and gives wanted execution. These procedures are useful for the trademarked dataset which comprises of data about various hand developments taken from various subjects. It is as yet a test for the specialists to build up an automated prosthetic hand which work immaculate like a typical human hand.

Since extensive advancement has been picked up in the field of prostheses dependent on sEMG control, different methodologies displayed in such manner pursue same system with regular advances which incorporate information securing, preprocessing, highlight extraction and a few computerized reasoning and sign handling strategies for grouping. Introductory phases of these methodologies require reasonable utilization of number and situation of cathodes which affects last outcomes. This examination is limited to the component extraction and characterization periods of sEMG investigation.

A few examinations have been led to think about various extraction draws near and their presentation was assessed based on definite bunching and order results [24-27]. These investigations demonstrated various outcomes by proclaiming distinctive way to deal with be increasingly exact. This contention might be because of disparity in the securing conventions and equipment arrangements. Another purpose behind such capricious outcomes is that past investigations didn't tried distinctive characterization systems for extraction techniques to investigate the better one; rather a solitary classifier was utilized.

Examiners utilized a few standard methodologies for arrangement reason, for example, Linear Discriminant Examination, Artificial Neural Systems, k-Nearest Neighbors and so forth and as of late Support Vector Machine (SVM) was investigated. It was accepted that element portrayals have more effect on the last aftereffects of the examination when contrasted with the classifiers, that is the reason researching different kinds of classifiers was not empowered. Hudgins et al, just because, examined that information of EMG signals homeless people that lead to muscle constrictions can be used for separating hand developments by utilizing time area highlights. He took a shot at ANN classifier to distinguish four unmistakable developments. Hargrove et al. looked at five changed classifiers and watched practically same execution proficiency [28]. Lorrain et al. led correlation among SVM and LDA classifiers utilizing autoregressive and time space includes and got proportional outcomes. However, different examinations directing correlations uncovered that different grouping methodologies give diverse execution results. The explanation behind separating variable outcomes might be because of distinction in the exploratory arrangement as effective nonlinear classifiers may have improved execution when contrasted with direct classifiers with increment in the quantity of developments to be watched [29].

The aim of this study is to find and analyze the best classifier for the classification of eight isotonic and isometric hand movements with a good number of accuracy to make sense of progressively strong classifier meaning to upgrade the productivity and functionality of EMG prostheses framework [30]. The reason for this examination is to discover an answer for this issue by looking at mainstream systems of highlight extraction and characterization exactness utilizing the openly accessible database NinaPro dataset [31]. Aside from this, this proposition expects to discover which procedure is similarly increasingly fit for securing alluring outcomes.

CHAPTER 3: METHODOLOGY

As described earlier about the EMG signals, it can be analyzed that the analysis of these signals is a difficult job to do. The reasons behind the difficult analysis of these signals are the complexity cause due to the interruption of many unwanted signals of the path. Noise in the signal may occur from the interference of motor signals at the time of extraction, and unstable amplitude of the signal may also cause noise in the signal. These unwanted factors affect the efficiency and reality of the data that lies in the EMG signals, to fetch the real information from the extracted data we need to pre-process the data. Noise can be removed from the data by using different filters to make it useful for the analysis.

In this research the focus is to extract different features from the already pre-processed data available from the benchmark NinaPro, where the data is accessible from anyone for the experimentation to bring improvements. Next is to use these extracted features and implement classifiers, four classifiers from different techniques have been chosen from the classification of eight hand movements. And then compare the accuracies of these classifiers to declare the best classifier for the available data.

3.1 Benchmark Database

Openly available and accessible for every researcher is the benchmark NinaPro, where the sEMG data extracted from both the subjects i.e. amputee and intact. The database is improving day by day and currently there are seven datasets are available with different hand, wrist and finger movements. The data extracted from different subjects is in controlled laboratory conditions where wireless electrodes 12 in number are used with the base station from Trigno Wireless System, Delsys Inc. the placement of eight electrodes is on the right forearm at the proximal section with equal distance. Further two electrodes were placed on the main point of activity at interior and posterior side of the forearm and rest of two were placed on the biceps and triceps respectively. Then subjects were directed to perform the directed movements and they repeat every movement for 5 times. And the experimental paradigm they followed was the 5 seconds of activity which means movement for 5 seconds and then rest for 3 seconds. The frequency at which the data was acquired is 2kHz, and the data was then processed which embraces filtration of signal, removal of inference occurred due to power line and labelling of movements to avoid any type of mismatch [32].

The database selected for this research work is the first set from the benchmark that contains the EMG data of 52 different movements with 5 repetitions of each movement which was obtained from 27 intact subjects. The data of these 52 movements is sub divided into four main classes that entails 12 finger movements, 8 different isometric and isotonic hand movements, 9 different angles of wrist remaining 23 includes grasping of hand and other activities left. Subsequent is the division of the classes into the exercises.

1. E1_12 Finger Movements.
2. E2_8 Isometric & Isotonic hand movements plus 9 angles of wrist.
3. E3_23 Grasping and other activities.

Further selected class for this study is E2 second class and the movements chosen are the 8 isometric and isotonic hand movements. In this available data of EMG 5 repetitions of each movement is available. Data set of all the sets have data in the form of matlab files along with the synchronized variables glove, emg, stimulus etc. the time duration for which the activities have been performed is the 16 minutes, 23 minutes and 31 minutes respectively [33]. The matlab files of the variable are then used for feature extraction, and then these features will be used by the four different classifiers to classify different movements of hand.

Types of 52 different movements and their shapes can be viewed in the subsequent figure 3-1

(a) 12 basic flexions and extensions of the fingers

(a) 8 isometric and isotonic hand configurations

(a) 9 basic wrist movements

(d) 23 grasp and functional movements

Figure 3-1: The 52 movements considered in the NinaPro dataset

3.2 Signal Processing

Datasets from the Ninapro site were downloaded as organized MATLAB .mat records. An in-house MATLAB program was composed to take the significant sEMG and development reiteration name detail from these records. This brought about a development signal network for every subject, comprising of 17 rows speaking to every development and 5 sections characterizing the development reiterations. Every reiteration comprised of a time-requested arrangement of sEMG voltage information from 12 electrodes, in the type of N × 12 matrix. Reiterations 1, 3, 4 and 5 were doled out to a preparation set leaving reiterations 2 and 5 for the test set and all information were standardized to have zero mean and unit standard deviation.

Because of the nonappearance of maximum voluntary contraction (MVC) data in the downloaded datasets, a most extreme reference esteem per cathode was additionally connected during standardization, acting as a substitute MVC. For each subject, this comprised of a vector of 12 sEMG values, distinguished as the subject's pinnacle sEMG voltages in the preparation set, estimated by every cathode through the whole work out (all movements). The cathode esteems in this vector were then used to standardize comparing terminal information for each development reiteration. This was an endeavor to limit the change between the subjects' sEMG information when it was utilized for between subject experimentation. It was esteemed essential after poor introductory intersubjective classification results.

As EMG sign is a crude information which ought to be prepared through different plants to get the ideal outcomes. The sort and situation of terminal utilized for sign discovery is chosen keeping in view the thickness of epidermal layer of skin and kind of the piece of the muscle to be dealt with. Anode made up of Silver – Silver Chloride is utilized so as to limit the undesirable interference of sign into the readings [34, 35]. Clamor can likewise be overwhelmed by keeping up good condition during the investigation, by picking reasonable terminal positions and legitimate sign handling and circuit design. The effectiveness of sEMG sign can be augmented by fixing anodes at the muscle's stomach away from ligaments. If there should arise an occurrence of bipolar design of anodes with three surfaces utilized for account, separation between the two terminals ought not to be more than 2cm. These surfaces are appended with the differential enhancer [36, 37].

EMG signal might be debased by different commotion factors, for example, causative elements for example direct influence which might be outward factors for example ill-advised cathode detachment and terminal position and so on and characteristic variables for example ecological or anatomical and so forth. The commotion factor brought about by nature should be decreased by expanding the sign to clamor proportion (SNR) of the EMG sign to get progressively helpful sign. So also the correct portion of terminals and hardware 13 may conquer the clamor drafted by electromagnetic gadgets. In the event that taking out commotion from EMG sign is disregarded, wanted outcomes can't be accomplished.

In the wake of account, every one of the information from the database are leveled up to the most astounding recurrence for example 100 Hz and after that low pass separated at 1 Hz. So as to evacuate the trash information put away during changing from rest to development state, information of every development is portioned into three equivalent parts and the data from the center fragment is gathered. At that point the information of the center portion is additionally prepared by taking its normal and one example for every development reiteration is chosen. Consequently ten examples are gathered for every development with ten reiterations. The information in this way acquired for each subject is then standardized at zero mean for sEMG sign having unit standard deviation.

3.3Feature Extraction

Following stage in the examination of sEMG sign is feature extraction. This method is utilized to get suitable arrangement of highlights known as highlight vector by gathering appropriate data and denying unessential information from the crude EMG information. To decide the exact features speaking to wanted yield undertakings, feature vector acquired ought to have all the helpful and effective data got from the EMG signals. On the off chance that these sign are exposed to arrangement strategies without handling them cautiously with features extraction, their yield execution won't be acceptable and will be wasteful computationally. So this progression is of high importance utilizing these highlights as contribution to the classifier to guarantee better arrangement results however, their properties, for example, computational cost, power, multifaceted nature and so forth ought to never be disregarded. Studies uncovered that the capability of examination of EMG signals for example acknowledgment is totally needy upon the choice of features.

Feature extraction can be done in time domain or frequency domain, features selected for the proposed work are in frequency domain. The reason behind the selection of features in frequency domain is that most of the electromechanical actuators are being operated in frequency domain. Three features named as Mean, Peak and Slope are selected for the extraction.

CHAPTER 4: ANALYSIS AND RESULTS

The characterization of EMG signal is indispensable for analysis of different sicknesses that should be basic, quick and solid. The grouping of developments is critical in the structure of restoration frameworks and robots and control of multifunctional prosthetic appendage. Since there is a contrast between the EMG sign taken from the sound people and from those with any sort of neurological ailment or inability having development issue, in this manner a few examinations used these sign got from the muscle tissue for the determination and ID of different sicknesses or neuromuscular exhaustion. Correspondingly exceptional work has been done as of late on creating productive sign examples for exhaustion order, applicable to the games science. The high arrangement exactness is exceptionally pivotal as it makes the life of patients having appendage inability much agreeable for which choice of value highlights for extraction is of extraordinary hugeness [38]. Besides, compelling dimensionality decrease strategies and reasonable classifiers must be acquainted all together with guarantee impeccable example acknowledgment.

Ongoing exploration work has been centered acutely around the arrangement of examples of EMG signals. Different kinds of classifiers were presented which are pertinent effectively for a few EMG purposes. Some of them are named as Artificial Neural System (ANN), Linear Discriminant Examination (LDA), Support Vector Machines (SVM) and Fuzzy classifier [39]. As referenced above, crude EMG sign is handled through component extraction to get an element vector which goes about as a contribution to be grouped for example acknowledgment. This progression improves the data robustness of the sign utilized for example grouping. Because of the eccentric idea of the crude EMG signals, they can't be straightforwardly provided to the classifier by overkilling it rather measurement decrease methodologies are connected to limit the highlights measurement. These techniques bring down the heap and computational time on the classifier. Principal Component Analysis (PCA) and LDA are utilized for this reason yet need progressively computational time for which scientists are acquainting different calculations with keep up strength and productivity of the arrangement procedure. These strategies are useful in upgrading the characterization precision of the EMG prosthesis [40]. Anyway a few analysts joined different procedures with PCA for this reason to accomplish surprisingly better characterization results. Late investigations are generally utilizing LDA classifiers as they are straightforward and simple to be executed and prepared [41].

LDA is a linear classifier which likewise goes about as dimensionality decrease strategy. It is useful in both double and multi-class arrangement with clear yield variable. Each info variable given to this model ought to have same difference and the information institutionalized with 0 mean and unit standard deviation. LDA predicts the likelihood that each class has new information sources set [42-43]. The class with high likelihood is anticipated to be the yield class. This model assesses the mean and change of information for each class. Another component space for the information is acquainted all together with increment the partition among the classes. For this situation, the spread of information isn't considered so the separation between the methods determined for each class may not be the main immaculate one. To take care of this issue, Ronald Fisher recommended the expansion in capacity that indicates the division between the methods for each class and decline in spread inside each class [44]. This supposition that is substantial for the informational index with Ordinary dissemination.

Likewise, SVM is a classifier that gives the hyperplane with the largest margin, which can be explained as it segregate the wanted and unwanted data more efficiently. Moreover, it has different kernels i.e. linear and non-linear which help to differentiate the data on the basis of their linearity. The kernel used in this work is linear, giving relatively better results when compared with the state of art. However, KNN is the classifier that caters the category of non-linear data as well. It is the classifier that comes under the category of supervised machine learning, it can be used to get the solution of classification and regression problems [45]. It does not give a straight line or a hyperplane, it works on the principle by assuming that similar things exist in the close proximity. It works by the finding the distances between a query and all the examples in the data. The decision boundaries it make are locally linear segments however in general it possess a complex shape.

When we execute all the eight isometric and isotonic hand movements the results of accuracies were disappointing. Combined accuracy of all 8 hand movements when classified together using different features has the following statistics

LDA

Minimum classification accuracy → 23.75

Maximum classification accuracy → 25.53

SVM

Minimum classification accuracy → 24.88

Maximum classification accuracy → 28.53

KNN

Minimum classification accuracy → 24.33

Maximum classification accuracy → 26.42

Classification Accuracy using SVM is highest in comparison to LDA and KNN. However, such reduced accuracies are unacceptable as it cannot be implemented on rehabilitation or assistive systems.

Subsequent is the table that entails the classification accuracy obtained from the implementation of three different classifiers LDA, SVM and KNN. All the three features are used for the classification and rest of 10 are the combinations of these features. The table is for the classification of first movement of hand with respect to its five different repetitions.

Linear Discriminant Analysis (LDA)							
Feature	**Movement**	**1st iteration**	**2nd iteration**	**3rd iteration**	**4th iteration**	**5th iteration**	**Average**
Mean	Thumbs Up	66.31	66.06	66.00	65.93	66.06	66.072
Peak		65.00	64.94	64.94	65.00	65.00	64.976
Slope		64.18	64.19	64.06	64.19	64.19	64.162
Mean Peak		66.68	66.69	66.56	66.56	66.63	66.624
Mean Slope		71.68	71.69	71.63	71.69	71.63	71.664
Peak Slope		68.50	68.63	68.38	68.25	68.5	68.452
Slope Peak		68.18	68.25	68.56	68.69	68.38	68.412
Mean Peak Slope		71.68	71.69	71.88	71.75	71.63	71.726
Mean Slope Peak		71.56	71.50	71.50	71.50	71.63	71.538
Peak Slope Mean		71.43	71.88	71.75	71.88	71.69	71.726
Peak Mean Slope		71.81	71.75	71.81	71.75	71.88	71.8
Slope Mean Peak		71.75	71.75	71.75	71.75	71.63	71.726
Slope Peak Mean		71.81	71.75	71.62	71.81	71.68	71.734
Support Vector Machines (SVM)							
Feature	**Movement**	**1st iteration**	**2nd iteration**	**3rd iteration**	**4th iteration**	**5th iteration**	**Average**
Mean	Thumbs Up	74.37	74.37	74.37	74.43	74.37	74.382
Peak		72.00	71.93	72.18	72.18	72.12	72.082
Slope		70.18	70.25	70.18	70.18	70.18	70.194
Mean Peak		74.25	74.18	74.18	74.12	74.18	74.182

Mean Slope		74.81	74.68	74.87	74.81	74.87	74.808
Peak Slope		72.62	72.68	72.62	72.62	72.62	72.632
Slope Peak		72.68	72.62	72.62	72.62	72.56	72.62
Mean Peak Slope		74.31	74.31	74.25	74.25	74.25	74.274
Mean Slope Peak		74.25	74.25	74.25	74.31	74.31	74.274
Peak Slope Mean		74.25	74.31	74.25	74.25	74.25	74.262
Peak Mean Slope		74.25	74.25	74.31	74.25	74.25	74.262
Slope Mean Peak		74.25	74.25	74.25	74.31	74.25	74.262
Slope Peak Mean		74.31	74.31	74.25	74.25	74.25	74.274
K-Nearest Neighbors (KNN)							
Feature	**Movement**	**1st iteration**	**2nd iteration**	**3rd iteration**	**4th iteration**	**5th iteration**	**Average**
Mean	Thumbs Up	73.62	73.06	72.43	72.87	72.81	72.958
Peak		71.50	71.50	71.31	71.68	70.93	71.384
Slope		67.68	67.62	66.93	67.50	67.25	67.396
Mean Peak		81.25	81.56	81.81	81.68	81.62	81.584
Mean Slope		83.81	84.43	83.68	83.50	84.62	84.008
Peak Slope		77.62	77.12	76.93	76.81	77.56	77.208
Slope Peak		77.06	77.37	76.68	76.87	77.31	77.058
Mean Peak Slope		85.37	84.37	85.75	84.50	85.00	84.998
Mean Slope Peak		85.56	85.18	85.13	85.06	85.62	85.31
Peak Slope Mean		85.18	84.75	84.75	84.93	85.06	84.934
Peak Mean Slope		85.12	84.62	85.12	85.31	85.18	85.07
Slope Mean Peak		84.81	84.81	85.50	85.00	84.93	85.01
Slope Peak Mean		84.93	84.87	85.25	85.00	85.00	85.01

Table 4-1: Classification accuracy of First Hand Movement

It can be seen vividly in the above table 4-1 that the highest classification accuracy from the classifier LDA we got is 71.8% with the combination of Peak Mean Slope, and the classifier SVM gave the maximum of it is 74.8% with the combination of 74.8% and KNN stood highest of all with the accuracy of 85.31% with the combination of Mean Slope Peak. If we compare our results with the state of art then we got improvement in the accuracies as 3.31% from KNN and 3.8% from SVM.

Next is the graphical representation of the classification accuracies of all the eight hand movements.

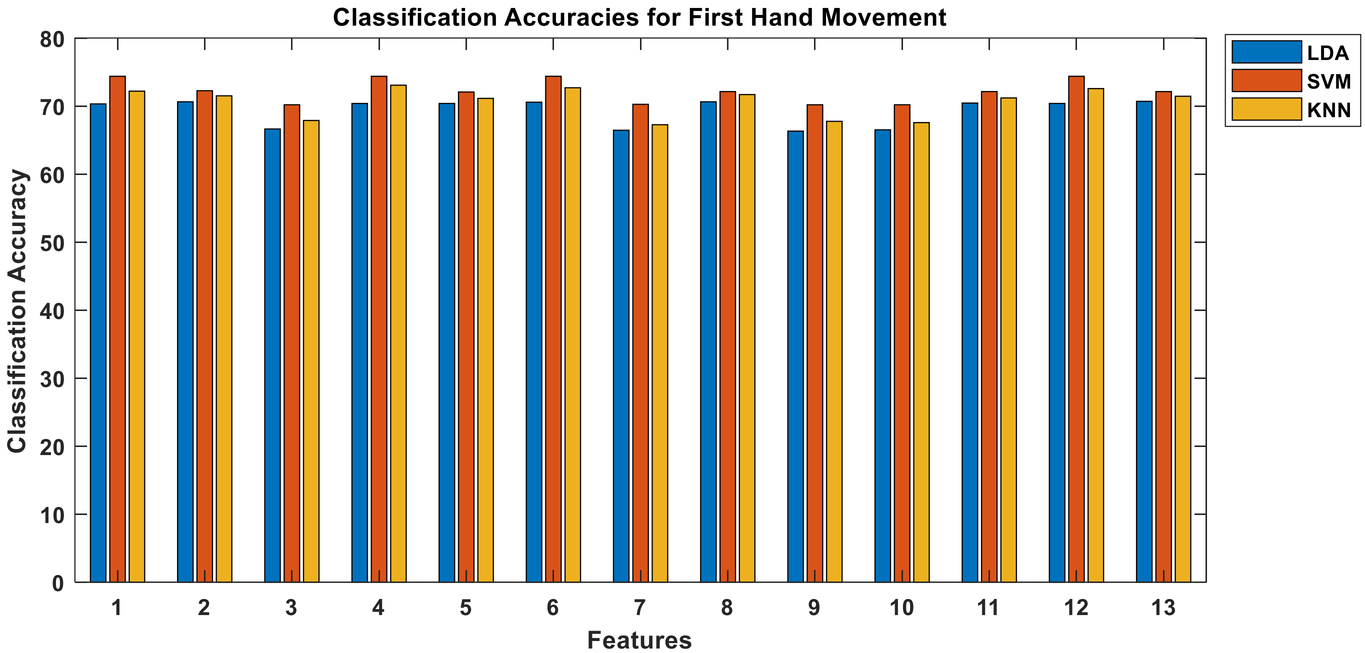

Figure: 4-1 Observation: Classification of SVM is highest for all the features

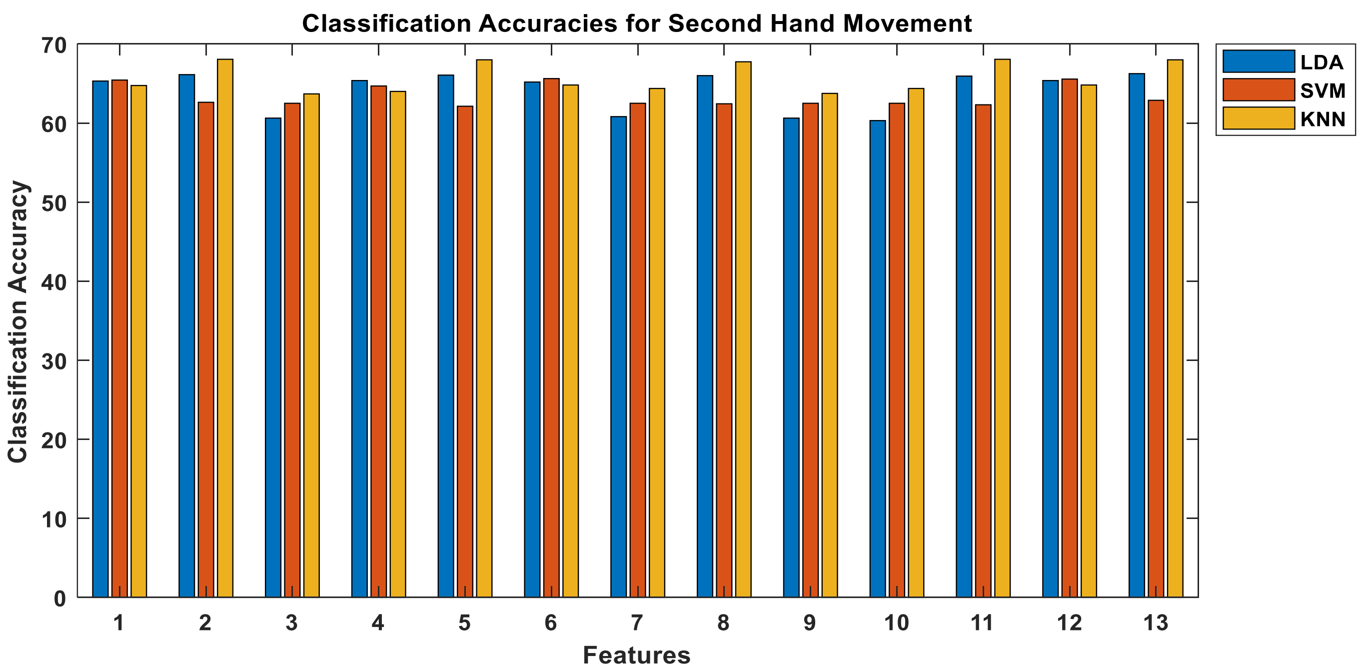

Figure: 4-2 Observation: Classification of KNN is mostly high for all the features

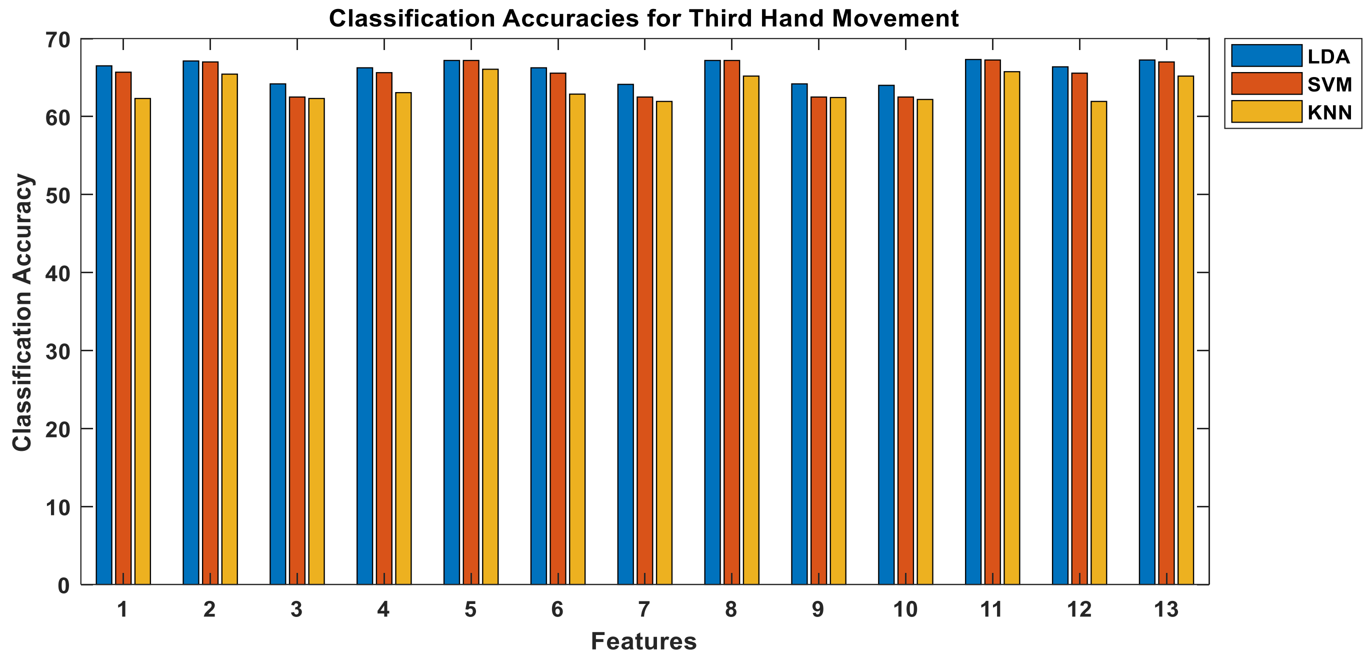

Figure: 4-3 Observation: Classification of LDA is highest for all the features

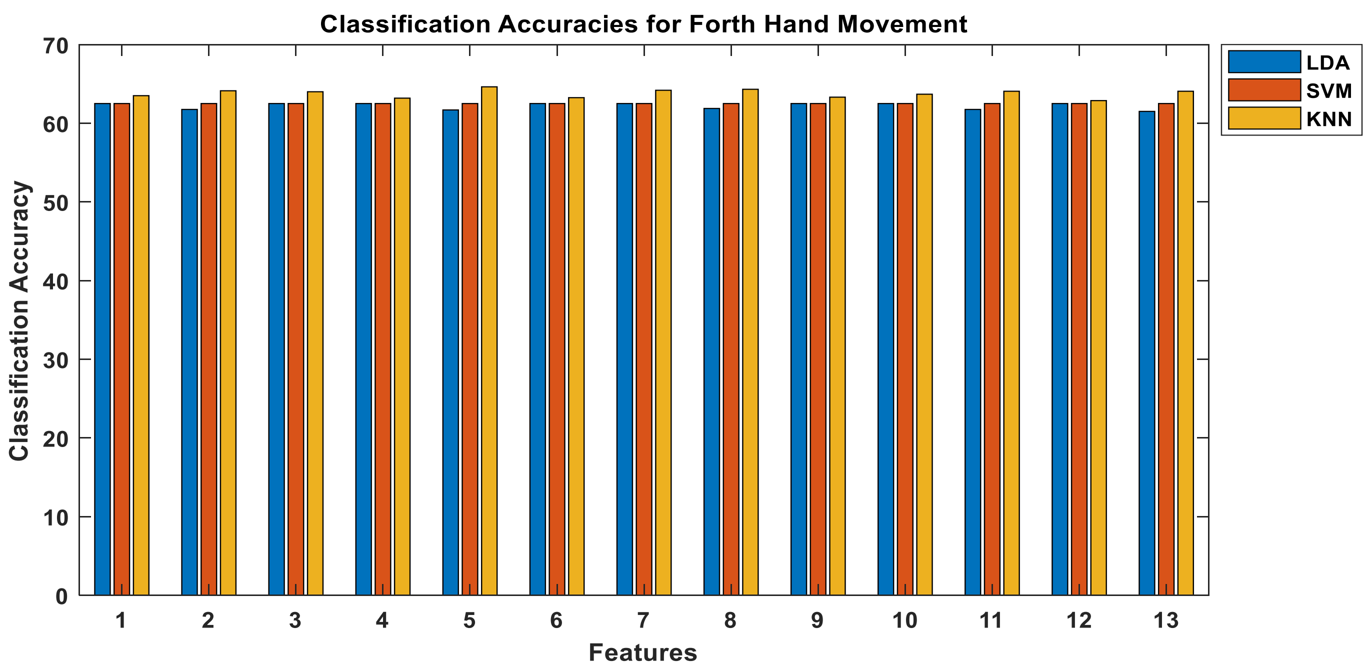

Figure: 4-4 Observation: Classification of KNN is highest for all the features

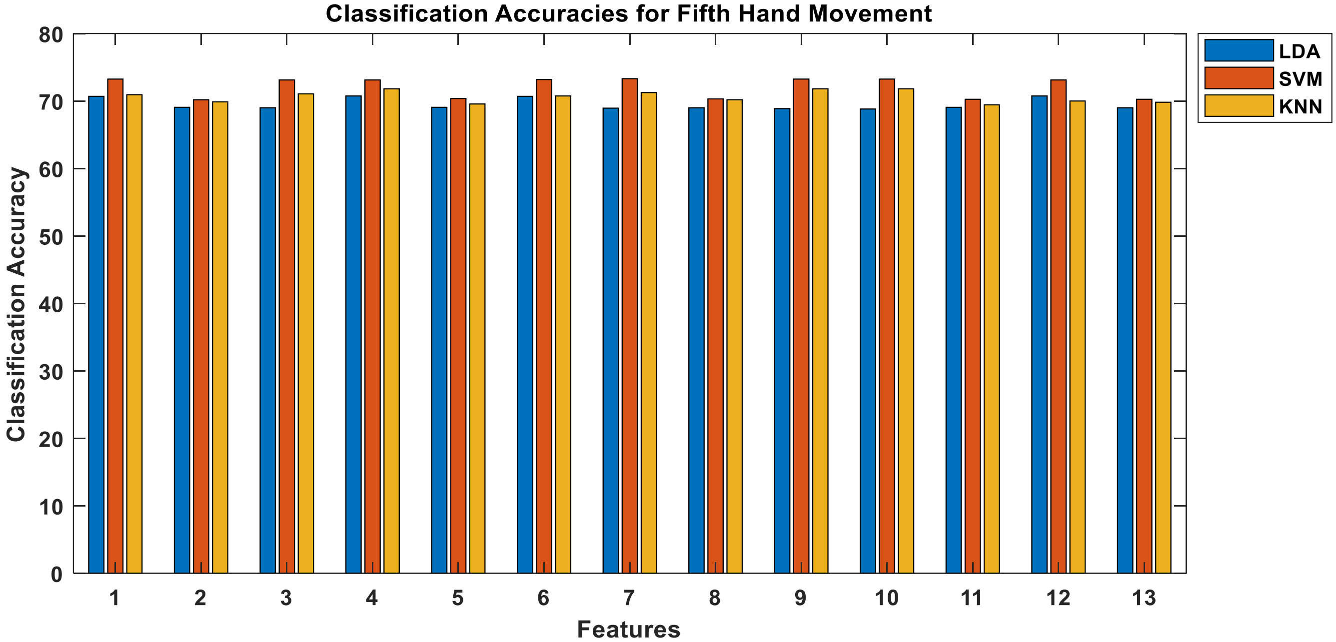

Figure: 4-5 Observation: Classification of SVM is highest for all the features

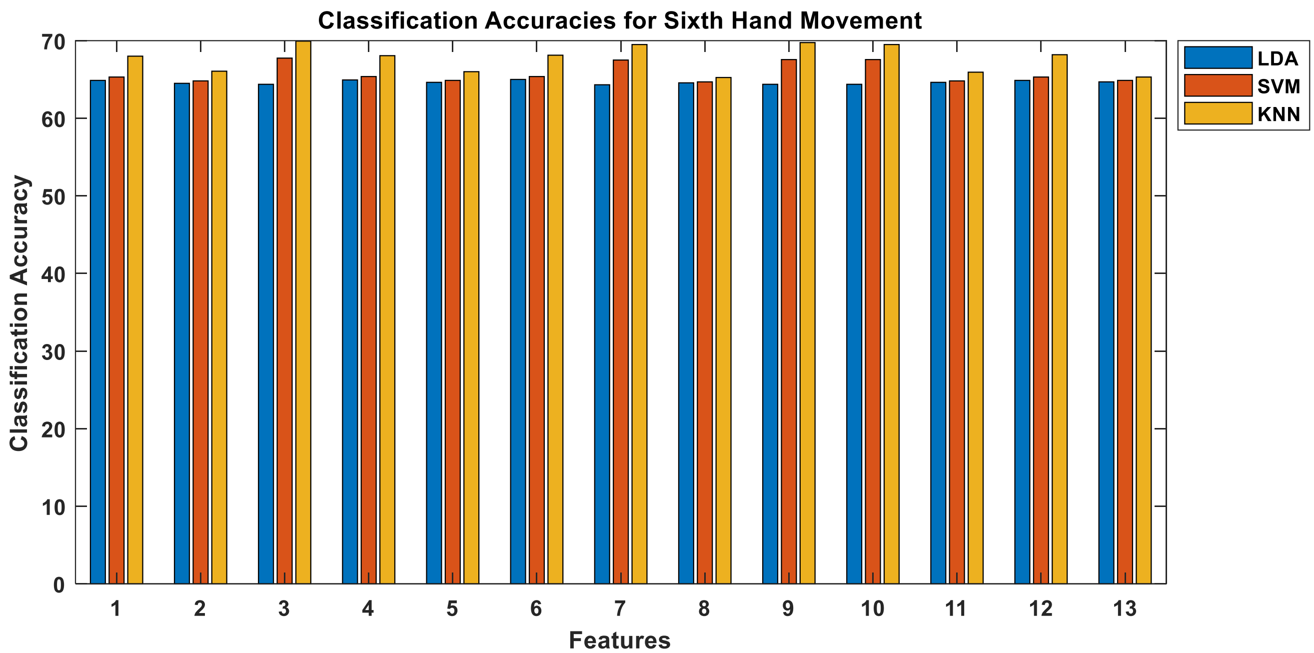

Figure: 4-6 Observation: Classification of KNN is highest for all the features

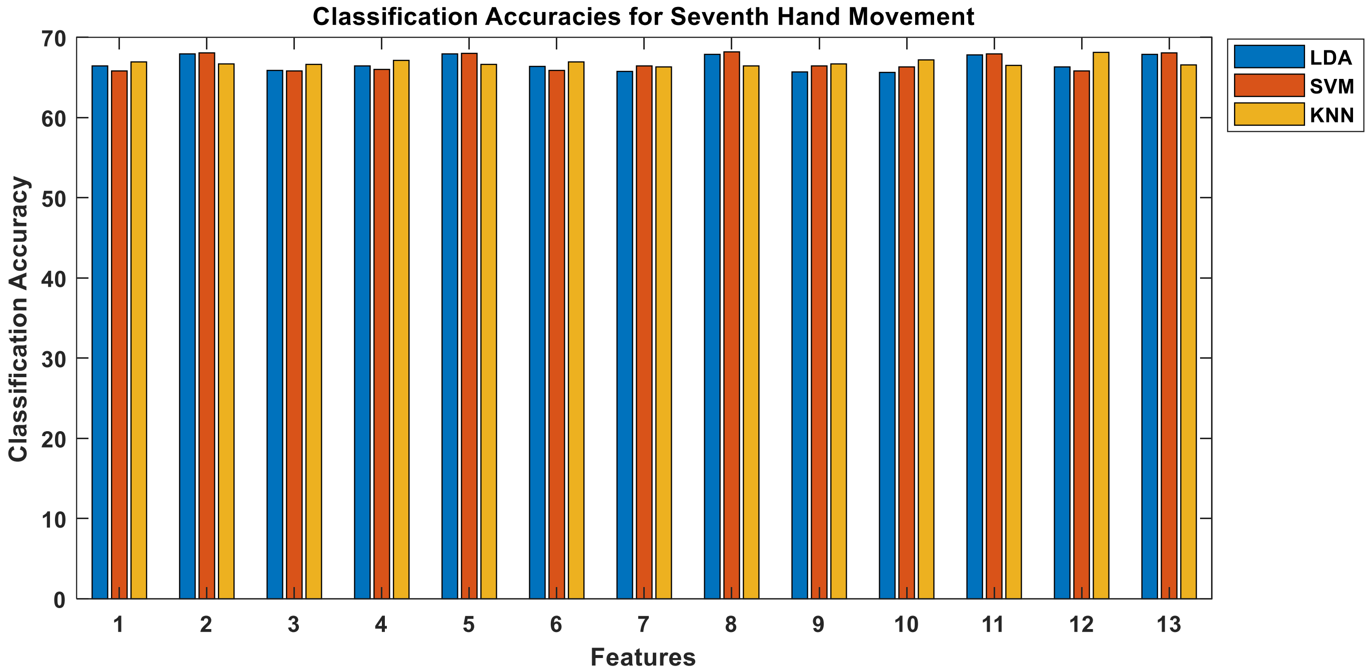

Figure: 4-7 Observation: Classification of KNN is highest for all the features

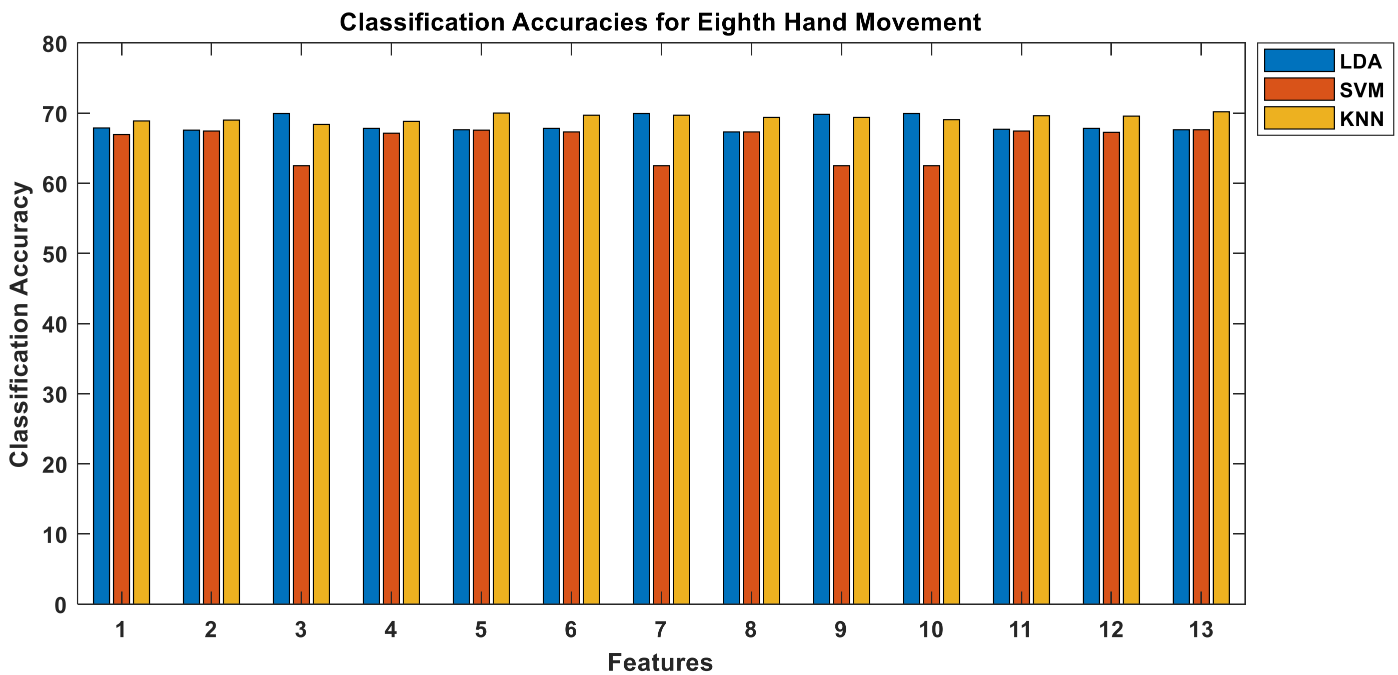

Figure: 4-8 Observation: Classification of KNN is highest for all the features

From the list of above figures it can be seen intensely that Overall KNN gives better result as compared to LDA and SVM. Thus it is not necessary that based on literature a conclusion can be developed. It is always important to apply classification techniques to data samples and based on results obtained the classifier should be declared as suitable in comparison to other available classifiers.

It can be analyzed from the above classified data that it is necessary to implement neural networks for the classification of EMG data to attain high number of accuracies from classifiers. Analysts have stressed the utilization of neural network classifier for EMG investigation as it can manage both direct and nonlinear properties of the information gathered for examination. ANNs look like the arrangement of organic neural systems and are nonlinear solo learning component fit for displaying and preparing EMG information measurably. Del and Park proposed the ANN as the best device to speak to the ongoing usage of EMG which can distinguish the myoelectric flag all the more unequivocally [37]. The yield acquired from this method means the degree to which immobilized muscle incitement is demanded over a collaboration. Studies have demonstrated that ANN has been utilized for the arrangement of six upper appendage developments [38]. Ongoing examination work has upgraded the utilization of this methodology for grouping reason with increasingly improved execution.

The contributions to the ANN might be a picture or example in vector structure signified by x(n) while n speaks to the quantity of sources of info. Neural systems pick the loads dependent on the data of the issue which demonstrates the nature of the interconnection between neurons inside the neural framework and each weight is increased to each relating information. All the subsequent sources of info are then summed up inside figuring unit. On the off chance that the entirety is zero, the framework yield is esteemed up by including inclination which consistently has unit info and unit weight. So the yield worth may go from 0 to unendingness. To get an ideal whole esteem, an exchange work as initiation capacity is connected to the aggregate by setting up an edge esteem.

Following are the graphs obtained when ANN applied to the given data for the set of all eight movements.

Input Data: EMG Hand Movement
Target Data: Feature (Combination of Mean Slope Peak)

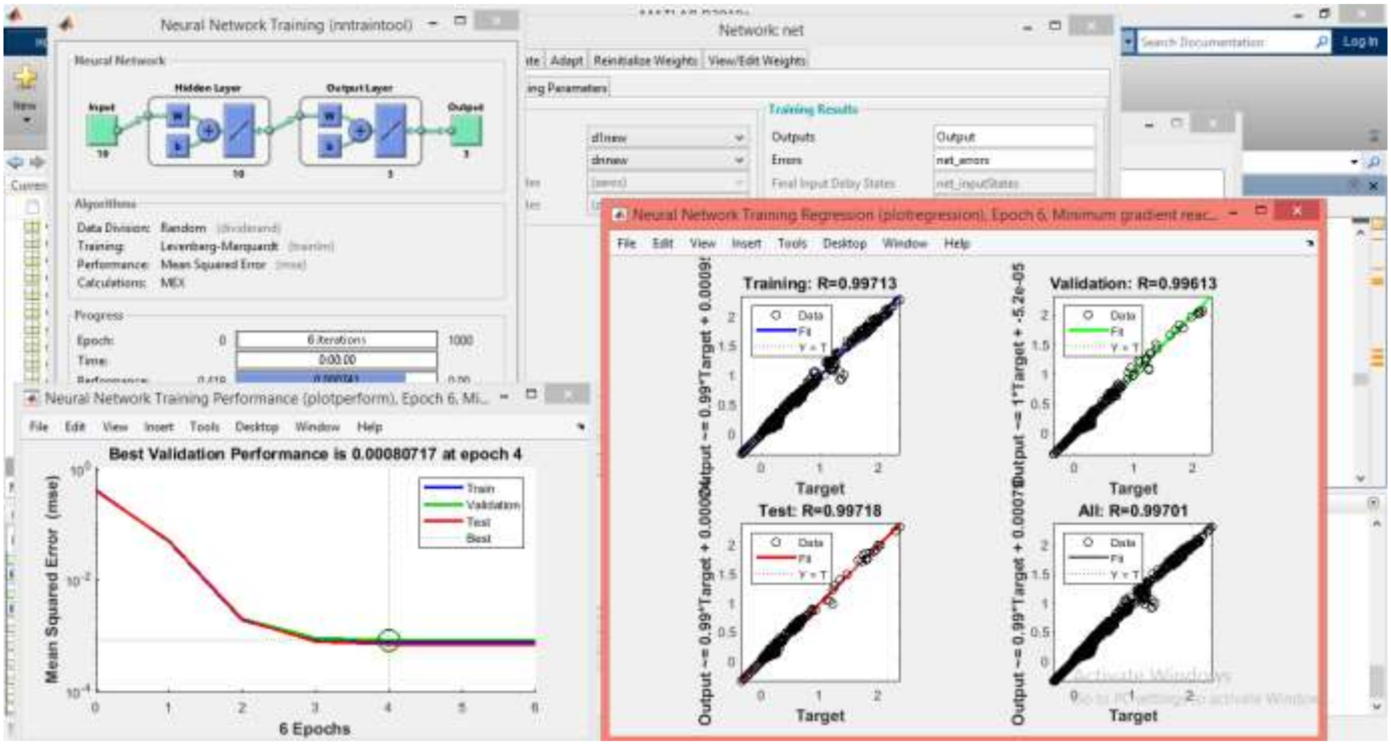

Figure: 4-9 First Hand Movement from ANN

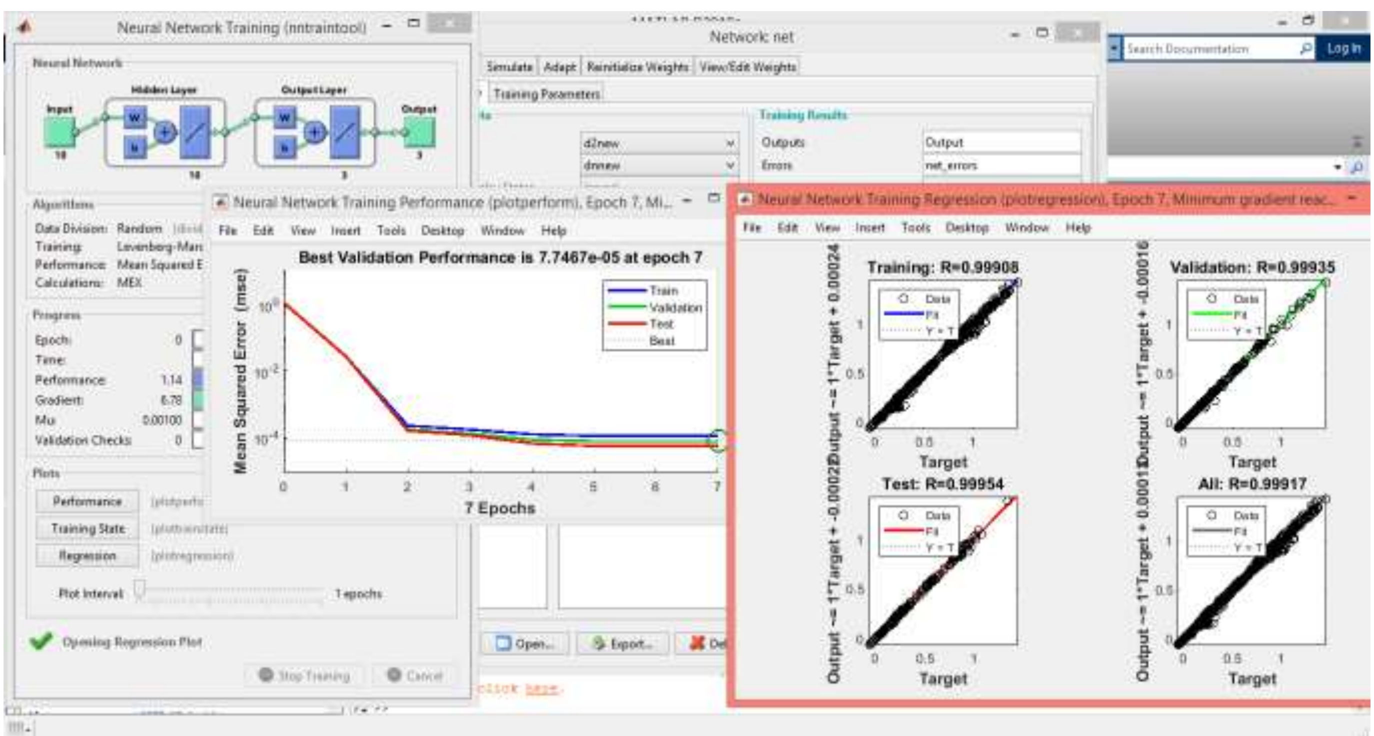

Figure: 4-10 Second Hand Movement from ANN

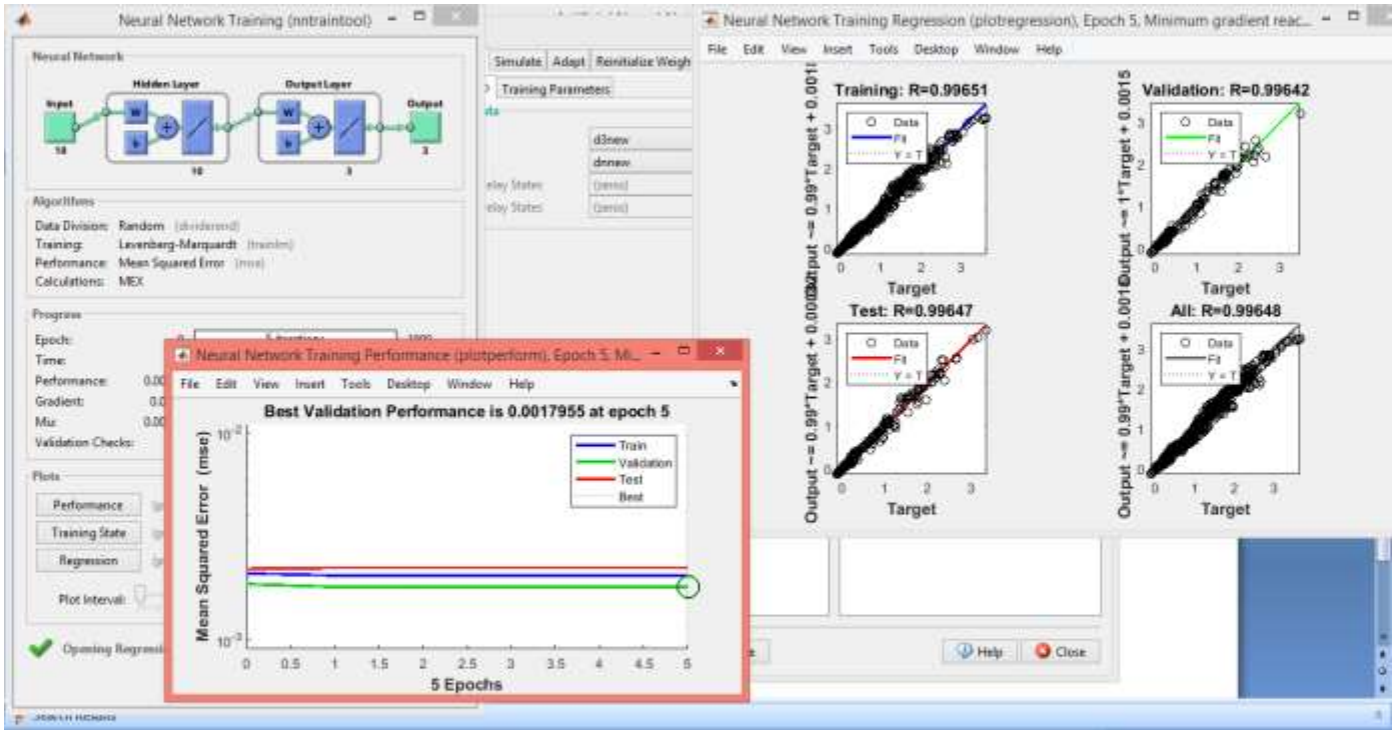

Figure: 4-11 Third Hand Movement from ANN

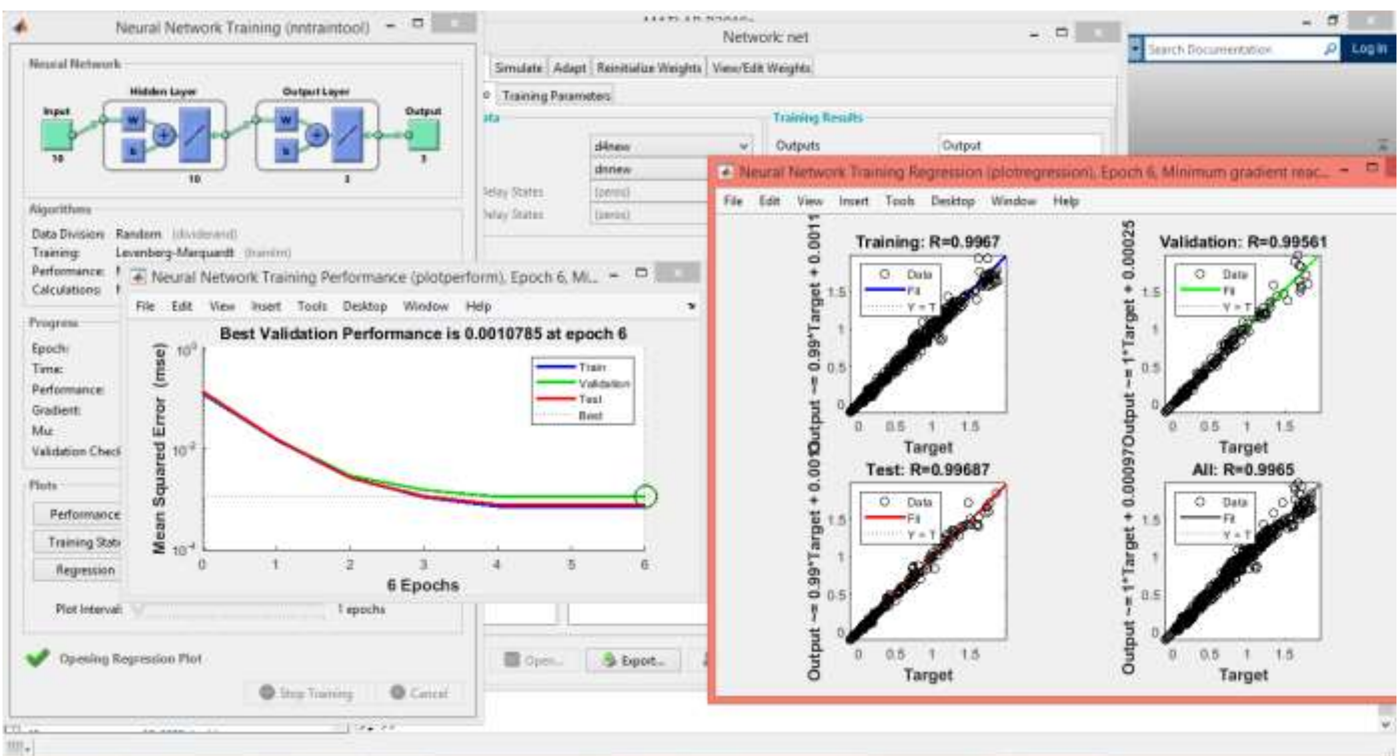

Figure: 4-12 Forth Hand Movement from ANN

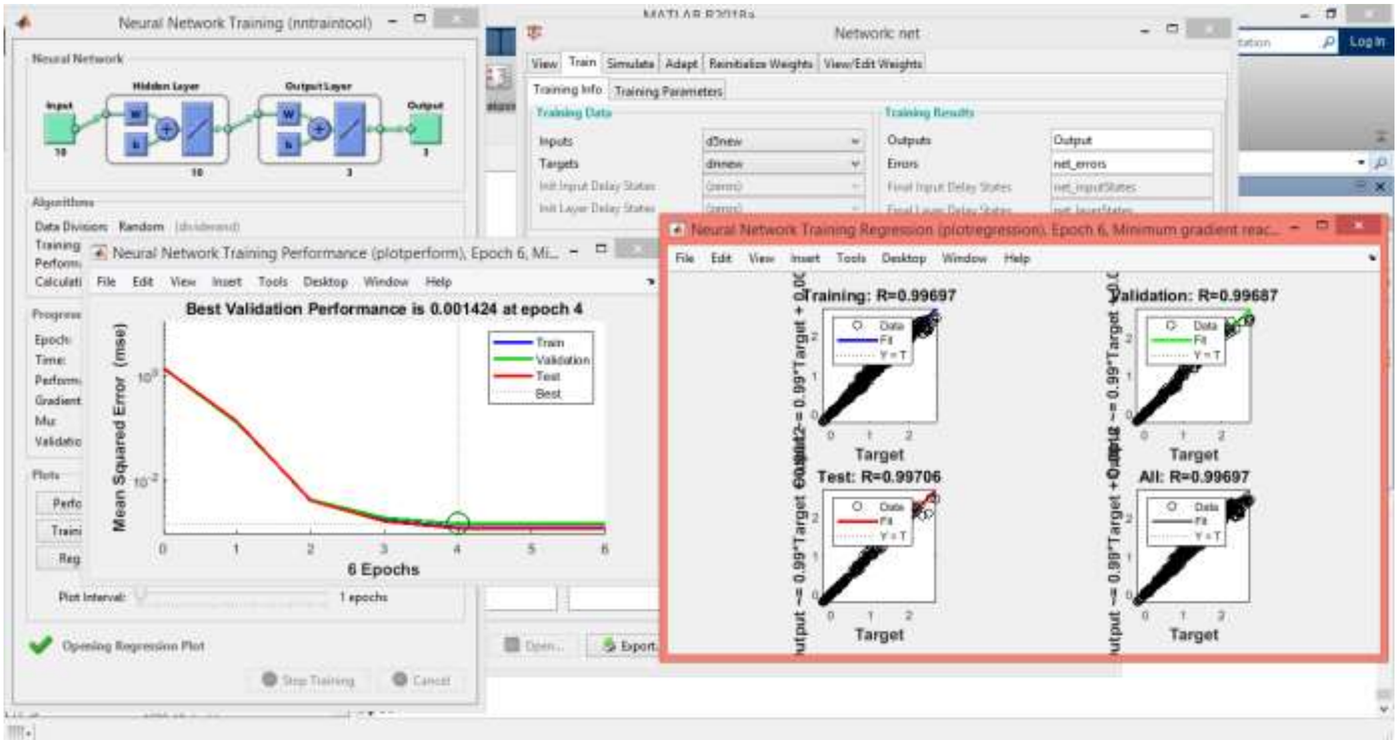

Figure: 4-13 Fifth Hand Movement from ANN

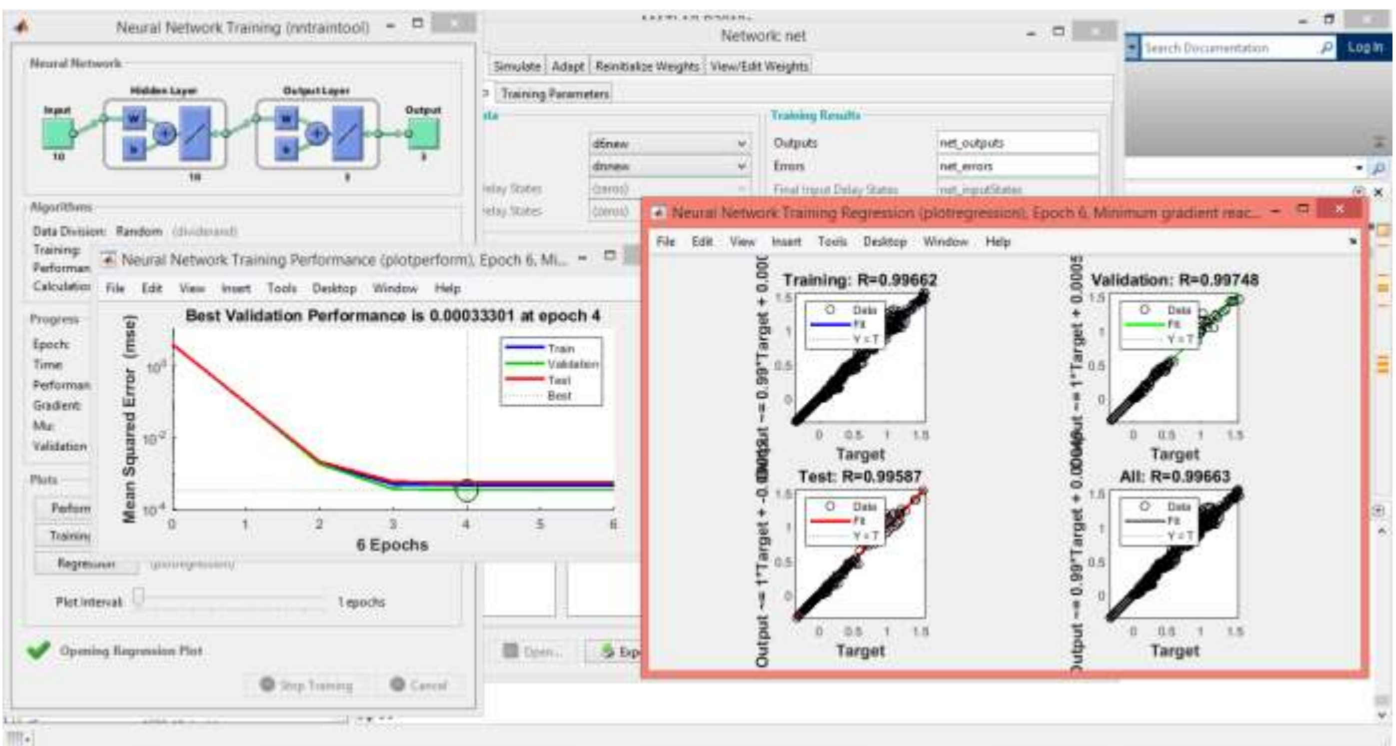

Figure: 4-14 Sixth Hand Movement from ANN

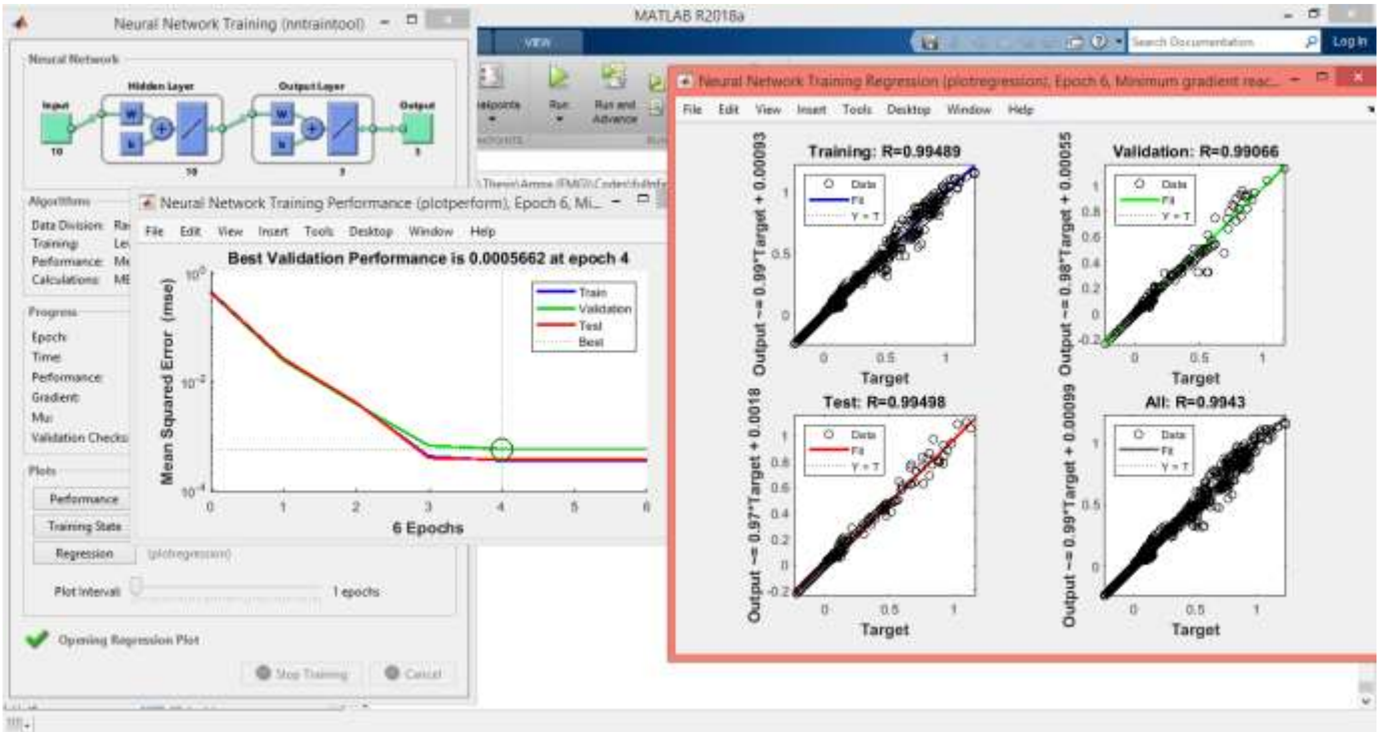

Figure: 4-15 Seventh Hand Movement from ANN

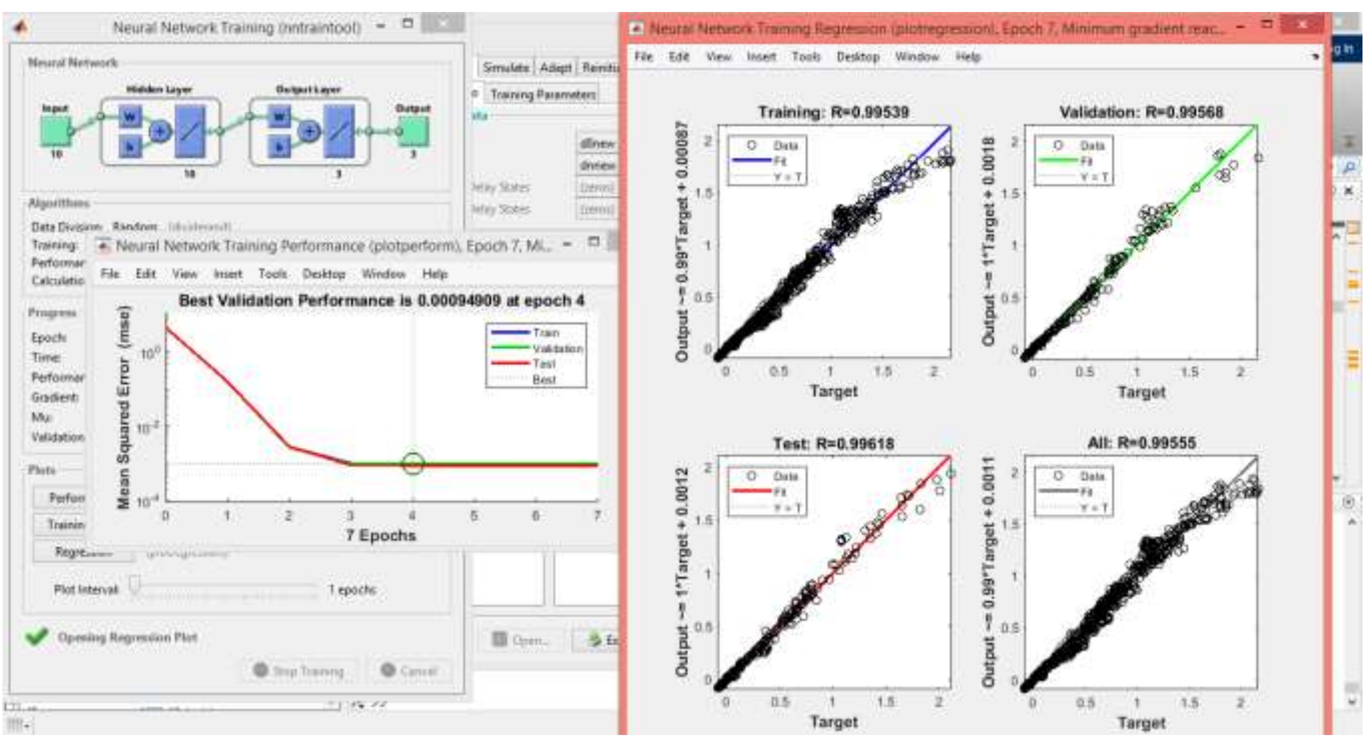

Figure: 4-16 Eighth Hand Movement from ANN

From the figures presented above it can be seen in the graphs of all the hand movements that with very less number of Epochs data converged to the desired output declaring that how neural networks work efficiently in the classification and regression as well.

CHAPTER 5: CONCLUSION

The point of this investigation is to finish up an exact perspective on procedures utilized for preparing EMG and to recommend more enhancements for the example acknowledgment draws near. The examination will help scientists to foresee the better classifier for the investigation of sEMG signals and the work dependent on this examination will be progressively useful in clinical, arm prosthetic and biomedical fields.

This work manages the examination of the crude EMG information obtained from the NinaPro database for the recognizable proof of eight isometric and isotonic hand movements. This openly accessible dataset contains information acquired from sign gathered with the assistance of cathodes from the muscle action of upper appendage for five reiterations of 52 distinct developments from 27 subjects. Out of 52 developments, eight hand developments for each subject were chosen to be distinguished for this examination. Four classifiers, LDA, SVM, KNN and ANN were assessed and thought about for the general percent order precision to distinguish these developments for four surely understood highlights. The aftereffects of this theory presumed that non-linear and from the deep learning of category of machine learning ANN classifier uncovered better execution results when contrasted with linear classifier LDA, SVM and non-linear KNN.

When classification of all the movements was executed at once then the accuracy was dropped to 23.75%, however 85.31% of maximum accuracy achieved with the KNN when the binary classification was done. Moreover when the classification accuracies were being compared with the state of art the result showed that KNN gave the accuracy of 82% for the same data and SVM was with 71%. Therefore the proposed work done was accomplished with improved accuracies with the conventional classifier as well.

The database utilized in this examination is no uncertainty exceptionally supportive for giving effectively accessible sEMG information, which is relevant proficiently for the acknowledgment and arrangement of upper appendage developments yet at the same time there are numerous difficulties looked by bio apply autonomy network and AI inquire about in myoelectric control and acknowledgment. This database perhaps redesigned by expanding the quantity of both sound and incapacitated subjects and changing it up of hand developments. This will further support the usefulness and flexibility of the database to accomplish increasingly solid outcomes. So as to address the difficulties went up against in this field, includes that are increasingly vigorous are to be chosen and novel highlights extraction methodologies must be proposed. By expanding the EMG channels tally and the quantity of highlights as contribution to the classifier, the tally of control directions of the order strategy is additionally expanded. This will secure the surprising grouping yields by giving further developed and critical data from EMG. In the event that huge number of highlights is wanted to be separated, LDA ought to be favored as a result of its dimensionality decrease property as information is changed over to a space vector having low measurements without squandering valuable data. Besides, the acknowledgment and control of developments perhaps upgraded by looking at the grouping capacity of an assortment of direct and non-straight classifiers and the mean precision accomplished in this examination might be additionally improved.

REFERENCES

[1] Carl Peter Robinson, Baihua Li, Qinggang Meng, and Matthew T.G. Pain. "Pattern Classification of Hand Movements using Time Domain Features of Electromyography". In Proceedings of MOCO '17, London, United Kingdom, June 28-30, 2017, 6 pages.

[2] Milica S. Isaković, Nadica Miljković, and Mirjana B. Popović "Classifying sEMG-based Hand Movements by Means of Principal Component Analysis" Telfor Journal, Vol. 7, No. 1, 2015.

[3] Manfredo Atzori1, Arjan Gijsberts2, Henning M¨uller1, and Barbara Caputo D. Farina, S. Member, N. Jiang, H. Rehbaum, and S. Member, "Classification of hand movements in amputated subjects by sEMG and accelerometers"

[4] "The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges," vol. 22, no. 4, pp. 797–809, 2014.

[5] B. Peerdeman, D. Boere, H. Witteveen, R. Huis in `t Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, and S. Misra, "Myoelectric forearm prostheses: state of the art from a user-centered perspective," J. Rehabil. Res. Dev., vol. 48, no. 6, pp. 719–738, 2011.

[6] C. Cipriani, C. Antfolk, M. Controzzi, G. Lundborg, B. Rosen, M. C. Carrozza, and F. Sebelius, "Online myoelectric control of a dexterous hand prosthesis by transradial amputees," IEEE Trans. Neural Syst. Rehabilitation. Eng., vol. 19, no. 3, pp. 260–270, 2011.

[7] H. Müller, J. Kalpathy-Cramer, I. Eggel, S. Bedrick, R. Said, B. Bakke, C. E. J. Kahn, and W. Hersh, "Overview of the CLEF 2009 medical image retrieval track," in Working Notes of CLEF 2009, Corfu, Greece, 2009.

[8] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The pascal visual object classes (VOC) challenge," Int. J. Comput. Vis., vol. 88, no. 2, pp. 303–338, 2010.

[9] The Ninapro Database: a Resource for sEMG Naturally Controlled Robotic Hand Prosthetics Manfredo Atzori and Henning Müller

[10] M. A. Oskoei and H. Hu, "Myoelectric control systems a survey," Biomedical Signal Processing and Control, vol. 2, no. 4, pp. 275–294, 2007.

[11] A. Phinyomark et al., "Evaluation of EMG feature extraction for hand movement recognition based on euclidean distance and standard deviation," in Electrical

Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010 International Conference on. IEEE, 2010, pp. 856–860.

[12] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “Feature reduction and selection for emg signal classification,” Expert Systems with Applications, vol. 39, no. 8, pp. 7420–7431, 2012.

[13] Ulysse Cˆot´e-Allard, Cheikh Latyr Fall, Alexandre Drouin, Alexandre Campeau-Lecours, Cl´ement Gosselin, Kyrre Glette, Franc¸ois Laviolettey, and Benoit Gosselin “Deep Learning for Electromyographic Hand Gesture Signal Classification Using Transfer Learning”

[14] Alexandros Pantelopoulos and Nikolaos G. Bourbakis. 2010. “A survey onwearable sensor-based systems for health monitoring and prognosis”. IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews 40, 1 (2010), 1–12.

[15] Erik Scheme and Kevin Englehart. 2011. “Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use”. Journal of Rehabilitation Research and Development 48, 6 (2011), 643–660.

[16] Dario Farina, Ning Jiang, Hubertus Rehbaum, Aleš Holobar, Bernhard Graimann, Hans Dietl, and Oskar C. Aszmann. 2014. “The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges”. IEEE Transactions on Neural Systems and Rehabilitation Engineering 22, 4 (2014), 797–809.

[17] D. Yang, J. Zhao, L. Jiang, and H. Liu, “Dynamic hand motion recognition based on transient and steady-state EMG signals,” Int. J. Humanoid Robot., vol. 9, pp. 11250007-1–11250007-18, 2012.

[18] T. Lorrain, N. Jiang, and D. Farina, “Influence of the training set on the accuracy of surface EMG classification in dynamic contractions for the control of multifunction prostheses,” J. Neuroeng. Rehabil., vol. 8, p. 25, 2011.

[19] E. Scheme and K. Englehart, “Training strategies for mitigating the ef- fect of proportional control on classification in pattern recognition based myoelectric control,” J. Prosthetics Orthotics, vol. 25, pp. 76–83, Apr. 1, 2013.

[20] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and O. Stavdahl, “Resolving the limb position effect in myoelectric pattern recognition,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 6, pp. 644–651, Dec. 2011.

[21] Y. J. Geng, P. Zhou, and G. L. Li, “Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classifi- cation in transradial amputees,”
J. Neuroeng. Rehabil., vol. 9, p. 74, Oct. 5, 2012.
30
[22] N. Jiang, S. Muceli, B. Graimann, and D. Farina, “Effect of arm position on the prediction of kinematics from EMG in amputees,” Med. Biol. Eng. Comput., vol. 51, pp.
143–151, Feb. 2013.
[23] J. Liu, D. Zhang, X. Sheng, and X. Zhu, “Quantification and solutions of arm movements effect on sEMG pattern recognition,” Biomed. Signal Process. Control, vol. 13,
pp. 189–197, 2014.
[24] M. Atzori, A. Gijsberts, H. Müller, and B. Caputo, “Classification of hand movements in amputated subjects by sEMG and accelerometers,” in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2014, p. 63.
[25]M. Oskoei and H. Hu, “Support vector machine-based classification scheme for myoelectric control applied to upper limb,” IEEE Trans- actions on Biomedical Engineering,
vol. 55, no. 8, pp. 1956–1965, 2008.
[26] M. Zardoshti-Kermani, B. Wheeler, K. Badie, and R. Hashemi, “EMG feature evaluation for movement control of upper extremity prosthe- ses,” IEEE Transactions on
Rehabilitation Engineering, vol. 3, no. 4, pp. 324–333, 1995.
[27]F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. Thakor,
“Decoding of individuated finger movements using surface electromyography,” IEEE
Transactions on Biomedical Engi- neering, vol. 56, no. 5, pp. 1427–1434, 2009.
31
[28] L. J. Hargrove, K. Englehart, and B. Hudgins, “A comparison of surface and intramuscular myoelectric signal classification,” IEEE Transactions on Biomedical
Engineering, vol. 54, pp. 847–853, 2007.
[29]P. C. Doerschuk, D. E. Gustafon, and A. S. Willsky, “Upper extremity limb function discrimination using emg signal analysis,” IEEE Trans- actions on Biomedical Engineering,
vol. 30, no. 1, pp. 18–29, 1983.
[30]K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, “Classification of the myoelectric signal using time-frequency based representa- tions,” Medical Engineering &

Physics, vol. 21, no. 6-7, pp. 431–438, 1999.

[31] M. Atzori, A. Gijsberts, S. Heynen, A.-G. M. Hager, O. Deriaz,P. van der Smagt, C. Castellini, B. Caputo, and H. Mu¨ller, “Building the Ninapro database: A resource for the biorobotics community (submitted),” in Proceedings of IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob 2012), 2012.

[32]M. Atzori and H. M u¨ller, “NINAPRO project first milestone: Set up of the data base,” Institute of Business Information Systems, Univer- sity of Applied Sciences Western Switzerland, Sierre, Switzerland, Tech. Rep., 2012, available at http://publications.hevs.ch/index.php/ publications/show/1165.

[33] Manfredo Atzori et al. 2014. “Electromyography data for non-invasive naturally controlled robotic hand prostheses”. Scientific data (2014), 1:140053. https://doi.org/10.1038/sdata.2014.53

[34] M. Atzori, A. Gijsberts, S. Heynen, A.-G. M. Hager, O. Deriaz,P. van der Smagt, C. Castellini, B. Caputo, and H. Mu¨ller, “Building the Ninapro database: A resource for the biorobotics community (submitted),” in Proceedings of IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob 2012), 2012.

[35] Chan, F.; Yang, Y.S.; Lam, F.; Zhang, Y.-T.; Parker, P. “Fuzzy EMG classification for prosthesis control”. IEEE Trans. Rehabil. Eng. 2000, 8, 305–311.

[36] Phinyomark, A.; Phukpattaranont, P.; Limsakul, C. “Feature reduction and selection for EMG signal classification”. Expert Syst. Appl. 2012, 39, 7420–7431.

[37] Asghari, O.M.; Hu, H. “Myoelectric control systems—A survey”. Biomed. Signal Process. Control 2007, 2, 275–294.

[38] Jiang, N.; Dosen, S.; Muller, K.-R.; Farina, D. “Myoelectric control of artificial limbs—Is there a need to change focus” IEEE Signal Process. Mag. 2012, 29, 152–150.

[39] Al-Mulla, M.R.; Sepulveda, F.; Colley, M. “A review of non-invasive techniques to detect and predict localised muscle fatigue”. Sensors 2011, 11, 3545–3594.

[40] Conforto, S.; D’Alessio, T.D.; Pignatelli, S, J. Electromyogr.
Kinesiol. “Optimal rejection of movement artefacts from myoelectric signals by means of a wavelet filtering procedure”.
1999, 9, 47–57.

[41] M.H.Jali, ‘I.M. Ibrahim, M.F.Sulaima, W.M Bukhari, T.A.Izzuddin and M.N.M. Nasir, “Features Extraction of EMG Signal using Time Domain Analysis for ArmRehabilitation

32 Device”, International Conference on Mathematics on Mathematics,Engineering and Industrial Applications (ICoMEIA), 2014.

[42] B. B, "Adult Hemiplegia: Evaluation and treatment." Oxford, Butterworth- Heinemann., 1990.

[43] S. D. C. G. C. Louise Ada, "Strengthening interventions increase strength and improve activity after stroke: a systematic review," Australian Journal ofPhysiotherapy, vol. 52, pp. 241-248, 2006.

[44] M. Z. Jamal, "Signal Acquisition Using Surface EMG and Circuit DesignConsiderations for Robotic Prosthesis," in Computational Intelligence in Electromyography Analysis –A Perspective on Current Applications and Future Challenges, InTech, 2012, pp. 427-448

[45] M. B. I. Reaz, "Techniques of EMG signal analysis: detection, processing, classification and applications," Cyberjaya, Selangor, www.biologicalprocedures.com, 2006, pp. 11-35.