EEG-Based Human Intention System for Classification of Finger Movements

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Abstract—Electroencephalography (EEG) is widely used to record human brain activity for using it to many Brain-computer interface (BCI) and other applications.In this experiment Antneuro EEG system is used for data acquisition to make a database for training the Machine model of Human for Human Machine Teaming (HMT) Research. Classifying the different movements of the fingers of one hand is challenging task based on many subjects.In this paper a pipeline for uniform preprocessing the database is made for removal of unwanted preprocessing artifacts.We are aiming (1) Distinguish between same movements from left and right hand and (2) Classify 4 different hand movements of one hand.The main focus in our research is on alpha (α) and beta (β) bands of EEG .A experiment has also been designed for data collection.We used major 8 features for classifying the data that have maximum amount of information regarding Motor Execution process.This includes ERD/ERS,Band Powers of bands,Hjorth parameters.Our main focus in this research is activity detection on the parietal lobe of the brain which is reason for (Sensorimotor area) SMR's and thus we have chosen 6 channels,3 from central lobe (C3,C4,CZ) and 3 from prefrontal part(P3,P4,Pz) .In our study we also compared four different methods of classifications i.e KNN, SVM, LDA & ANN of the EEG data using different classification models.We are able to achieve classification accuracy of 96.6%.This states that the method we are using is good and effective for the theoretical and technical support in the field of EEG and Sensory Motor Detection.

Index Terms—EEG, Pipeline, ANN, Motor Execution,Human Machine Teaming,Sensory Motor Rhythms.

1 Introduction

For development in HMT we aim to achieve machine model of human which contains all the factors related to human.One of these essential factors is human intention decoding [5].The aim is to accurately classify the finger movements from hand.With this EEG based system we are correlating for capturing motor-correlates, rely mostly on the processing of SMRs (sensory motor rhythms) or MRCPs (movement related cortical potentials).

At present the most common way of the preprocessing is slow and might contains some of differences for bigger data.We used ICA for the removal of the power frequency interference and signal noises.Thus here we build a preprocessing pipeline.As we are dealing with time frequency domain of the signal wavelet analysis is the best option for feature extraction.Using that we are able to classify the signals in different bands thus can use it for band selection.We choose alpha and beta bands for further evaluation.For feature extraction we used Power Spectrum & ERD/ERS analysis.Power Spectrum basically shows the energy change of the signal.Then the features namely ERD/ERS,Power Spectral Density(PSD), Hjorth Complexity, Hjorth Activity,Hjorth Movement, Band Powers are calculated for the alpha and beta bands.We used 4 methods for the classification of data namely LDA,KNN,SDA and ANN.

This paper is organised as follows: Section II describes the method briefly which is used in the experiment.Section III explains briefly the preprocessing part and the thresh holds used in the projects.Section IV discuss features and methods of their extractions and Section V tells about the classification approach taken.Section VI is discussion of the results obtained and Section VII is about the conclusion.

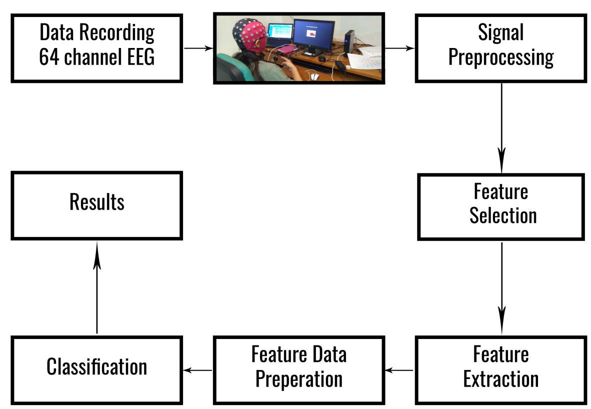

Fig. 1. Workflow of the system

2 Method

2.1 Subjects and Data Recording

The participants we took in this study were all healthy and are self volunteers from the Institute of Nuclear Medicine & Allied Sciences.There are 20 participants who took part in the study which comprises of 9 males and 11 females with a average age of 21.65 .All the subjects are right hand dominant in general and has either normal or corrected vision.Out of 20 subjects 3 subjects are pre-instructed to use their non dominant hand for the experiment and other 17 were instructed to use their dominant hand for the experiment.The data acquisition of subjects was carried out in a closed room with the subject sitting comfortably in a chair with arms rested on a hand rest.Before the experiment

begins a proper consent form were being filled from every participant.
We used a 64 channel Ant neuro EEG system for data recording.Placement of electrodes is standardized with a specific anatomical landmark with the distance between the electrodes as 10% and 20% of the total length. [6]

2.2 Experiment Design

The subject were asked to perform the movements shown on a computer screen that were displayed using a customised game.Game is designed using a software named Opensesame.In the game we displayed 4 figures of a hand performing different movements with the fingers.The subject is asked to mimic the hand movement show in the figure 2.

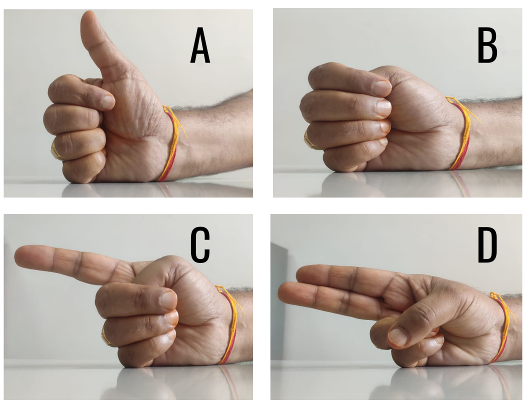

Fig. 2. Hand Movements, (A) Is thumb movement. (B) Is fist movement. (C) Is index finger movement. (D) Is two (index and middle) finger movement.

The start of experiment shows a instruction window with agree to participate column.Then a fixation dot is appeared on the screen for 2 sec interval [3].After that 1 random figure out of 4 figures is displayed and the subject is asked to mimic the movement shown in the figure with the hand asked to them (Right/Left). Each movement lasted five seconds and one trial is of 1 minute and 15 seconds

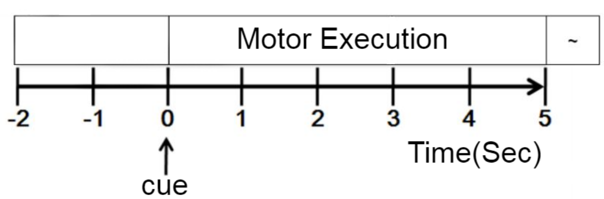

Fig. 3. Timeline of 1 trial

3 Preprocessing

Preprocessing is the most important part for signal analysis in EEG data.The raw data contains a lot of artifacts and noise and can not be processed like that thus we have to make sure that a effective, fast and yet uniform preprocessing is needed.We make a approach of analysing data using a automatic pipeline which uniformly preprocess data removing all type of non-synchronous errors [9].Preprocessing includes following steps

1. Down-sampling
2. Filtering
3. Importing channel locations
4. Removing and interpolating bad channels
5. Re-referencing
6. Independent Component Analysis

The data is been downsampled to 250Hz from 500Hz.We selected alpha and beta band for the analysis as we are dealing with sensorimotor rhythms of the brain [2]. So we used butter worth filter with a low pass filter of 8Hz and high pass filter of 30Hz has been applied [1].For cleaning the data we have used a threshold which rejects the data after 5 sec of flat line in a epoch or a channel.If channel is correlated at less than a certain value to a reconstruction of it is based on other channels,data portions whose variance is larger than this threshold relative to the calibration data are considered abnormal in the given time window.We have to re-referencing the channels of EEG to avoid data overlapping by the channels thus used average re-referencing for all the electrodes for this purpose [4] average reference is computed by subtracting the average of all electrodes from each channel:

$$(Ei–F)–(E1–F) + (E2–F) + ... + (En–RF/n$$

$$= (Ei–F) + F–(E1 + E2 + ... + En)/n$$

$$= Ei–(E1 + E2 + ... + En)/n$$

$$= Ei–0, undertheassumptionthat(E1 + ... + En) = 0 \quad (1)$$

We used Independent Component Analysis (ICA) which used to extracts hidden factors within data by transforming a set of variables to a new set that is maximally independent [4].We have 3 factors in ICA 1.Eye Component 2.Muscle Component 3.Heart Component

4 Feature Selection

In case of motor rhythms we know the signal varies with time in a particular time window.The data analysis of a signal is based on what type of data we dealing with.In between spectral,temporal and spatial type of data analysis.Spectral type analysis is based on power change of signal,temporal analysis is based on time change and spatial type is based on the channels selection.We selected spectral analysis and thus we got 2 domains that we can work on and as the signal is dependent on time we have to deal with Time frequency domain.Thus the analysis can only take place if we are able to extracts bands from the signal and process it.Thus Wavelets formation is used to ensure data segmentation and band extraction.This decomposition of signal leads to a set of coefficients called wavelet coefficients.Based on this we selected eight features wwhich include ERD/ERS,Band Power based on alpha (α) and beta (β) bands and Hjorth Parameters.

5 Feature Extraction

Our parietal lobe is the root of motor execution processes thus considering all these factors we decided to take 6 major channels C3, CZ & C4 for the central part of brain and P3 ,Pz & P4 for parietal part of the brain for feature extraction of the data [13].These 6 channels represent central and parietal lobes of brain.EVENT-RELATED DESYNCHRONIZATION AND EVENT-RELATED SYNCHRONIZATION are time-locked to the event but not phase-locked.ERD/ERS measures the power within the frequency bands relative to the power of the same EEG signal.To calculate these features we have used wavelet tranform to segregate required bands from the data i.e alpha (α) and beta (β) bands.For each channel we have performed Daubechies order-2 wavelet decomposition with a sampling frequency of 250 Hz [11].

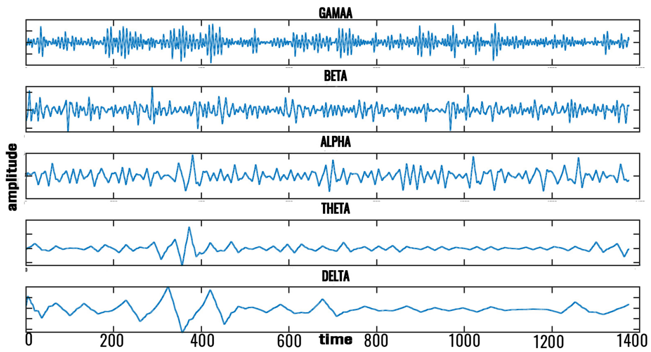

Fig. 4. Approximate and detailed wavelets of EEG signal

Then to calculate the ERD/ERS the data is being squared and then epoched data is averaged and evaluated using the following expression

$$\mathrm{ERD}_i(\%) = \frac{Act_i R}{R} 100 \tag{2}$$

Act represents epochs that are averaged the R in equation 2 is calculated using following expression

$$R = \frac{1}{k+1} \sum_{i=r0}^{k+r0} Act_i \tag{3}$$

R is averaging of values in the interval [r0,r0 + k], which r0 is 2 seconds before the epoch and r0 +k is approximately 5 seconds after the epoch/event.

Power Spectral Density (PSD) is used for extraction of band powers of alpha and beta bands.It is technique which use signal power over frequency and show the amplitude of the signal over different bands. We used Welches method to evaluate the value [7].The formula used is

$$P_{welche}(f) = \frac{1}{L} \sum_{i=0}^{L-1} P(f) \tag{4}$$

where P(f) is defined as [7]

$$P(f) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i(n) w(n) e^{-j2\Pi f} \right|^2 \tag{5}$$

The 3rd important feature of our study is Hjorth parameters which include mobility,activity and complexity.Hjorth parameters are basically the statistical features of the time frequency domain.The **Activity** in this parameter return values depends on frequency component of the signal.**Mobility** defined as the square root of the ratio of variance of derivative of signal. **Complexity** indicate how much the shape change is similar to a sine wave.The more signal is similar the more the value close to 1 [8]. The remaining features are the statistical features used to find and generate the simple power based relations.These features include mean,median and variance [10].

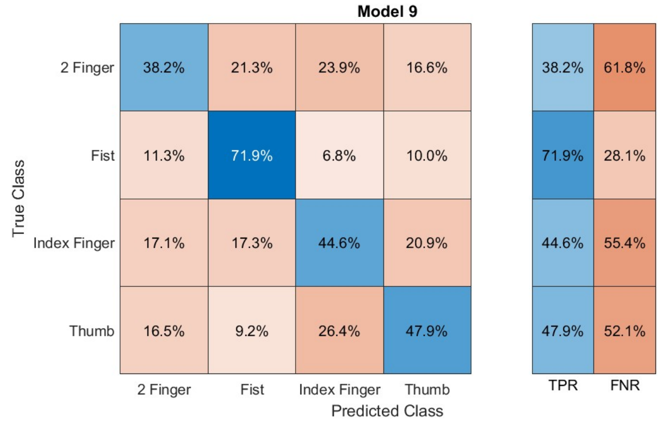

Fig. 5. Confusion Matrix of LDA with 50.6% accuracy

6 Classification

Deep learning is most efficient way for making use of raw data and us it for learning good feature classifications.Deep Learning is a layer by layer learning method.For preparing data for a effective classification we have to make feature vectors and that is done considering number of features,channels we are accounting in our study.We have performed 5 fold cross validation method because we have 4 main classes that got 4 folds of data for training and 1 fold of that data will be used to test the classifier.We have used 1 vs all multi-class method.After cross validation we trained 4 models of classifiers to compare which provides the best accuracy.

1.Linear Discriminant Analysis (LDA)
2. K-Nearest Neighbor(KNN) Algorithm
3. Support Vector Machine (SVM)
4. Artificial Neural Network (ANN)

LDA makes predictions by estimating the probability using Bayes Theorem to estimate the probabilities that a new set of inputs belongs to each class. The class that gets the highest probability is the output class and a prediction is made.

$$P(Y = x|X = x) = (PIk^* fk(x))/sum(PIl^* fl(x)) \tag{6}$$

We got a accuracy of 50.6% using LDA as a classifier.

The basic KNN use to calculate the distance from all points in the proximity and filter out the shortest distance to a path this may cause some errors for scatter this may give a false output.Using the KNN model we acquired accuracy of 84.5% shown in the fig 6+ Next we tested SVM algorithm which finds the closest point of the lines from both the classes which is called support vectors.We have performed

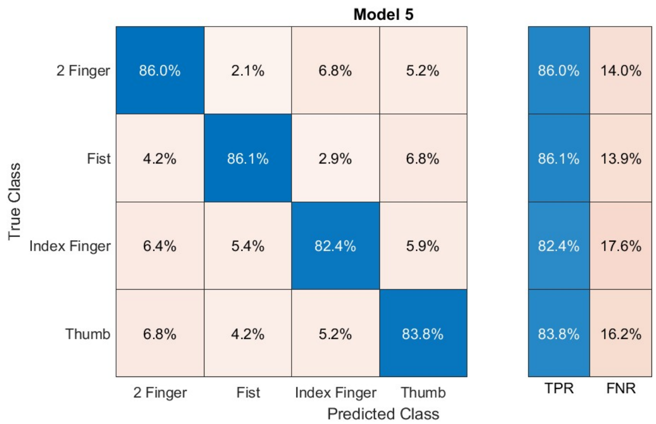

Fig. 6. Confusion Matrix of KNN with 84.5% accuracy

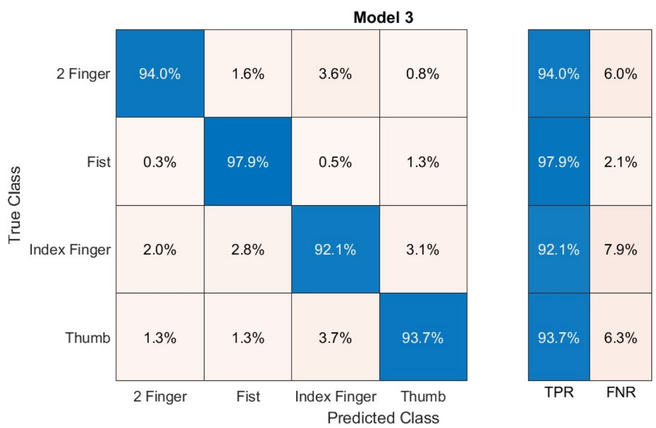

Fig. 7. Confusion Matrix of SVM Cubic with 94.4% accuracy

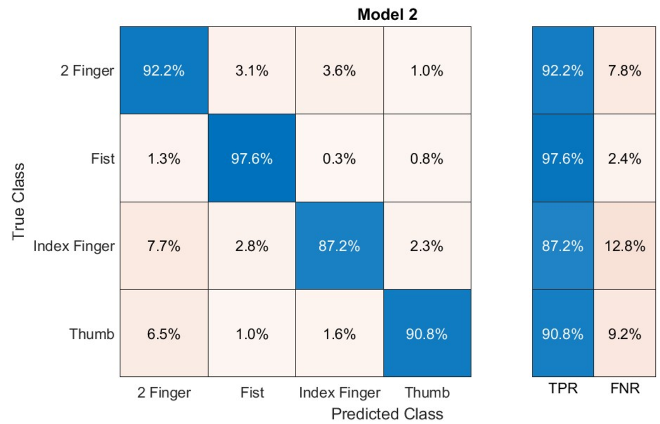

Fig. 8. Confusion Matrix of SVM Quadratic with 91.9% accuracy

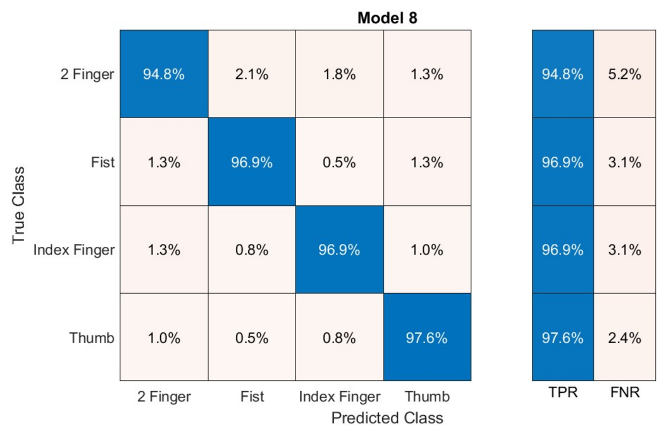

Fig. 9. Confusion Matrix of ANN with 96.6% accuracy

classification using 2 SVM models.Cubic SVM is explained using the equation given below

$$k(x_i, x_j) = (x_i^T x_j + 1)^3 \tag{7}$$

Cubic SVM gives a accuracy of 94.4%

Quadratic function is little less computational and it gives accuracy of 91.9%

$$k(x_i, x_j) = 1 - \frac{||x_i - x_j||^2}{||x_i - x_j||^2 + c} \tag{8}$$

Artificial Neural Network are multi layered fully connected neural nets [12]. The parameters used for ANN classifications are 1 fully connected layer with first layer size of 100 .The activation type is ReLU with a iteration limit of 1000.This is considered to be wide type neural network. This neural network gives us a accuracy of classification of about 96.6% which is highest among the classifiers.

7 Discussion

For the purpose of the analysis we have taken the data from subjects with the assigned hand to perform experiment is right and left.To check the difference in the activity of brain during different hand for a same event/movements we will compare the Event Related Potential(ERP) of the channels which are more significant for this type of movements.As we know through various literature reviews that the parietal part of the brain is most affected on sensory motor rhythms.Thus we choose 2 channels for this analysis in 10-20 system P3 and P4 with Pz as reference. From the fig 10 we can depict the fact that to some extent the right lobe that is depicted by P4 is having more +ve voltage change when left hand movement is dominant.Similarly the left lobe of brain depicted by P3 is showing major power change with respect to Right hand movement.This confirms the cross processing nature of the brain.

Now if we look to the topographic maps of brain at the time points where the activity in brain is mostly due to movements of the finger.On comparing we can co relate the active brain region with the brain map and we concluded that **left hand** dominant subjects are tend to have more activity in central and little bit **inclined to right hand side** lobe of the brain. But in case of right handed subject the **central and left lobe** of the brain is in showing most activity.Thus confirming the fact each hemisphere is in charge of the opposite side of the body.

Now focusing on classification discussion the confusion matrix shows accuracy for how many time the feature was correctly classified in the class to which it belongs to the training model.We compared the data obtained from these 4 classifiers.The individual accuracy 2 finger movement classification is achieved most accurately by ANN with

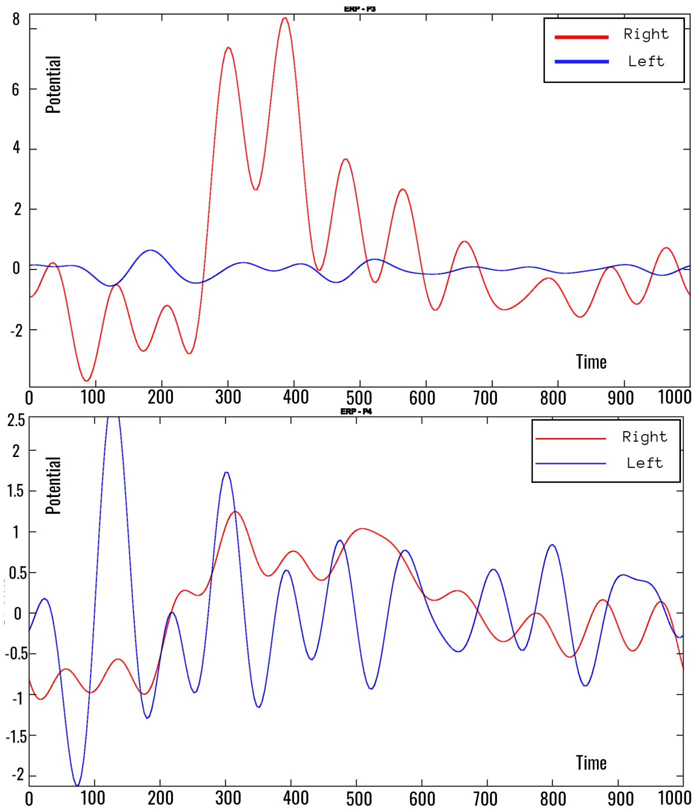

Fig. 10. P3 and P4 channels ERP for 2 subjects Right Handed Dominant and Left Handed Dominant

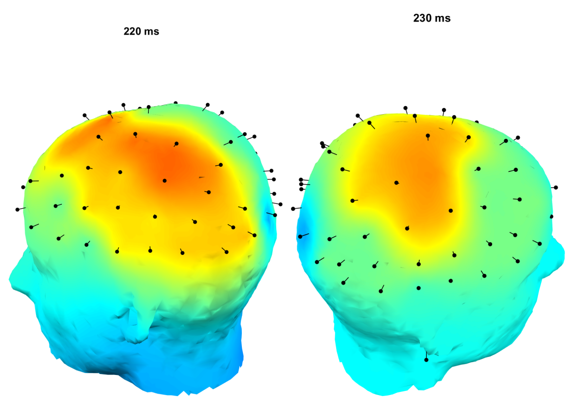

Fig. 11. Right Handed vs Left Handed Topography on same event

94.8%.SVM achieved most accuracy for Fist classification of 97.9%.Index and Thumb both are most accurately classified by ANN with 96.9% & 97.6%

	2 Finger	Fist	Index	Thumb
LDA	38.2	71.9	44.6	47.9
KNN	86	86.1	82.4	83.8
SVM Quadratic	92.2	97.6	87.2	90.8
SVM Cubic	94	97.9	92.1	93.7
ANN	94.8	96.9	96.9	97.6

Fig. 12. Classification Model Comparison

8 Conclusion

The suggested approach of automated uniform preprocessing pipeline along with multiple feature selection based on power spectrum density and event related potentials and computing them with use of wavelet transform for band extraction is proved to be suitable approach for the accurate classification of the data.The classification method is proposed to recognise the hand movements (Index,2 finger,Thumb,Fist) of left and right hand.The classification result gives us accuracy of 96.6% with a 5 fold 1 layered Artificial Narrow Neural Network deep learning model.The method proposed in this study can be used to make a theoretic basis and technical support to make the study useful in making a system that can be used for real time processing of live signal.

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