Different Models for Limb Movement Classification Using Surface EMG Signals

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Abstract - *This paper presents the comparison of machine learning models as pattern recognition systems to classify surface electromyography signals (sEMG) into 6 select hand motions from 5 subjects. With advancement in muscular sensing and processing power have made the possession of electromyography (EMG) signal, which is valuable. EMG is a technique for recording and analyzing the electrical activity of muscles in organisms. Muscle cells produce this electrical activity when they are neurologically activated. The activity is measured in form of electric potential, which is measured by an Electromyography. Using surface EMG signals to detect and classify limb movements is an interesting area of work with applications in human-robot interactions, prosthesis industry etc. This paper will compare multiple models that can be used for the classification of various hand movements based on the EMG signals emanating from human nerves.*

Key Words: **Surface EMG data, multi-channel EMG system, Artificial Neural Networks, multi-class classifiers, Linear SVM, Linear Regression classifier, Logistic Regression classifier.**

1. INTRODUCTION

Machine learning is increasingly being used in the research setting to improve bio-signal control of prostheses. Feature Extraction - Hudgins et al.[2] in a paper in 1993 showed that raw EMG signals had a deterministic quality vis-a-vis muscle contractions. However, they showed that using raw EMG data as input for classifying body movements yielded sub-optimum results, compared to the classifiers built on the basis of features extracted from the raw data. This has become the established norm in this research field, with different researchers extracting various features from raw EMG data and building classifiers based on those features to determine their efficacy. Electromyography (EMG) signals can be used for limb movements classification. Due to their nonlinear and time-changing properties, it is hard to classify the EMG signs and its basic to utilize fitting calculations for EMG include extraction and example classification. Measuring Techniques - There are two main techniques for measuring EMG signals, namely surface EMG recording and intramuscular EMG recording. Surface EMG recording is a non-invasive technique in which electrodes attached to the skin surface just above a muscle or nerve are used to record the EMG signals. This technique is the preferred mode of data collection for research purposes. Intramuscular EMG recording involves the use of needle electrodes, which are inserted into the subject's body to connect directly to the muscle or nerve, which is to be observed. This technique is not very popular among researchers and is mainly used for diagnostic purposes. Surface electrodes provides a limited assessment of muscular activity. At least 2 electrodes are needed to measure surface EMG readings as it measures the potential difference between the two electrodes. EMG signals present an exciting way of mapping our neurological activity with the body functions we perform. The nature of surface EMG signal collection ensures that it has very exciting prospects in terms wearable data collection tools, especially compared to devices based on EEG signals. EMG signals from muscles have been used to identifying motion commands used to control external peripherals/devices. There exist many pattern recognition techniques to classify the motion using the features extracted from EMG signal. It has been found that most researchers used Artificial Neural Network for the processing of bioelectrical signals [1].

2. Literature Survey

The idea of using bioelectrical signals to map and predict body movements is not new. Classification of EMG signals have several application in real life. It can be used for developing prosthetic limbs for amputees, which can be controlled by them intuitively, it can be used to develop better models for human-robot interaction, and it can be used to detect biomechanical abnormalities in patients. Classifiers built using surface EMG signals can be used to build prosthetic limbs for amputees, which can provide real-time service without any major discomfort due to the non-invasive nature of data collection.

2.1 Related Work

Christos Sapsanis et al. present a pattern recognition model to classify object grasping hand movements. The methodology involved using surface EMG signals captured through a 2-channel EMG system as data. The raw data captured from subjects was used to determine Intrinsic Mode Functions using Empirical Mode Decomposition. Eight features were extracted from the original 2-channel data and the IMFs determined from the raw data. A linear classifier was used for classification by the authors. The authors have found that feature extraction and classification using a combination of information coming from the raw data and the IMF data yields a better result as compared to a classifier based only on raw data. However, the findings are constrained due to the small size of the dataset and the limited number of subjects. Using a better classifier (as compared to a linear classifier) and optimising the features involved to only relevant ones can lead to an improvement in the experimental results obtained in this paper[4]. Christos Sapsanis et al. present an improved methodology of hand movement recognition using feature extraction and classification. The methodology involves using surface EMG signals captured through a 2-channel EMG system as data. The raw data captured from subjects is used to determine Intrinsic Mode Functions using Empirical Mode Decomposition. The authors suggest an improvement over the methodology presented in their previous work by including features extracted from the three IMFs in the frequency domain and using feature reduction frameworks like Principal Component Analysis and RELIEF to reduce redundant information. The authors have used a linear classifier to perform detection. The authors found that using the extracted information from frequency domain increased the accuracy of the method compared to previous works that used just the time domain information. Improvements in results also accrue from reduction in the dimensions of the feature vector, suggesting that features carry complementary information. Better classification algorithms can be used to reduce the behaviour variations in the classifier for different subjects. Increasing the signal database for better classifier training can also improve the results[3].

3. System Architecture

3.1 Collection of raw EMG Data

We began with a dataset of raw EMG signals collected from the forearm muscles of 5 subjects. This dataset contains 2-channel raw EMG data sampled at a rate of 500 Hz. It was collected from 5 healthy subjects, who were made to grasp different objects based on different grips (Spherical, tip, palmar, lateral, cylindrical and hook) while the EMG readings were noted based on the electrodes placed at muscle locations in their forearms. This dataset consists of EMG readings per subject, per grasp, per channel recorded. The sign was recorded from two Differential EMG Sensors and furthermore the signs were transmitted to a 2- channel EMG framework. This dataset is out there at UCI Machine Learning repository[5]. The subjects were asked to repeatedly perform the subsequent movements, which may be considered as daily hand grasps:

a) Spherical: for holding spherical tools
b) Tip: for holding small tools
c) Palmar: for grasping with palm facing the thing
d) Lateral: for holding thin, flat objects
e) Cylindrical: for holding cylindrical tools
f) Hook: for supporting a heavy load

Two different databases are included:

1) 5 healthy subjects (two men and three women) of similar age approximately (20 to 22-year-old) conducted the six grasps for 30 times each. The measured time is 6 sec.
2) 1 healthy subject (men, 22-year-old) performed the six grasps for 100 times each for 3 consecutive days. The measured time is 5 sec.

3.2 Feature Extraction

It is the process of dimensionality reduction of data to extract features useful for the classification. These features can be fed to the classification algorithms to get the required results. The machine learning classification algorithms cannot directly work on textual data therefore it needs to be converted into numbers for the working of algorithms thus feature extraction is necessary as it gives data that can be fed to the machine learning algorithms. We used windowing techniques to divide the raw data into segments and then extracted 15 features from the raw data, 10 in time domain and 5 in frequency domain. We then used EMD technique to decompose the raw data into multiple IMFs, again extracting all features from these IMFs. We used the features extracted from both input channels and IMFs to train our classifiers.

Features of Time Domain:

■ Average value
■ Willison Amplitude : This component is characterized as the measure of times that the adjustment in EMG signal adequacy surpasses an edge.
■ Kurtosis : It is a proportion of whether the information are substantial followed or light- followed comparative with a typical dissemination.
■ Variance : This feature is the measure of the EMG signal's power.
■ Skewness : It alludes to bending or asymmetry in a balanced chime bend, or ordinary conveyance, in a lot of information.
■ Zero Crossing (ZC) : ZC is the number of times signal x crosses zero within an analysis window.
■ Slope Sign Changes (SSC) : Slope sign change is identified with signal recurrence and is characterized as the occasions that the incline of the EMG waveform changes sign inside an investigation window.
■ Waveform Length (WL) : This feature provides a measure of the complexity of the signal. It is characterized as the combined length of the EMG signal inside the investigation window.
■ RMS value : Root Mean Square value.
■ Auto Regressive model : It is the point at which an incentive from a period arrangement is relapsed on past qualities from that equivalent time arrangement.

Features of frequency Domain:
■Median Frequency (FMD)

- Mean Frequency (FMN)
- Total Power
- Mean Power (MNP)
- Power spectrum Ratio (PSR)

3.3 Application of classifiers on extracted features

We trained 4 classifiers and determined the classification accuracy for each one of them.

3.3.1 Artificial Neural Network

ANN are computing systems inspired from biological neural network, these systems learn to perform task from examples. An ANN depends on assortment of hubs/units called artificial neurons, which freely speak to the neuron in biological cerebrum. Every association, similar to the neurotransmitters in a biological mind, can transmit a sign to different neurons. An artificial neuron that gets a sign at that point forms it and can flag neurons associated with it. ANN is particularly useful in tasks like complex pattern recognition or classification. The capacity of gaining from models, the capacity to imitate discretionary non- straight elements of info, and the profoundly equal and customary structure of ANNs make them particularly reasonable for pattern classification assignments [6]. A large portion of the ANN based research work has been completed with MLP containing one hidden layer and back-propagation (BP) calculation for training. Some different scientists have utilized combination of neural system with various fuzzy engineering. ANN can be used to do binary classification also it can be used as multi class classifier. Binary classification means classifying the elements of a given set into two groups, predicting which group each element belongs to. Binary classification has several use cases in real world like analysing a patient for a particular disease whether he is positive or negative, analysing a customer behaviour whether or not he/she will buy a particular product, many more. In multi class classification is a problem of classifying instances into one of three or more classes.

Artificial Neural Network –

1. 1 Input Layer, 1 Hidden Layer, 1 Output Layer.
2. Activation functions - relu, softmax.
3. Input dimensions - 30/60 output dimensions - 6
4. Layers Layer 1 - input dimensions - 30/60, output dimensions - 6, activation function – relu
Layer 2 - input dimensions - 6, output dimensions - 10, activation function - relu
Layer 3 - input dimensions - 10, output dimensions - 6, activation function - softmax
5. Error function - binary cross entropy

3.3.2 Support Vector Machine

SVM are supervised learning models with related learning algorithms that break down information utilized for grouping and relapse examination. Given a lot of training models, each set apart as having a place with either of two classifications, a SVM training calculation assembles a model that allots new guides to one classification or the other, making it a non-probabilistic binary classifier. A SVM model is a portrayal of the models as focuses in space, mapped with the goal that the instances of the different classifications are partitioned by a reasonable hole that is as wide as could be expected under the circumstances. New models are then mapped into that equivalent space and anticipated to have a place with a class dependent on the side of the hole on which they fall Support Vector Machine – Kernel used - linear. Multiclass classification done using one vs. rest classifier.

3.3.3 Linear Regression Standard

linear regression with the data being normalized before regression by subtracting the mean and dividing by the l2-norm.

3.3.4 Logistic regression

It is a supervised learning grouping calculation used to anticipate the likelihood of an objective variable. The idea of target or ward variable is dichotomous, which implies there would be just two potential classes. In basic words, the reliant variable is binary in nature having information coded as either 1 (represents achievement/yes) or 0 (represents disappointment/no). Numerically, a calculated relapse model predicts P(Y=1) as a component of X. It is one of the least difficult ML algorithms that can be utilized for different characterization issues, for example, spam recognition, Diabetes forecast, malignancy location and so on.

Logistic Regression-

Standard logistic regression with tolerance - 10e-4.

3.4 Comparative Analysis of accuracy of classifiers.

Lastly, we have delivered a comparative analysis of the different classifiers to identify the best classifier for this job.

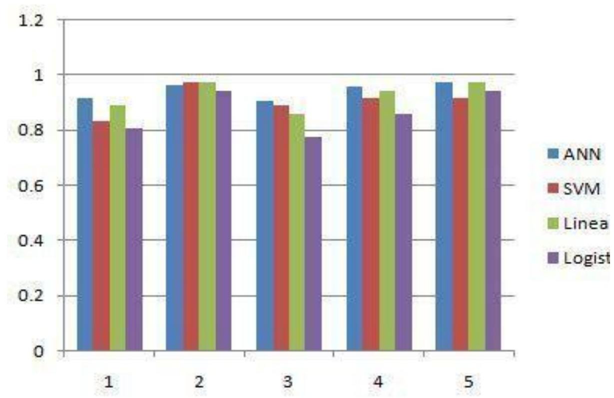


Fig 1. A Comparison of Classification Accuracies of different Classifiers

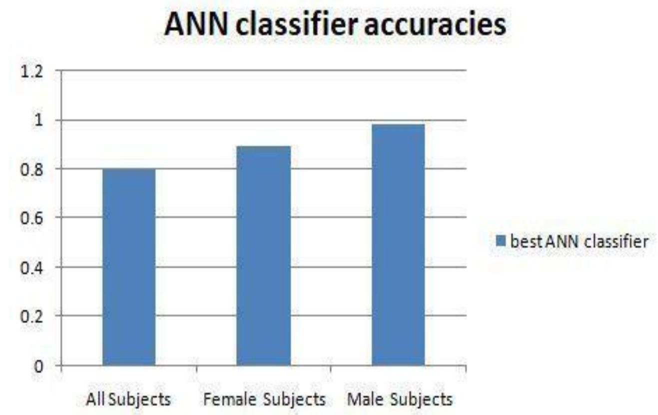
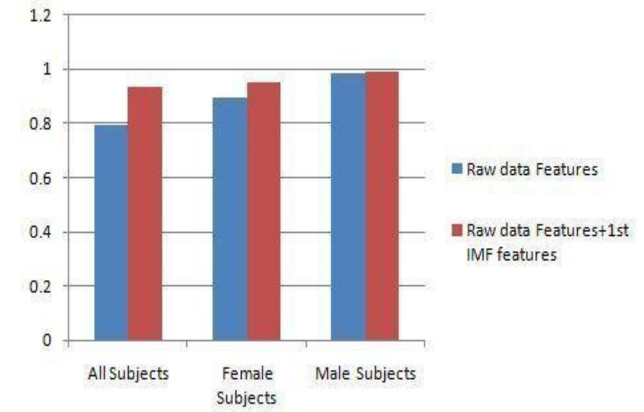


Fig 2. A comparison of classification accuracies when subjects were grouped together

Fig 3. A comparison of classification accuracies between Raw data features used as input and both raw data and 1st IMF features used as input.



- Features extracted from first IMFs when added to the features extracted from raw data resulted in higher accuracy in all cases.
- Poor performance of a generalised classifier can be attributed to different biological makeup of males and females.

4. Conclusion

Comparison of different models for classification of hand movements have been done to classify the EMG signals, Here in this paper we have discussed various models that can be applied for the classification of EMG signals, We studied different features that can be extracted from raw EMG data, We modelled different classifiers and studied their relative accuracies for every individual subject, We determined that an Artificial Neural Network was the best performing classifier, we determined that the use of features from IMFs improves the accuracy of classifiers substantially, We performed further classifications using ANN and determined that it is better to use different classifiers for male and female subjects.

5. REFERENCES

[1] M. Ahsan, M. Ibrahimy, and O. Khalifa, "Advances in electromyogram signal classification to improve the quality of life for the disabled and aged people," Journal of Computer Science, vol. 6, 2010, pp. 706-715.
[2] B. Hudgins, P. Parker and R. N. Scott, "A new strategy for multifunction myoelectric control," in IEEE Transactions on Biomedical Engineering, vol. 40, no. 1, pp. 82-94, Jan. 1993
[3] C. Sapsanis, G. Georgoulas and A. Tzes, "EMG based classification of basic hand movements based on time-frequency features," 21st Mediterranean Conference on Control and Automation, Chania, 2013, pp. 716- 722.
[4] C. Sapsanis, G. Georgoulas, A. Tzes and D. Lymberopoulos, "Improving EMG based classification of basic hand movements using EMD," 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, 2013, pp. 5754-5757.
[5] UCI Machine learning repository http://archive.ics.uci.edu/ml/datasets/sEMG+for+Basic+Hand+movements
[6] A. Subasi, M. Yilmaz, and H.R. Ozcalik, "Classification of EMG signals using wavelet neural network," Journal of neuroscience methods, vol. 156, 2006, pp. 360–367.