International Journal of Technical Research and Applications e-ISSN: 2320-8163,
www.ijtra.com Volume 1, Issue 5 (Nov-Dec 2013), PP. 23-32

3-ARY CLASSIFICATION OF EXTRACTED POWER SPECTRAL OF NON-MOVEMENT-MENTAL-TASK-TYPE EEG SIGNALS USING MODERN AND CLASSICAL AI

Udit Bhatia, Shalvi Pandita
Jaypee Institute of Information Technology
Noida, Uttar Pradesh, India

***Abstract*— To enhance Human interaction with machines, the research interest is increasing in the field of Brain Computer Interaction which allows people to communicate with external systems just by their mental activity. Until now the applicability of Brain Computer Interface has been strongly restricted by low bit-transfer rates, slow response times and long training sessions for the subject. There is a need to improve both classification performance and reduce the need of subject training. This paper discusses the effectiveness and accuracy of the proposed novel approach for Classifying three Non-Movement-Mental-Tasks namely- Math task, Counting Task and Idle Mental Task through a Wavelet decomposition of EEG Signals and then classifying the selected features of Power Spectral and Power spectral Difference using a new classifier system which incorporates Modern as well as Classical Artificial Intelligence. In the Classical AI we have used deduction based classification, for which we introduced a new concept of Voting among Segmental-Components of any EEG trial while the modern AI was based on Support Vector Machine (SVM). The key motivation of this paper has been the improvement in the following two situations – 1) Finding out the perfect feature for classification of Segmental Samples and 2) Increasing the accuracy with respect to classification of actual Samples or Trials instead of Segmental Samples. According to the experimental results we have confirmed the feasibility of the proposed novel approach by comparing the results with the previous research results.**

Keywords*— *EEG Signals, SVM, Decision Tree, Wavelet Decomposition, Voting, Spectral Power Difference, Modern and Classical AI

I. INTRODUCTION

The ultimate aim of any Brain Computer Interaction is to achieve more appropriate features of brain activity of especially severely disabled or locked- in patients that could be mapped to his/her motive to execute the control. There are mainly seven types of brain activities or Neuromechanisms – Sensorimotor Activities, Slow Cortical Potentials (SCP), P300, Visual Evoked Potential (VEP), Response to Mental Activity, Activity of Neural Cells (ANC) and Complex Neuromechanism. Through various experiments it has been observed that each Neuromechanism when performed produces physiological signals that can be classified and then mapped to control external devices through the intervention of a computer interface. This paper revolves around the study of the least explored of these Neuromechanisms which is the study of Response to Mental Activity.

To collect these physiological signals produced by the electro-chemical nature of the communication between neurons, the most efficient, reliable and cost-effective method is by recording the signals through Electro Encephalography (EEG). The EEG is the summation of electrical activities of billions of nerve cell connections in the brain cortex. It is measured using electrodes that are placed on several locations on the scalp. However, these signals are very complex in nature and extremely sensitive because they vary for every subject, vary for different cognitive response of the same subject and vary for same cognitive response of the same subject. Therefore, setting the sampling frequency of obtained data, extracting and selecting near perfect features from these signals and then classifying them accurately is totally based on the effectiveness of the algorithm applied and the nature of experiment to be performed.

There has been an extensive research in the area of Feature Extraction, Feature Selection and Classification of the Selected Features. Dan Xiao, Zhengdong Mu and Jianfeng Hu applied the Energy-Entropy of the signal for pre-processing, short term Fourier Transform for extraction and then used Fisher classifier with 85% accuracy [26]. Li Ke and Rui Li used Multi-scale filter with different varying size of filter window as spectral analysis and after retrieving major frequency bands, PCA was used for feature extraction and reduction in dimension. Accuracy to an average of 91.13% was attained [27]. Farid Oveisi transformed data using Independent Component Analysis, used Linear ICA to separate the artefacts from EEG and applied various classifiers for baseline or idle task and multiplication task [28]. BT. Skinner and DK .Liu adopted Autoregressive mode and FFT for feature's retrieval and applied learning classifier system XCS with an average efficiency of 88.9% [29]. Nai-Jen, Huan, and Palaniappan Classified mental-tasks using fixed and adaptive auto-regressive models of EEG signal [35]. A similar concept was used by Tugce Balli and Ramaswamy Palaniappan in which they insisted on a 6th order Fixed Autoregressive model which used 6 channels in the EEG and 6 autoregressive coefficients per channel to give a total of thirty six features [36]. M. Vatankhah and M. Yaghubi used a totally different concept of Fractal dimensions for extraction and Adaptive-Neuro-Fuzzy Inference Systems for classification (ANFIS) [31]. In yet another research Jiang Feng Hu was able to achieve accuracy ranging from 75% to 80% for subject authentication and 75% to 78.3% for identification using 6 channels [42]. In the study, subjects were asked to imagine left and right hand movement, tongue and foot movement.

In this paper we have suggested a proficient way for EEG Signal Classification corresponding to the Neuromechanism of Non-Movement-Mental-Tasks namely- Math task, Counting Task and Idle Mental Task. We have suggested Wavelet decomposition of EEG Signals into distinct predefined frequency bands – theta, delta, gamma, mu, alpha and beta rhythms/waves and then classifying the features of Power Spectral and Power Spectral Difference of the selected frequency bands using a new classifier system which incorporates Modern as well as Classical Artificial Intelligence. The training set uses only the modern AI Approach while the testing set uses both. In the Classical AI we have used a deduction based classification, for which we introduced a new concept of Voting (*Majority-Voting and Confused-Voting*), among Segmental-Component of any EEG trial while the Modern AI was based on Support Vector Machine (SVM). The proposed method and the reasons for each step have been explained further in detail in the following section.

The structure of this paper is as follows: a detailed explanation of the proposed approach is described in Section 2. In Section 3, several experimental results used to verify the performance and the reliability of the proposed methods are shown. Discussions about experimental results, conclusions, and future research plans are presented in Section 4.

II. METHODOLOGY

In the previous section we introduced briefly about the proposed method and also discussed the works of various researchers. In this section we will advance towards the proposed approach to classify the Non-Movement-Mental-Tasks which are Math task, Counting Task and Idle Mental Task with a novel and efficient technique. We shall discuss and analyse all the stages of the proposed technique starting from the experimental setup to Pre-processing followed by Feature Extraction/Selection and finally the Classification stage, step by step in detail. A primary methodology flow of the proposed method has also been shown in Fig 1.

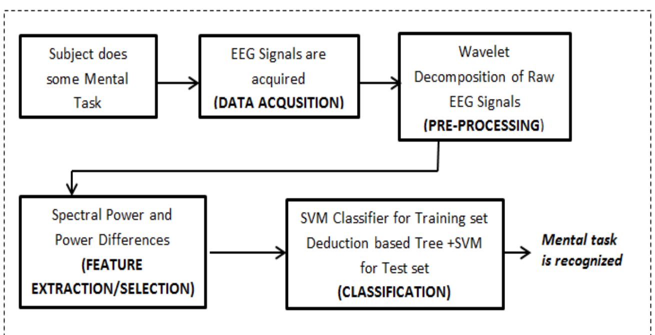

Figure 1: Primary methodology Flow

A. Experimental Setup

Data Acquisition is a very difficult task because EEG Signals are highly dependent on the ability of the subject to focus on a single mental task and his/her mood, motivation, tiredness etc. at that particular instant of time. Secondly, introduction of the artefacts are inevitable because it is very rare that a person can keep his mind singly focused. Therefore it is very important to have a calm environment while recording EEG Signals of a subject.

The EEG dataset used for this experiment was obtained by Kiern and Aunon. It is available at the following link http://www.cs.colostate.edu/~anderson. The subject in this case was made to sit in an Industrial Acoustics Company where a room with dim lighting was set up and noise was controlled using noiseless fan. An Electro-Cap was employed to sense EEG signals from the scalp positions C3,P3,O1,C4,P4,O2 (Fig 2), which is mentioned in the 10-20 system of scalp electrode placement. The impedance maintained of all electrodes was << 5 KOhm. Reference potential was obtained from electrically linked mastoids, A1 and A2. Sampling frequency was taken as 250 Hz. Signals were recorded for 10s during each task and each task was repeated for 2 sessions where the sessions were held on different weeks.

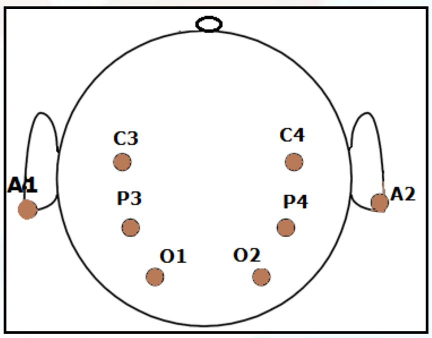

Figure 2: Electrode Placements

The EEG Signals were recorded from a subject for three classes of mental task. These classes are described as follows:

Class 1: Math task – The subject was assigned big multiplication problems which were designed such that an immediate answer was not visible. For example the subject was told to attempt 34 x 12 irrespective of whether the answer was correct or incorrect. It was observed that no subject solved the expression in less than 10 sec per recording session.

Class 2: Counting task - The subject performed mental visual counting by visualizing a blackboard and integers being written on the board.

Class 3: Idle Mental task -This was the idle or baseline task where the selected subject got the chance to take rest and think of nothing in particular.

B. Pre-processing Stage

Pre-processing is a very crucial step because it decides the efficiency and accuracy of the following stages. For our experiment we required only a specific part of frequency band out of the entire EEG Signal. There are various techniques for Spectral Analysis of EEG Signals and most prevalent being Fast Fourier Transform but for this purpose we preferred Wavelet Decomposition over Fast Fourier Transform because for making Real-time applications we need Non-Stationary EEG Signal. Fourier transform is a powerful tool for analysing the components of a Stationary signal but it fails in case of Non-Stationary Signal and that is where the Wavelet Decomposition comes to rescue. Detailed explanation has been given by Akin [48].

As mentioned above, we extracted only specific bands of the EEG Signal through Wavelet Decomposition. The Distinct bands into which EEG Signal was broken down are shown in Table 1:

Type	**Frequency (Hz)**
Delta	up to 4.00 Hz
Theta	4.00 Hz – 8.00 Hz
Alpha	8.00 Hz – 13.00 Hz
Beta	>13.00 Hz – 30.00 Hz
Gamma	3.00 Hz – 100.00+ Hz
Mu	8.00 Hz – 13.00 Hz

Table 1: Distinct frec
Wavelet Deco

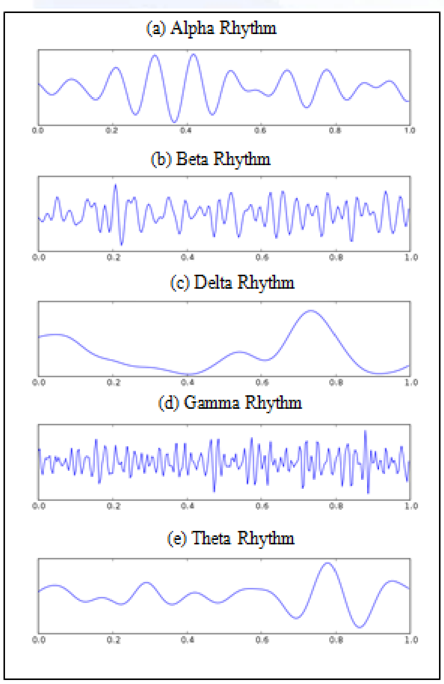

Figure 3: Distinct Frequency Rhythms after Wavelet Decomposition

These predefined bands are also called Rhythms. The following figure (Fig 3) shows these different Rhythms / Bands that were plotted corresponding to one channel of a trial of the subject.

After decomposition we observed from the diagrams shown below in (Fig.4) that not all Rhythms/bands are equally important for the classification of any provided type of mental activeness. In the diagram given below we have 5 Rhythms/ frequency-band Plots for the same channel taken at two

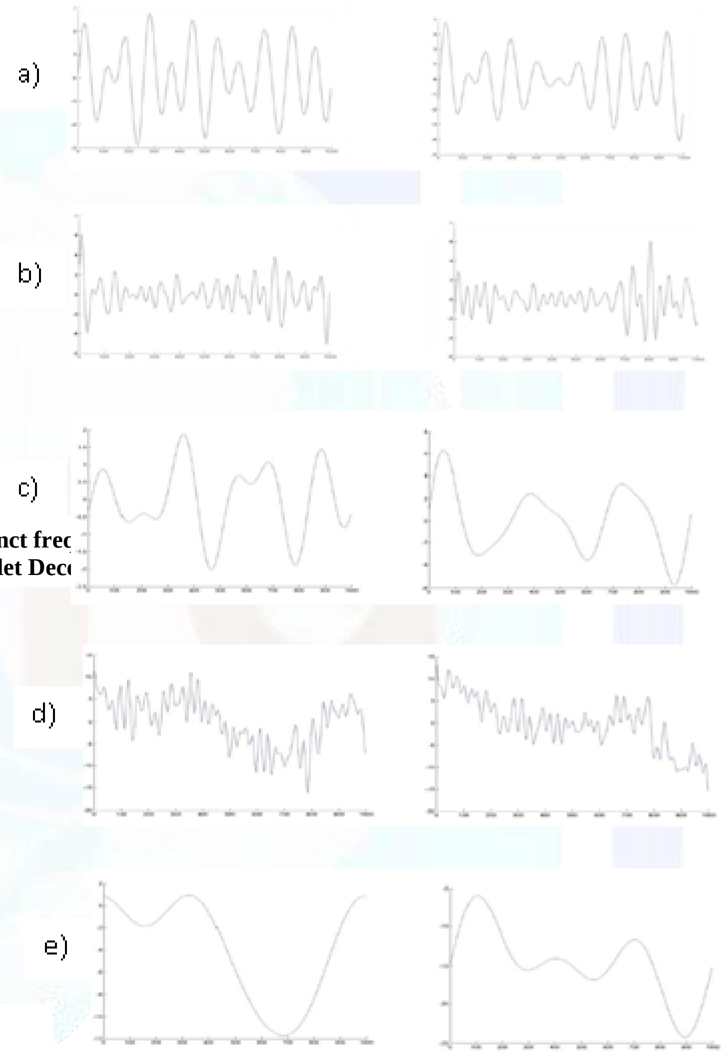

Figure 4: Plot for Channel 0 and Channel0 of Trials 0 and 1 respectively for (a) Alpha Rhythm, (b) Beta Rhythm (c) Delta Rhythm, (e) Gamma Rhythm and (f) Theta Rhythm

different trials.

We observed that low frequency Delta Rhythm is less related for the experiment as there is significant dissimilarity between the plots of the two trials and that too for same channel (channel 0).

Therefore Pre-processing involves mainly two steps explained below in detail-

***Step 1*:**

The EEG signal recording of duration 10 seconds for each mental task (or a class) is divided into 20 segments of duration 0.5 seconds each. The sampling rate measures 250.0 Hz. Since each trial corresponding to a class consists of approx. 2500 samples, so each EEG segment (Total: 20 Segments) is 125 (2500/20) samples in length.

NOTE: A Class or Mental Task are equivalent and refer to the same thing.

With respect to any single class or mental task for a subject we have a total of 10 trials or samples therefore, after segmentation we have 10*20=200 (10 Trials * 20 Segments) trials. We will refer these samples as ***Segmental-Samples*** in later sections.

***Step 2*:**

After generating Segmental-Samples we perform ***Wavelet – Decomposition-Analysis*** to decompose signals into predefined frequency spectrums i.e. predefined rhythms which are - Gamma, Theta, Beta, Mu and Alpha Rhythms. The wavelet function we use is *"db8"*.

After the pre-processing stage we need to have a feature vector corresponding to each segment of each trial of each subject. We deal with this in the next subsection.

C. Feature Extraction/Selection Stage

After the Pre-processing stage comes the Feature Extraction/Selection stage. This part of the stage is the backbone of the entire classification process. Classification of EEG Signals into the correct classes is majorly dependent on the quality of features extracted and selected during feature extraction/selection stage. After the feature extraction/selection we become ready to adopt some appropriate classifier algorithm for the classification.

Diversified selection of features has been made by previous researchers as mentioned in the Introduction section and the overall accuracy of the classifier has been observed to be directly proportional to the quality of feature. It is quite implicit and natural that more is the discriminating power of the feature better is the quality of the feature. According to Ali Bashashati, Fatourechi, Rabab Ward and Birch [1, 2] feature choice is greatly dependent upon the type of Neuromechanism we are dealing with. In this paper we are concerned with non-movement mental tasks only therefore we adopt spectral powers and spectral power differences as feature set.

As described in the previous subsection for different non movement mental tasks we had 10 corresponding trials for each. In the pre-processing stage we segment (*at a sampling frequency of 250 Hz*) each trial of duration 10 seconds (or sample length 2500 approx.) into 20 segments of duration 0.5 seconds (or sample length 125 approx.) also known as ***Segmental-Samples***. Each segment in turn consists of recordings of 6 channels. And each channel is decomposed into various Rhythms/ Bands – Alpha, Beta, Gamma, Mu and Theta in the Wavelet Decomposition phase. Therefore, in all we have 200 segments for all 10 trials corresponding to a single class of mental task.

Now we will show how we calculated spectral power and spectral power differences to form a feature vector for the segmental-samples.

Step 1:

For each signal (S_i) – [Alpha, Beta, Gamma, Mu, Theta] we calculate its power using the following formula:

$$\boxed{P_s = \sum_1^n (s_i)^2}$$

Step 2:

After computing power for each signal we calculate the power differences between each channel pair of same signal in the spectral band (that is Alpha, Beta, Gamma, Mu, Theta) for all the signals one by one. In case of our dataset which is the Segmental-samples, for one spectral band signal, since we have 6 channels, there would be (6)*(6-1)/2=15 or ${}^6C_2$ channel pairs and corresponding differences.

Power difference in each spectral band was computed using:

$$\boxed{Power_{Diff} = \left[\frac{p1 - p2}{p1 + p2}\right]}$$

Where p1 represents power in one channel signal of the pair and p2 represents the power of another channel signal.

Overall, this gave 5 x 6 (5 Rhythms x 6 Channels) =30 spectral powers and 5 x 15 (5 Rhythms x 15 Differences per rhythm) =75 spectral power differences, with a total of 30+75=105 features for each Segmental-Sample.

D. Classification Stage

Finally we have the classification stage which classifies the given EEG Signal into a particular class which in turn generates a particular control command depending upon the application. According to Bashashati and his research team, [1] Neuromechanisms play a regulative role in the selection of classification algorithm also. We have adopted Support Vector Machine (SVM) as our classifier for the training dataset. Although SVM is a 2-ary classifier and we were required to classify EEG signal among three classes, we used SVM because of its good accuracy. However to deal with multiple classes we incorporated Decision Tree which is best for dealing with such situations.

In order to understand it better let us suppose we have 3 classes and we want to classify any signal into one of the three classes, then we need to have total of 3 classifiers, viz. Classifier that classifies between class 1 and 2, classifier that classifies between class 2 and 3, and the classifier that classifies between class 1 and 3. Here we use best suited decision tree which takes the final decision as shown in Fig 5.

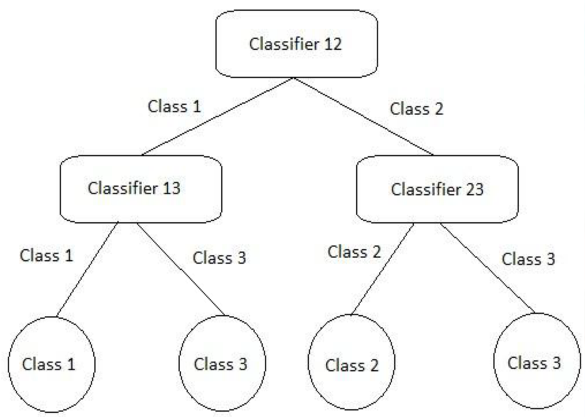

Figure 5: Decision Tree Classifier for 3 Classes

Let us look at the Classification stage in more detail. For the Classification stage we have focused primarily on two contexts – 1) Classification with respect to Segmental Samples and 2) Classification with respect to Actual Trials.

Context 1

By Classifying with respect to Segmental Samples we aimed at finding out the perfect features that could assess the drastic positive changes in efficiency of the segmental Samples and hence focused on mending the changes ahead upon the work of Palaniappan [35, 36, 37, and 46] where features were achieved as already discussed in Feature Extraction Section.

In this case 80% of total 400 segmental-samples per pair of classes (320) were chosen as training samples and remaining 20% (80) segmental-samples were chosen as testing samples. These samples were then used with the SVM Classifier.

Context 2

When Results were obtained for context 1 where segments were sampled into training and testing datasets, we observed a small loophole in that method which no one detected so far. Although the previous method with respect to context 1 gave very good results but we noticed that there was a high probability that all possible combinations of datasets were trained beforehand, which led to the accuracy of the results. Hence to further improve we switched to context 2 which was based on classifying with respect to actual trials by sampling actual trials into training and testing dataset respectively instead of sampling the segmental-samples formed by all the actual trials.

Let us discuss this context in detail –

-
- For every class we had 10 sample trials (each 10 seconds long). So a total of (10*2=) 20 samples per pair of classes.
- For the binary classification through SVM, we took 8*2=16 samples (i.e. 80%) for training and 2*2=4 (i.e. 20%) samples for testing.

Let us now proceed with the ***training part*** –
A total of (8+8) 16 samples were used as the training dataset.

1. For each trial we break the original trials or signal data into segments of 0.5 seconds each i.e. we get 20 segments (10seconds/0.5seconds=20) per trial.

    a) Instead of treating one whole trial as one sample, we consider each of these segmental parts as one separate sample or pattern and call them *Segmental-Samples*. Class label of each of these segmental-samples will be same as the classification label of the main trial or signal from which any segment is segmented out.
    b) In total we have 20*10=200 segmental-samples per class. Therefore for two classes we have total 400 segmental-samples.

2. For each of the 400 samples we extract our features: spectral powers and spectral power differences as discussed in the previous section of Feature Extraction-

    - Obtain each rhythm (gamma, beta, theta, alpha and delta) from each channel per sample.
    - Calculate power of each spectral signal obtained.
    - Calculate power differences between each channel pair within same spectrum.
    - Take these spectral powers and power differences as features.

So for our 6 channel data we have (6 channels * 5 rhythms=) 30 spectral power features and (${}^{6}C_{2}$ channel pairs * 5 rhythm =) 75 power differences. So a total of 30+75=105 features are present.

3. Now we train our SVM using of this dataset and feature set.

Note: One Important thing to be kept in mind here is that the classifier would be trained to classify each segmental-sample, which are actually segments obtained after segmenting the main signals/trials.

Now**,** let's move towards **testing part**:

1) We had total 10 trials per class. We used 80.00% of them in the training module (i.e. 8 trials per class * 2 classes =16 trials for above training), but with their corresponding segmental patterns. So we used (16 trials * 20 segments per trial=) 320 segmental-samples or training.

2) Now we use remaining 20% trials to verify the approach.
The approach given below was proposed to adopt classification of our test trials using the already trained classifier, which was trained for classifying segmental-samples.

For each ***test trial***:

a) Obtain segmental-samples, i.e. 20 segmental-samples for the given trial and their corresponding features as obtained in the training phase.
b) Predict the class of all those 20 segmental-samples using the trained classifier.
c) Now the class label which is predicted for **majority** of the segmental-samples of the particular trial is the class label of that trial. We call this step as **Voting Phase** because segmental-components (segmental-samples) of the given trial vote to predict the class label of the given trial.

For example: To classify any trial which has 20 segmental-samples:

I. We need to first get the class predictions (+1 or -1) corresponding to all the 20 segmental-samples.
II. Suppose 16 out of 20 segmental-samples predict that they correspond to (+1) class and remaining 4 correspond to the other (-1) class, then class of the trial would be predicted as (+1).

To raise the performance of this voting phase we introduced an intermediary step in voting phase known as **Rejection of Confused-Votes,** in which we discarded all those predictions that were considered as **Confused-Votes** described below

***Confused-Votes*:** Any binary classifier's (e.g. SVM's) prediction is considered to be a Confused-Vote if the output of the SVM is in the range [-th, +th] where |th| is real number near to 1.0, known as **Confusion Threshold**.
For example, we have used |th| =0.8, so if any SVM output falls in range [-0.8, 0.8] then it is said to be Confused Prediction and hence during voting, these sort of votes are discarded.

Following points conclude this whole approach:

i. For training purpose we train the classifier for classifying segmental-samples and not the main samples.
ii. Further for prediction we use the trained classifier and voting phase**.**
iii. The interesting conclusion for this complete approach is that we have merged Modern AI (Where we used SVM as a classifier) with classical AI **(**where Voting Phase constitutes our deduction based intelligent system).
iv. Accuracy is 100% in majority of X_Folds (explained in the Result section in detail) that we have tested.

Further for 3-ary classification we built a total of 3 classifiers, viz. Classifier $\mathbf{C_{12}}$, that classifies between class 1 (Math Task) and class 2 (Counting task), classifier $\mathbf{C_{23}}$, that classifies between class 2 (Counting task) and class 3 (Idle Task), and the classifier $\mathbf{C_{13}}$ that classifies between class 1 and class 3. This process is also explained diagrammatically in (Fig.5).
Note: that the classifier that has high accuracy would be remarked in high position in the decision tree. We observed that C_{12} has highest accuracy and hence our decision tree would look like as shown in (Fig 5).

III. RESULTS AND DISCUSSIONS

A. Results of Classification of segmental-samples (as discussed in Context 1)

- Total number of segments per class=200
- Total number number segment patterns=200*2=400, available for binary classification training and testing.

I. <u>Results for the classification of Class1 and Class2 (i.e. Math Task and Counting Task)</u>

- For Training Data Set, 80% i.e. 320 out of 400 patterns were taken randomly for training the classifier.
- Remaining 20% i.e. 8 patterns were taken for the testing.

a) ***Test results***

Test result came out to be 93.75% for segmental patterns from classes corresponding to math task and counting task. The Screenshot for the result is shown in (Fig. 6)

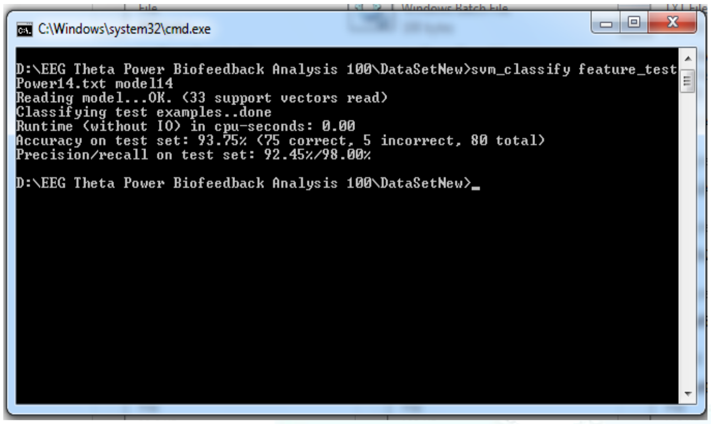

Fig 6: Results of Class 1 and Class 2

II. <u>Results for the classification of Class1 and Class3 (i.e. Math Task and Idle Task)</u>

- For Training Data Set, 80% i.e. 320 out of 400 patterns were taken randomly for training the classifier.
- Remaining 20% i.e. 8 patterns were taken for the testing part.

Test results

Test result came out to be 90% for segmental patterns from classes corresponding to math task and counting task. The Screenshot for the result is shown in (Fig.7)

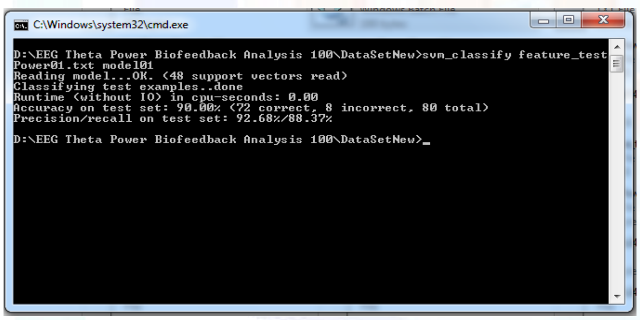

Fig 7: Results of Class 1 and Class 3

Comparison with the previous works done using Elliptic-Finite Impulse Response (FIR) spectral filtering and MLP as a classifier for classes I and III: (Table 2)

Table 2: Comparison with Previous Research

Previous work (Using FIR and MLP)	Our results (Using Wavelength Decomposition and SVM)
81%	90%

III. <u>Results for the classification of Class2 and Class3 (i.e. Counting Task and Idle Task)</u>

- For Training Data Set, 80% i.e. 320 out of 400 patterns taken randomly for training the classifier.
- Remaining 20% i.e. 8 patterns were taken for the testing.

Test results

Test result came out to be 91.25% for segmental patterns from classes corresponding to math task and counting task. (Fig.8)

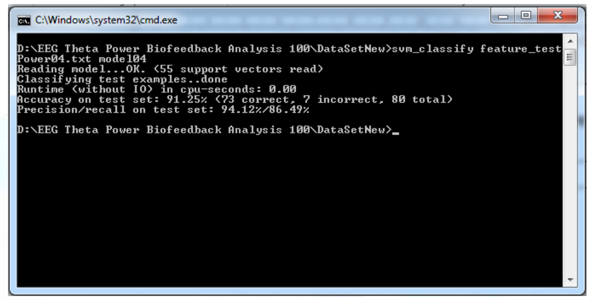

Fig 8: Results of Class 2 and Class 3

Comparison with the previous works done using Elliptic-Finite Impulse Response (FIR) spectral filtering and MLP as a classifier for classes II and III (Table 3)

Table 3: Comparison with Previous Research

Previous work (Using FIR and MLP)	Our results (Using Wavelength Decomposition and SVM)
86.5%	91.25%

B. Results of Classification of segmental-samples (as discussed in Context 2)

I. <u>Results for the classification of Class1 and Class2 (i.e. Math Task and Counting Task respectively)</u>

Total number of trials=20
Number of folds for X-Fold Cross Validation=10
Number of training samples=16
Number of testing samples=4

Table 4: Classification Results for Class 1 and Class 2

Fold #	Test trial-1 (% of Segmental Samples Voted For Correct Class	Test trial-2 (% of Segmental Samples Voted For Correct Class	Test trial-3 (% of Segmental Samples Voted For Correct Class	Test trial-4 (% of Segmental Samples Voted For Correct Class	Number of Test Samples Classified correctly
Fold #1	64.70588235	83.3333333	100	100	4 out of 4
Fold #2	88.88888889	100	100	100	4 out of 4
Fold #3	100	100	100	100	4 out of 4
Fold #4	100	100	100	100	4 out of 4
Fold #5	100	100	100	94.73684211	4 out of 4
Fold #6	100	100	89.47368421	85.71438751	4 out of 4
Fold #7	100	100	87.5	100	4 out of 4
Fold #8	100	73.3333333	100	93.75	4 out of 4
Fold #9	70	93.75	92.30769231	93.30769231	4 out of 4
Fold #10	94.11764706	75	100	100	4 out of 4

In the above table (Table 4) we can see that in each x-fold for the all the four test trials, majority (>50%) of their segmented-samples have been voted correctly, i.e. it has predicted the correct class. That is why in the last column in each x-fold we get 4/4=100% accuracy.

II. Results for the classification of Class1 and Class3 (i.e. Math Task and Idle Task respectively)

Total number of trials=20
Number of folds for X-Fold Cross Validation=10
Number of training samples=16
Number of testing samples=4

Table 5: Classification Results for Class 1 and Class 3

Fold #	Test trial-1 (% of Segmental Samples Voted For Correct Class	Test trial-2 (% of Segmental Samples Voted For Correct Class	Test trial-3 (% of Segmental Samples Voted For Correct Class	Test trial-4 (% of Segmental Samples Voted For Correct Class	Number of Test Samples Classified correctly
Fold #1	94.11764706	100	61.53846154	35.29411765	3 out of 4
Fold #2	94.44444444	100	45	100	3 out of 4
Fold #3	95	68.42105263	95	90	4 out of 4
Fold #4	35.29411765	52.63157895	100	100	3 out of 4
Fold #5	68.75	100	100	100	4 out of 4
Fold #6	100	94.73684211	100	89.47368421	4 out of 4
Fold #7	94.73684211	100	89.47368421	100	4 out of 4
Fold #8	100	100	95	90	4 out of 4
Fold #9	90	94.73684211	100	84.21052632	4 out of 4
Fold #10	95	95	84.21052632	70	4 out of 4

In the above table (Table 5) it's clearly shown that in each x-fold (except 1st, 2nd and 4th) for all the four test trials majority (>50%) of their segmented-samples have been voted correctly. In 1st, 2nd, and 4th Folds, 4th, 3rd and 1st trials respectively, had majority (>50%) of segmental-samples that were voted incorrectly. Yet it's clear that in the maximum cases of x-folds the accuracy is **4/4=100%**. However the average accuracy of the performances of all x-fold cases would be 37/40.

III. Results for the classification of Class2 and Class3 (i.e. Counting Task and Idle Task respectively)

Total number of trials=20
Number of folds for X-Fold Cross Validation=10
Number of training samples=16
Number of testing samples=4

Table 6: Classification Results for Class 2 and Class 3

Fold #	Test trial-1 (% of Segmental Samples Voted For Correct Class	Test trial-2 (% of Segmental Samples Voted For Correct Class	Test trial-3 (% of Segmental Samples Voted For Correct Class	Test trial-4 (% of Segmental Samples Voted For Correct Class	Number of Test Samples Classified correctly
Fold #1	92.30769231	73.3333333	100	100	4 out of 4
Fold #2	56.25	88.8888889	100	95	4 out of 4
Fold #3	95	84.21052632	100	95	4 out of 4
Fold #4	83.33333333	73.68421053	95	70.58823529	4 out of 4
Fold #5	88.23529412	76.47058824	73.68421053	93.75	4 out of 4
Fold #6	81.81818182	80	87.5	86.61538462	4 out of 4
Fold #7	100	100	86.66666667	77.77777778	4 out of 4
Fold #8	100	94.73684211	75	94.44444444	4 out of 4
Fold #9	100	94.11764706	82.35294118	44.44444444	4 out of 4
Fold #10	94.73684211	89.47368421	61.11111111	100	4 out of 4

In the above table (Table 6) it's observed that in each x-fold for the all four test trials, majority (>50%) of their segmented-samples have been voted correctly. That's why in the last column in each x-fold rows we get 4/4=100% accuracy.

IV. CONCLUSION AND FUTURE WORK

Keeping in mind to obtain better features which could efficiently classify EEG Signals corresponding to non-movement mental tasks we progressed in the direction where we found that Wavelet Decomposition Analysis is a better spectral analysis tool and SVM suits best for our feature set that comprises Spectral Power and Spectral Power Differences. Efficiency of our approach is also evident from the results obtained and discussed in the previous section.

We have basically introduced a new classifier system that incorporates both Modern as well as classical AI. Training Phase is purely based on Modern AI while Testing Phase contains modern AI pipelined with classical AI. In the Classical AI we have used deduction based classification, for which we introduced concept of voting among Segmental-Component of any EEG trial and the theory of Confusion Threshold which eliminates Segmental-Sample that is less sure about its class, while Modern AI included classification through SVM.

We have covered every step from Experimental setup to Pre-processing to Feature Selection and finally to Classification in detail in the previous sections. One important observation that we made for getting accurate classification of EEG Signals from the best of our trials was that we could rely on patterns available in segments of whole EEG Signal as majority of segmental samples may show a proper pattern instead of the whole signal which may show very difficult patterns for pattern recognition. Hence we were successful in exploiting a new way of classifying with 100% accuracy in most of the cases.

As far as EEG signal classification is focused, future work can include implementing a classifier system that can accept the EEG signals captured without any expert monitoring and yet give a better performance. This can help in simplifying user interface for users of BCI. We are further expecting to get better and speedy classifier systems that can work efficiently even for classification of EEG signals corresponding to inter-neuromechanisms.

REFERENCES

[1] Ali Bashashati, Mehrdad Fatourechi, Rabab K Ward and Gary E Birch "A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals", J. Neural Eng. 4 (2007) R32–R57, March 2007

[2] S. G. Mason, A. Bashashati, M. Fatourechi, K. F. Navarro and G. E. Birch, "A comprehensive survey of brain interface technology designs", Ann. Biomed. Eng. vol. 35, no.2, pp. 137-169, Feb.2007

[3] Jasper H and Penfield W 1949 Electrocortiograms in man: effect of voluntary movement upon the electrical activity of the precentral gyrus Arch. Psychiat. Nervenkr. 183 163–74

[4] Kozelka J W and Pedley T A 1990 Beta and mu rhythms J. Clin. Neurophysiol. 7 191–207

[5] Niedermeyer E and Lopes da Silva F 1998 Electroencephalography: Basic Principles, Clinical Applications, and Related Fields 4th edn, ed C Mitchell (Baltimore, MD: Williams & Wilkins)

[6] Pfurtscheller G and Aranibar A 1977 Event-related cortical desynchronization detected by power measurement of scalp EEG Electroencephalogr. Clin. Neurophysiol. 42 817–26

[7] Babiloni C, Babiloni F, Carducci F, Cappa S F, Cincotti F, Del Percio C, Miniussi C, Moretti D V, Rossi S, Sosta K and Rossini P M 2004 Human cortical responses during one-bit short-term memory. A high-resolution EEG study on delayed choice reaction time tasks Clin. Neurophysiol. 115 161–70

[8] Deecke L and Kornhuber H 1976 Voluntary finger movement in man: Cerebral potentials and theory Biol. Cybern. 23 99–119

[9] Neumann N, Hinterberger T, Kaiser J, Leins U, Birbaumer N and Kubler A 2004 Automatic processing of self-regulation of slow cortical potentials: evidence from brain–computer communication in paralysed patients Electroencephalograph. Clin. Neurophysiol. 115 628–35

[10] Allison B Z and Pineda J A 2003 ERPs evoked different matrix sizes: implications for a brain–computer interface (BCI) system IEEE Trans. Neural Syst. Rehabil Eng. 11 110–3

[11] Kubler A, Kotchoubey B, Kaiser J, Wolpaw J R and Birbaumer N 2001a Brain–computer communication: unlocking the locked Psychol. Bull. 127 358–75

[12] Gao X, Xu D, Cheng M and Gao S 2003b A BCI-based environmental controller for the motion-disabled IEEE Trans. Neural Syst. Rehabil. Eng. 11 137–40

[13] Donoghue J P 2002 Connecting cortex to machines: recent advances in brain interface Nat. Neurosci. 5 1085–8

[14] Olson B P, Si J, Hu J and He J 2005 Closed-loop cortical control of direction using support vector machines IEEE Trans. Neural Syst. Rehabil. Eng. 13 72–80

[15] Niedermeyer E. and da Silva F.L. (2004) Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. Lippincot Williams & Wilkins ISBN 0781751268

[16] Atlas of EEG & Seizure Semiology. B. Abou-Khalil; Musilus, K.E.; Elsevier, 2006

[17] Wolpaw, J.R. Birbaumer, N. Heetderks, W.J. McFarland, D.J. Peckham, P.H. Schalk, G. Donchin, E. Quatrano, L.A. Robinson, C.J. Vaughan, T.M., "Brain-computer interface technology: a review of the first international meeting," *IEEE Transactions on Rehabilitation Engineering*, Vol. 8, Issue 2, pages 164-173, 2000

[18] Wolpaw, J.R. McFarland, D.J. Vaughan, T.M., "Brain-computer interface research at the Wadsworth Center**"** *IEEE Trans. on Rehabilitation Engineering*, Volume 8, Issue 2, pages 222-226, 2000

[19] Benjamin Blankertz, "Wadsworth BCI Dataset: P300 Evoked Potentials," http://www.bci2000.org, July 2009

[20] Kshitij and S. Sanyal, "EEG Signal Classification", IIIT Allahabad, thesis/desertation Submision, July 2011

[21] BCI dataset 3

[22] BCI dataset 4

[23] Theresa M. Vaughan, Dennis J. McFarland, Gerwin Schalk, Willium A. Sarnacki, Dean J. krusienski, Eric W. Sellers, and Jonathan R. Wolpaw, "The Wadsworth BCI Research and Development Program: At Home With BCI," *IEEE Trans. On Neural System and Rehabilitation Engg.*,Vol. 14, No. 2, June 2006

[24] Leonard J. Trejo, Roman Rosipal, and Bryan Matthews, "Brain–Computer Interfaces for 1-D and 2-D Cursor Control: Designs Using Volitional Control of the EEG Spectrum or Steady-State Visual Evoked Potentials**,**" *IEEE Trans. On Neural System and Rehabilitation Engg.*,Vol. 14, No. 2, June 2006

[25] T. Joachims, Making large-Scale SVM Learning Practical Advances in Kernel Methods - Support Vector Learning, B. Schölkopf and C. Burges and A. Smola (ed.), MIT-Press, 1999

[26] Dan Xiao, Zhengdong Mu, and Jianfeng Hu, "Classification of motor imagery EEG signals based on energy entropy," In *Proceedings of the 2009 International Symposium on Intelligent Ubiquitous Computing and Education*, pages 61-64, 2009

[27] Li Ke and Rui Li, "Classification of EEG signals by multi-scale filtering and PCA," In *Proceedings of IEEE International Conference on Intelligent Computing and Intelligent Systems*, pages 362 – 366, 28 December 2009

[28] Farid Oveisi, "EEG signal classification using nonlinear independent component analysis," In *proceedings of icassp 2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, Pages 361-364, 2009

[29] B. T. Skinner, H. T. Nguyen, and D. K. Liu, "Classification of EEG signals using a genetic-based machine learning classifier," In *proceedings of IEEE conference of Eng Med Biol Soc.* pages 3120 – 3123, 2007

[30] Anderson C., Stolz E., and Shamsunder S. "Multivariate Autoregressive Models for Classification of Spontaneous Electroencephalogram During Mental Tasks", *IEEE Transactions on Biomedical Engineering*, vol. 45, no. 3, pages 277-286, 1998

[31] Maryam Vatankhah and Mehdi Yaghubi, "Adaptive Neuro-fuzzy Inference System for Classification of EEG Signals Using Fractal Dimension," *Third UKSim European Symposium on Computer Modeling and Simulation*, Pages 214-218, 2009

[32] C.Gope, N.Kehtarnavaz, and D.Nair, "Neural network classification of EEG signals using time-frequency representation," In *Proceedings of IEEE International Joint Conference on Neural Networks*, vol. 4, pages 2502 – 2507, 2005

[33] Anurag Kumru, Mihir N Mohantyand, and Aurobinda Routray, "Design of support vector machines with time frequency kernels for classification of eeg signals," in *Proceedings of the 2010 IEEE Students' Technology Symposium, IIT Kharagpur, Pages 330 – 333,* 3-4 April 2010

[34] Pritish Ranjan Pal and Rajanikant Panda, "Classification of EEG signals for epileptic seizure evaluation" in *Proceedings of the 2010 IEEE Students Technology Symposium, IIT Kharagpur. Pages 72 – 76,* 3-4 April 2010

[35] Nai-Jen, Huan, and Ramaswamy Palaniappan, "Classification of mental tasks using fixed and adaptive autoregressive models of EEG signals," in Proceedings *of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA*. Pages 507 – 510, September 1-5, 2004

[36] Tugce Balli and Ramaswamy Palaniappan, "A Combined Linear & Nonlinear Approach for Classification of Epileptic EEG Signals," in *Proceedings of the 4th International IEEE EMBS Conference on Neural Engineering Antalya, Turke, Pages 714 – 717,* April 29 - May 2, 2009

[37] Nai-Jen, Huan and Ramaswamy Palaniappan, "Classification of Mental Tasks Using Fixed and Adaptive Autoregressive Models of EEG Signals," in *Proceedings of the 2 International IEEE EMBS Conference on Neural Engineering Arlington, Virginia*, Pages 5-8, March 16 - 19, 2005

[38] M. Dalponte, F. Bovolo, and L. Bruzzone. Automatic selection of frequency and time intervals for classification of EEG signals. *Electronic Letters* Volume 43(25), pages 1406 – 1408, 2007

[39] Ashkan Yazdani, Touradj Ebrahimi, and Ulrich Hoffmann, "Classification of EEG Signals Using Dempster Shafer Theory and a K-Nearest Neighbor Classifier," in *Proceedings of the 4th International IEEE EMBS Conference on Neural Engineering Antalya, Turkey*. pages 327 – 330, April 29 - May 2, 2009

[40] Sarah M. Hosni, Mahmoud E. Gadallah, Sayed F. Bahgat, and Mohamed S. AbdelWahab- Classification of eeg signals using different feature extraction techniques for mental-task BCI. In *International IEEE conference on Computer Engineering & Systems, ICCES '07* Pages 220 – 226, 2007

[41] Inna Zhovna and Ilan D. Shallom, "Automatic detection and classification of sleep stages by multichannel eeg signal modeling," in *proceedings of 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada*, Pages 2665 – 2668, August 20-24, 2008

[42] Boyu Wang, Feng Wan, Peng Un Mak, Pui In Mak, and Mang I Vai, "EEG Signals Classification for Brain Computer Interfaces Based on Gaussian Process Classifier," in *proceedings of 7th International Conference on Iformation, Communications and Signal Processing, ICICS 2009*, Pages 1 – 5, 2009

[43] E Estrada, H Nazeran, P Nava1, K Behbehani, J Burk, and E Lucas, "Itakura Distance: A Useful Similarity Measure between EEG and EOG Signals in Computer-aided Classification of Sleep Stages," in *Proceedings of IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China*, pages 1189 – 1192, September 1-4, 2005

[44] Dr. R.Sukanesh and R.Harikumar, "Minimum Relative Entropy (MRE) Method for Fuzzy based Classification of Epilepsy Risk Levels from EEG Signals," in *proceedings International Conference on Biomedical and Pharmaceutical Engineering, ICBPE 2006*, pages 93 – 98, 2006