Classification and Analysis of EEG signals for Imagined Motor Movements

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***Abstract*—This paper presents a data driven approach to explore the variations in the electroencephalogram(EEG) signals when a person tries to imagine movements like moving his or her left hand, right hand, foot and tongue. The paper tries to find out the type of variations that occur in the EEG signals when such type of imagined movements are undertaken by a person and also the regions in the brain where the variations of EEG signals are the most pronounced. EEG data corresponding to the said actions was captured from three different persons using multiple electrodes placed over the head. Features based on auto regressive power spectral density and entropy measures have been used to analyze this data. This was followed by feature selection process to reveal the most prominent of the features. Analysis of the selected features revealed the positions of the electrodes which were picking up the variations in the EEG signals. This resulted in the identification of the regions in the head where the signal variations were most prominent. It was found that the positions were not fixed but varied from person to person. The findings have been backed up by time-frequency maps of the signals which describes the type of variations that happens in the EEG signals when different kinds of movements are imagined and how varied these variations are with respect to individual subjects as well as the types movements performed.**

Keywords: Electroencephalogram (EEG), Motor Imagery, Common Average Reference (CAR), Event Related Potential (ERP), Support Vector Machine (SVM)

I. Introduction

Electrical activity inside the brain can be affected by various kinds of actions like movement of arms and legs, as well as visualization, problem solving or even just by imagination. Measuring this electrical activity of the brain can be done using electrodes placed over the scalp. The recorded signal is the electroencephalogram or EEG. There are variations in the EEG when a person moves his or her hands and legs. Not only that, even when a person tries to imagine such kind of motor movements, then also, there are variations in the EEG signals. The paper tries to identify four different types of imagined movements, namely, movement of right hand, left hand, legs and tongue movements from a person's EEG signal. The paper uses machine learning approach to learn a classifier about the variations in the EEG signals from different subjects and for different kinds of imagined motor movements and later on use the learned classifier to identify the imagined event from new EEG signals. The paper also tries to give an idea about the type of variations that happens in the EEG signals when such kind of imagined movement is performed and also the regions in the brain that are affected while performing those movements. Once the affected regions are identified, time frequency maps of EEG signals from those regions have been analyzed to get an idea about the variations in the signals. These variations are revealed through the perturbations in the power spectrum in certain frequency bands when different kinds of imagined movements are performed. It has been observed that the changes in the power spectrum and the affected frequency bands differ both subject to subject as well as for different types of movement. Moreover, the variations of the EEG signals also differ based on the location of the head from where it was recorded. That is, for the same subject and for the same kind of imagined movement, different variations in EEG signal can be observed at different regions of the head. This whole study has been portrayed through the following sections. Section II describes the EEG data that has been used here. The source of the data has been the BCI Competition III dataset. Section III provides information about preprocessing of the EEG signals to reduce the content of noise that comes with it. Section IV describes the various feature extraction techniques that have been considered here based on algorithms like auto-regressive power spectral density estimation and different kinds of entropy measures.Section V takes a deeper look into the features extracted from algorithms discussed in the previous section. Here, all the features were combined together and subjected to feature selection algorithm. The selected features revealed a lot of information about the relevancy of certain features and electrode positions as well as their variations from person to person.Section VI provides a comparative study of the classification accuracies. Section VII gives an idea about the variations in the EEG signals by studying the time-frequency analysis of the same. Section VIII concludes the paper.

II. EEG Data

The data set of EEG signals used here is taken from BCI Competition III (Dataset IIIa) [1]. This data set contains data from three subjects pertaining to four different kinds of imagined movements. These are imagined left hand, right hand, foot and tongue movements. The EEG data was collected from 60 channels placed over the scalp. The experiment consisted of several runs with the subject being displayed different types of arrows (pointing left, right, up and down) , each indicating a different type of movement to imagine.Left arrow corresponds to imagining of movement of left hand, right arrow for right hand movement imagination, up arrow for feet and down arrow for tongue movements. Each trial lasted 10 seconds in duration, with the arrow being displayed from 4th till 7th second. Further details of the experiment can be found here in [2]. The data set consists of multiple trials from each subject with each trial having 60 channels and each channel containing EEG signal sampled at 250Hz.

III. Preprocessing

For this paper, signals starting from 4 to 8 seconds have been separated out from each trial. This was done to capture the variations for different kinds of imagined movements because the visual cues displayed to the subjects were also during the same period. A Common Average Reference (CAR) [3] filter was then applied on each of the trials. CAR takes the mean of the data from all the channels involved in each trial and subtract the same from each of the channels. This helps in minimizing the effects of uncorrelated random noise occurring from a single or multiple set of electrodes. [19]. The data set have been tested with different kinds of classification algorithm and for each and every case, the application of Common Average Reference Filter has improved classification accuracy.The performance have been detailed in Table I.

All of the signal data were band passed between 8-30Hz to remove the possibility of the influence of any ocular or muscular artifacts as the frequency of such artifacts mostly lie between 1-5Hz frequency range. The EEG signals were further subdivided into the following frequency bands 8-12Hz, 12-16Hz, 16-20Hz, 20-24Hz, 24-28Hz and 26-30Hz. This was done because the sub bands responsible for capturing variations of EEG signals vary from person to person.

IV. Feature Extraction

Instead of relying on a set of features coming from a single feature extraction algorithm, features were extracted from quite a few different kinds of algorithms namely auto-regressive power spectrum density based features and entropy based features. Auto-regressive algorithms were chosen as they provide better frequency resolution even in case of short data record. Entropy has been another popular method for analyzing complex biological systems. Entropy basically provides a measure of the uncertainty or complexity of a signal and has been extensively used to study epileptic brain signals [16], Alzheimer disease [4] and also for doing sleep study [8].Given the non-stationary and non-linear nature of EEG signals [17], entropy calculation becomes an easy pickup as a feature extraction method. Three different types of entropy measures have been used here for extraction of features namely Shannon entropy, Sample entropy, Renyi entropy and Log Energy entropy based on the extensive usage of such algorithms in analyzing EEG signals [10], [21], [14], [13], [18], [13]. For auto-regressive power spectral density both Burg and Yule-Walker has been used.

V. Feature Selection

In order to find out the areas of the brain where the EEG signals are most affected due to different types of imagined movements, it was required to identify the the channels which are responsible for capturing the variations in EEG signals. As a result, features extracted from individual algorithm as discussed in Section 3 were combined together to form a large feature set. A feature selection algorithm based on chi-square was applied to extract out a subset of the features good enough to differentiate the different types of movements from the signals. A good study of the selected features revealed certain electrode positions that were getting selected more often than others through feature selection procedure. This has been detailed in Table II.

Table III shows the positions of the electrodes for all the three subjects as selected by the feature selection algorithms. The selected electrodes have been marked with bold circular boundaries.

If observed carefully, the positions of the selected electrodes seemed to represent certain particular localized regions of the head. for Subjects K3B and L1B, most of the selected electrodes were from the left and right positions of the head whereas for subject K6B the left side of the head showed more prominence than the right. But, until and unless we can gain knowledge about the nature of the EEG signals recorded at these electrode positions, nothing more can be revealed from here. In section VII, the time-frequency analysis of the EEG signals have been studied and the revelations have been quite interesting. For each subject, the selected electrodes can be divided into two groups, based on the characteristics of the EEG signals recorded by them. EEG signals from electrodes, localized to one group, showed similar kind of characteristics than electrodes belonging to another group. This has been studied in details in section VII.

In order to verify that the selected electrode positions indeed were the ones capable of differentiating one type of imagined movement from the other, we have looked at the individual binary class classification accuracies as well as the overall multiple class classification accuracy for all the three subjects. The results have been detailed in the next section.

VI. Feature Classification

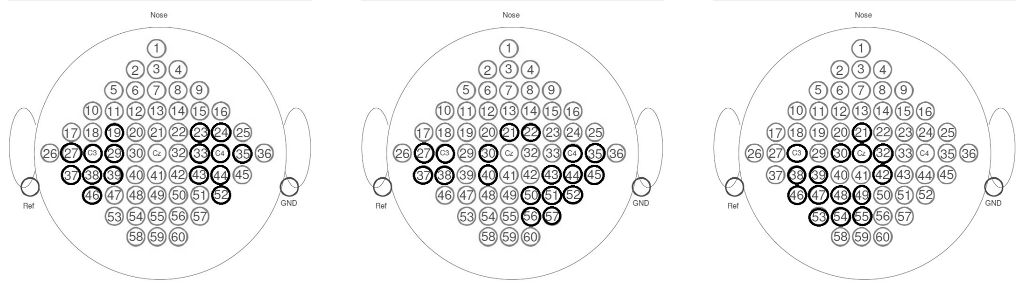
In order to see the effectiveness of the findings as stated above, the selected features were subjected to a linear Support Vector Machine (SVM) classifier to find their accuracy in identifying the various types of imagined movements from one another. Both binary (one vs one) and multiple (all vs all) class classifications were studied and their results have been shown in Table IV and and Table V. The idea behind choosing a linear SVM classier was that, the dimensionality data being already quite high, there was no need of a kernel to further project the data into any higher dimensions. Moreover, calculating the mapping functions for kernels like RBF, might

	Burg Autoregressive PSD		Yule-Walker Autoregressive PSD		Entropy Measure	
	Without CAR	With CAR	Without CAR	With CAR	Without CAR	With CAR
K3B	82.78	87.22	83.33	88.88	63.88	84.44
L1B	57.50	78.33	58.83	78.33	54.16	73.33
K6B	58.33	68.33	60.83	71.66	54.16	66.66

TABLE I: Accuracy Comparison with and without applying CAR

TABLE II: Channel Selected by Feature Selection Algorithm

Subject K3B	19, 23, 24, 27, 28, 29, 33, 34, 35, 37, 38, 39, 43, 44, 46, 52
Subject L1B	21, 22, 27, 28, 30, 34, 35, 36, 37, 38, 40, 43, 44, 45, 50, 51, 52, 56, 57
Subject K6B	21, 28, 30, 31, 32, 38, 39, 42, 46, 47, 48, 49, 53, 54, 55



(a) Subject K3B (b) Subject L1B (c) Subject K6B

TABLE III: Electrode Positions for Selected Channels for different Subjects

prove to be quite expensive when one already has a large set of features.

Table V shows the multiple class classification accuracies using the features selected through the feature selection technique

TABLE V: Multiple Class Classification Accuracy

	K3B	*L1B*	*K6B*
Feature Selection	**90.56**	**80.83**	**76.67**

When compared with the multiple class classification accuracy from individual algorithms used in this work as detailed in Table VI, it was found that the feature selection procedure seemed to produce better results.

TABLE VI: Comparison of Accuracy from Individual Algorithms and from Feature Selection Method

	K3B	*L1B*	*K6B*
Yuler-Walker PSD	86.67	73.33	71.66
Burg PSD	87.22	78.33	68.33
Shannon Entropy	84.44	65.00	61.67
Renyi Entropy	84.44	73.33	66.66
Log Energy Entropy	83.89	68.33	58.33
Sample Entropy	83.80	68.33	58.33
Feature Selection	**90.56**	**80.83**	**76.67**

The accuracies depicted in Table V are also comparable to classification accuracies as obtained by others on the same data sets [6]. The comparison has been drawn out in Table VII.

TABLE VII: Comparison of Accuracy with other Authors on the same EEG Dataset

	K3B	*L1B*	*K6B*
Hill & Schrder	96.11	55.83	64.17
Guan, Zhang & Li	86.67	81.67	85.00
Gao, Wu & Wei	92.78	57.50	77.83
AlZoubi, Koprinska1 & Calvo	93.89	61.67	78.33
Ours	**90.56**	**80.83**	**76.67**

VII. Time Frequency Analysis

The results, as discussed in the previous section, seems to indicate that the feature extraction process was able to identify certain variations in the EEG signal which are unique for a particular type of imagined movement. The best way to analyze these variations and to get a better understanding of what is really happening inside the brain, the event related potentials or ERP [20] at the electrodes selected though the feature selection process has been analyzed in this section. ERP is understood to be the result of post synaptic potentials of a large number of neurons which got activated simultaneously with the invocation of certain events. The events, looked at in this paper, involves the imagined movements of left hand, right hand, foot and tongue. The changes in the post synaptic potentials, if any, will be reflected in the EEG signals and captured by the recording electrodes. To understand the same, the time frequency analysis of the EEG signals were studied for the selected electrodes. It was found, that, for all subjects and for all kinds of imagined movements, there was a change in power in the selected electrodes, right at the start of an event.

TABLE IV: Individual Classification Accuracy

	Left Hand vs Right Hand	Left Hand vs Tongue	Left Hand vs Foot	Right Hand vs Tongue	Right Hand vs Foot	Tongue vs Foot
K3B	98.89	94.44	98.89	97.78	97.78	91.11
L1B	90.00	96.67	98.33	95.00	98.33	90.00
K6B	68.33	85.00	96.67	86.67	93.33	98.33

A. ERP during Movement Initiation

Table VIII shows the time frequency analysis of an electrode for the left hand imagined movements for all three subjects. The duration of the EEG signals used to draw the figures are of length 6 seconds consisting of with 3 seconds before and 3 seconds after the occurrence of an event. In each of the sub-figures, the time has been plotted along the X-axis with duration with 0, marked by a vertical line, representing the time when the event starts. The labels, -3000 to 0 and 0 to 3000, represents the duration in milliseconds, before and after the event occurs. The frequency, mapped along the Y-axis, ranges from 0-50Hz. The power in the frequency components are described with color codes with blue and red representing the lower and higher end of the spectrum. It can be clearly observed, that there are perturbations in the power spectrum, marked by bold rectangle boundaries, in certain frequency bands which start at the onset of an event i.e. around the time t=0 as shown in the figure.

Thus it can be confirmed that the there are indeed some variations that occur in the EEG signals when a person starts to imagine some kind of motor related movement. Though the variations themselves vary subject wise, but still imagined motor movements do trigger some perturbations in the signals that are picked up by the electrodes placed over the scalp.

B. Electrode Localization

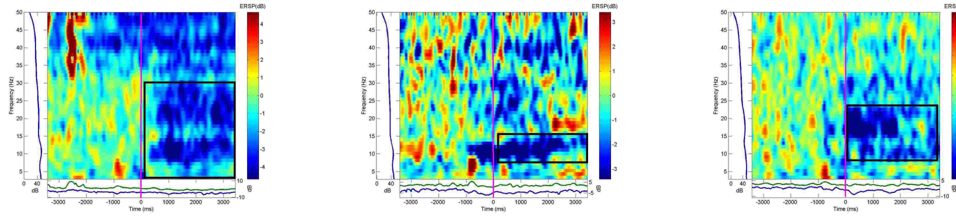
Analysis of the event related potentials of the selected electrodes revealed an interesting pattern. Based on their time frequency characteristics, the selected electrodes can be subdivided into two separate groups, with electrodes from each group showing similar characteristics among themselves but different characteristics when compared with electrodes belonging to the other group. This feature can be seen for all the three subjects although the positions of the groups may differ from subject to subject. This has been detailed in figure IX. The figure shows the groups of electrodes, as marked by curved boundaries, which shows similar characteristics among themselves for all the three subjects. The electrodes in the overlapped regions shows characteristics common to both groups. It can be seen, that for Subject K3B, the electrode groups form at the central-left and central-right regions of the head. For L1B, the group formation takes place in the central-left and central-right along with the posterior-left region. The electrode positions at the center have features similar to both the regions and cannot be put in any of the groups. The grouping of electrode positions is quite different for subject K6B where the formation takes place in left-central and left-posterior region of the head.

C. Time Frequency Analaysis for Imagined Motor Movements

Till now, what has been observed is that, there are variations in the EEG signal at the onset of any type of imagined movement. Moreover, these variations themselves vary based on the region of the head from where the EEG signals were recorded. To get a better understanding of the variations in the EEG, a comparative study of the EEG signals has been done using time-frequency analysis of the event related potentials. The comparison has been done among EEG signals for all types of imagined movements among different subjects and also among EEG signals from different head positions of the same subject. This has been detailed in tables X, XI and XII. Each of the table depicts the time-frequency analysis of EEG signals taken from two electrodes for different types of imagined movements. As discussed before, for each subject, there are two localized regions in the head whose EEG signals showed different characteristics. The electrodes were chosen in such a way that they represent one from each group. There are five columns in each table. The first column shows the electrode position whose EEG signal has been analyzed. The next four columns display the time-frequency maps for four types of imagined movements. The two rows represent the two selected electrodes.

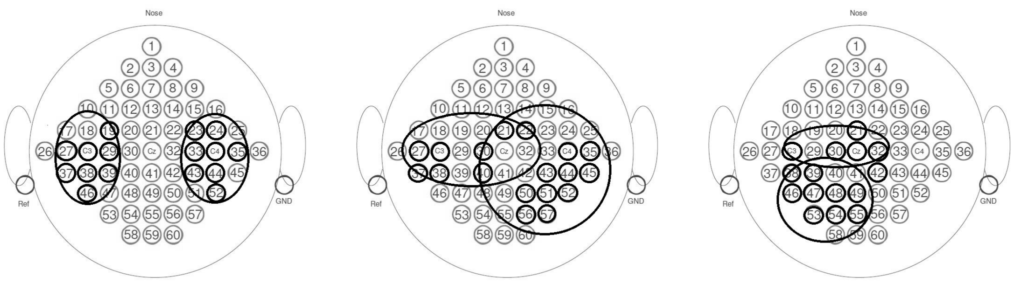
1) Subject K3B: Table X displayed the event related potentials (ERP) for Subject K3B. For left hand imagined movement, it can be observed that there is a decrease in the power of the EEG signal in the 8-16 Hz and 20-24Hz frequency bands for the electrode placed on the central-left region. In case of the electrode placed on the central-right region of the head, the decrease in power can be noticed in the whole of 8-30Hz frequency band. The right hand imagined movement displays almost contrasting characteristics where the decrease in power in the 8-16Hz and 20-30Hz frequency bands is more for the EEG signal coming from the central-left region of the head than the one coming from the central-right. For imagined foot movement, an increase in power can be noticed in the 8-16Hz and 20-24Hz frequency bands for the central-left electrode whereas the other electrode displays a decrease in power spectrum in the 26-30Hz band. For tongue movement also there are contrasting characteristics in the EEG signals from the left and right region of the head. While the ERP of the left electrode shows an increase in power spectrum in the 8-16Hz band, the ERP of the right electrode displays a decrease in power in the 26-30Hz frequency band.

2) Subject L1B: For the subject L1B, though not much of a difference can be noticed between the EEG signals recorded from the left and right regions of the head for left hand imagined movement, there is still a decrease in power



(a) Subject K3B (b) Subject L1B (c) Subject K6B

TABLE VIII: Time Frequency Analysis of EEG signals before and after the onset of an Left Hand Imagined Movement



(a) Subject K3B (b) Subject L1B (c) Subject K6B

TABLE IX: Electrode Positions for Selected Channels for different Subjects

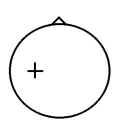
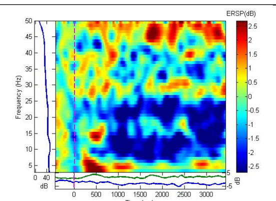
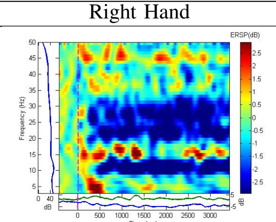
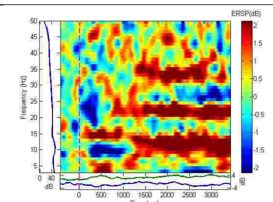
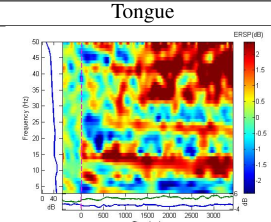
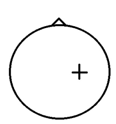
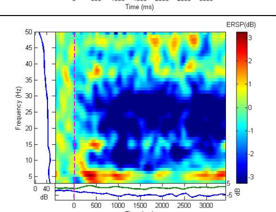
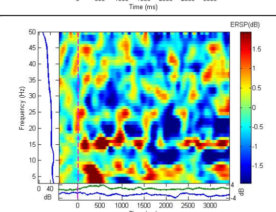
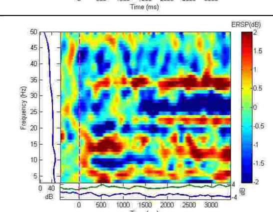
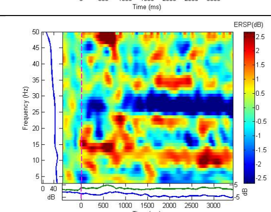
Position	Left Hand	Right Hand	Foot	Tongue
				
				

TABLE X: ERP Analysis for Differnt Types of Movement for Subject K3B

spectrum in and around the 12-16Hz frequency band for the electrode placed on the left which is absent for the one placed on the right. The decrease in power in the 24-30Hz is also clearly visible in the potential from the left electrode but the duration lasts only for a second with the onset of the event. In case of right hand imagined movement, there is a role reversal in the potentials of the electrodes placed in left and right regions of the head. Here the decrease in power in the specified frequency bands is displayed over the electrode placed on the right is more than the one placed on the left. For imagined foot movement an increase in power spectrum in the 26-30Hz band can be noticed in the potential for the right electrode. This is not observable in the potential for the electrode placed in the left region of the head. For imagined tongue movement, a relatively small increase in power spectrum in the 8-20Hz frequency band can be observed for the electrode on the left than on the right.

3) Subject K6B: In case of subject K6B, as discussed earlier, the positions of the two different groups of electrodes are quite different from the other two subjects. Here, the groups are formed in the central-left and posterior-left region of the head. Two electrodes, one from each group has been selected to study the event related potentials (ERPs) for each type of movement. For left hand imagined movement, the ERP shows a relative decrease in power in the 10-24Hz frequency band for the electrode placed on the central-left region than that of the other whereas an increase in power can be noticed in the 8-12Hz band for the right hand imagined movement in the same electrode. Foot and tongue imagined movements resulted in an increase in power in the 15-20Hz frequency band 15-25Hz frequency band respectively in the left-posterior region when compared with the EEG signal from central-left region.

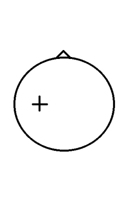
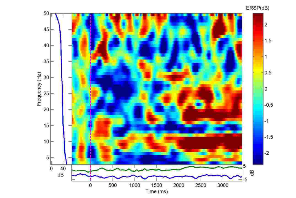
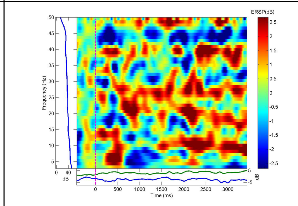
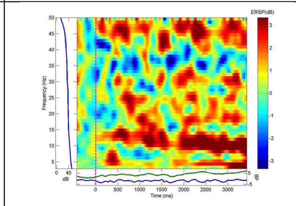
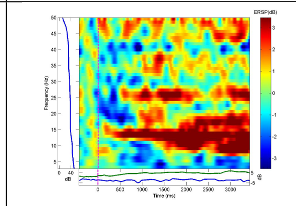
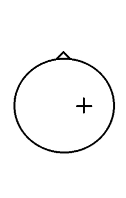
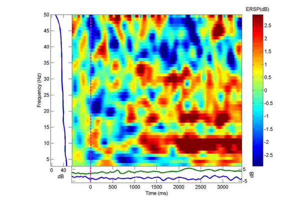
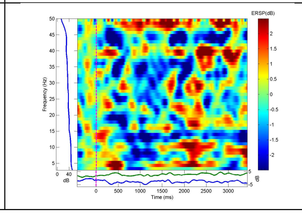
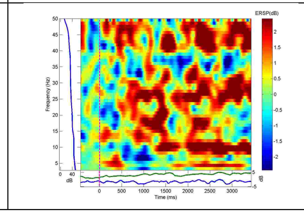
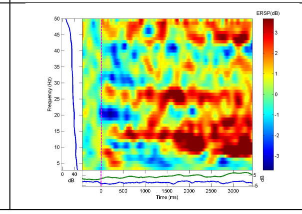
Position	Left Hand	Right Hand	Foot	Tongue
				
				

TABLE XI: ERP Analysis for Differnt Types of Movement for Subject L1B

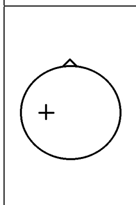
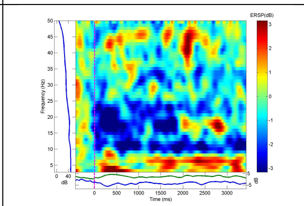
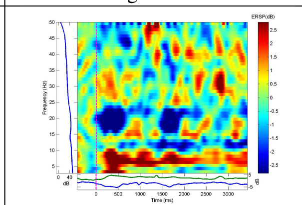
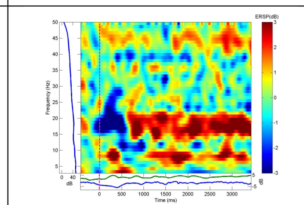
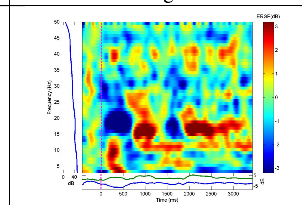
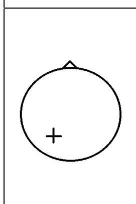
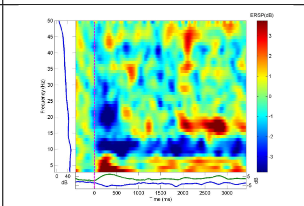
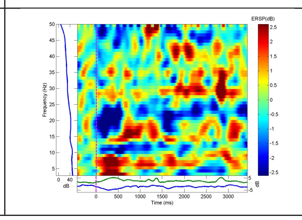
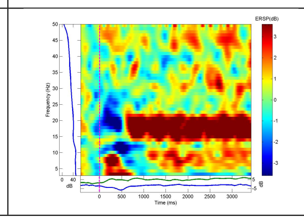
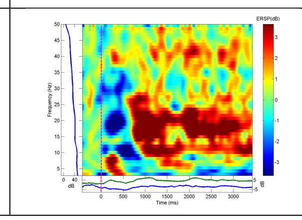
Position	Left Hand	Right Hand	Foot	Tongue
				
				

TABLE XII: ERP Analysis for Differnt Types of Movement for Subject K6B

It can be seen that there are variations in the EEG signals when a person tries to imagine a type of movement. These variations are different for different types of movements imagined as well as for different regions of the head. Moreover, the variations also vary for same type of movements if compared against different subjects. If the event related potentials of EEG signals recorded from the same position of the head and for the same kind of imagined movement is compared for different subjects, its quite hard to find a commonality among the variations of the EEG signals. This is true for the imagined movements and the subjects considered in this paper. Even the positions of the head where the EEG signals seems to get affected the most due to various types of movements seemed to differ subject to subject. To verify this fact, from the data-centric point of view, the EEG signals from all the three subjects were combined together to form a large training set and passed through the same feature extraction, feature selection and classification procedures as discussed in earlier sections. The plan was to find out, if there is any increase in accuracy for any of the subjects. An increase in accuracy would mean that there is indeed a common effect due to imagined movements which was missing from the time-frequency maps. Whereas a decrease in the accuracy would second the claim that its quite hard to find any commonality in the EEG variations for the various types of movements.

The comparison of the combined accuracy as well as individual subject wise accuracy has been detailed in Table XIII.

TABLE XIII: Multiple Class Classification Accuracy

	K3B	*L1B*	*K6B*
Individual Accuracy	**90.56**	**80.83**	**76.67**
Combined Accuracy	**81.67**	**74.17**	**56.67**

It can be observed, that for all the three subjects there has been a decrease in accuracy when trained with features belonging to other subjects. To further verify the difficulty of building a cross subject model, data belonging to one subject was tested against a classifier trained with data belonging to the other two subjects and the accuracy was found to be quite low as showed in table XIV. The figures marked in bold denote the classification accuracies of the individual test data for each of the three subjects when the data used for training is taken from the other subjects.

TABLE XIV: Cross Subject Multiclass Classification Accuracy

		Training Data		
		K3B + L1B	K3B + K6B	L1B + K6B
Test Data	K3B	82.78	86.11	**31.11**
	L1B	75.83	**33.33**	75.00
	K6B	**28.33**	60.00	64.17

VIII. CONCLUSION

The paper has tried to explore the variations in the EEG signal that result from imagining various types of motor movements. It can be observed that there are indeed changes that occur in the EEG signals at the onset of any kind of imagined movement. These changes get reflected as perturbations in the power spectrum of the signals in selected frequency bands. Again such kind of variations do differ based on the region of the brain from where they are emanating, the type of movement performed and also on the type of subject doing the activity. It was found, that, most of the variations in the EEG signals were observed over the sensory motor region but the exact area varies from subject to subject. The regions were recognized through a feature selection procedure which identified the positions of the electrodes that were picking up the event related potentials. The approach used here was different in the sense that instead of preselecting the electrodes and then extracting features form the selected ones, features were extracted from all the electrodes and then selected through a feature selection procedure to find out electrode positions that captured the variations of EEG signals while doing imagined movements. This was backed up by time-frequency analysis of the signal potentials which clearly showed the variations in the power occurring at specific frequency bands. Though, the results of the experiment showed good classification accuracy when subjects were trained individually, the accuracy decreased when the training data from all subjects were combined together. The accuracy became worse when the training dataset did not contain the features from the EEG signals of the subject against which the accuracy was being tested. Thus, it was hard to find a common set of features which will work well for all subjects and this is what which requires further investigation and can be taken up as the future work henceforth.

REFERENCES

[1] BCI Competition III.

[2] DescriptionIIIa - desc_iiia.pdf.

[3] Electrocortical Activation and Human Brain Mapping - Google Books.

[4] D Absolo, R Hornero, P Espino, D lvarez, and J Poza. Entropy analysis of the EEG background activity in Alzheimer's disease patients. *Physiological Measurement*, 27(3):241–253, March 2006.

[5] Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat. Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains. *ISRN Neuroscience*, 2014, February 2014.

[6] Omar Alzoubi, Irena Koprinska, and Rafael A. Calvo. Classification of Brain-Computer Interface Data. In *IN: 7TH AUSTRALASIAN DATA MINING CONFERENCE (AUSDM*, pages 123–132, 2008.

[7] Serap Aydin, Hamdi Melih Saraolu, and Sadik Kara. Log energy entropy-based EEG classification with multilayer neural networks in seizure. *Annals of Biomedical Engineering*, 37(12):2626–2630, December 2009.

[8] Naoto Burioka, Masanori Miyata, Germaine Cornlissen, Franz Halberg, Takao Takeshima, Daniel T. Kaplan, Hisashi Suyama, Masanori Endo, Yoshihiro Maegaki, Takashi Nomura, Yutaka Tomita, Kenji Nakashima, and Eiji Shimizu. Approximate Entropy in the Electroencephalogram During Wake and Sleep. *Clinical EEG and neuroscience : official journal of the EEG and Clinical Neuroscience Society (ENCS)*, 36(1):21–24, January 2005.

[9] Center for History and New Media. Zotero Quick Start Guide.

[10] Phung Dinh, Tran Dat, Ma Wanli, Nguyen Phuoc, and Pham Tien. Using Shannon Entropy as EEG Signal Feature for Fast Person Identification. *ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014*, April 2014.

[11] Jianbo Gao, Jing Hu, and Wen-wen Tung. Entropy measures for biological signal analyses. *Nonlinear Dynamics*, 68(3):431–444, December 2011.

[12] Takashi Hanakawa, Ilka Immisch, Keiichiro Toma, Michael A. Dimyan, Peter Van Gelderen, and Mark Hallett. Functional Properties of Brain Areas Associated With Motor Execution and Imagery. *Journal of Neurophysiology*, 89(2):989–1002, February 2003.

[13] G. Inuso, F. La Foresta, N. Mammone, and F.C. Morabito. Brain Activity Investigation by EEG Processing: Wavelet Analysis, Kurtosis and Renyi's Entropy for Artifact Detection. In *International Conference on Information Acquisition, 2007. ICIA '07*, pages 195–200, July 2007.

[14] Ge Jiayi, Zhou Peng, Zhao Xin, and Wang Mingshi. Sample Entropy Analysis of Sleep EEG under Different Stages. In *IEEE/ICME International Conference on Complex Medical Engineering, 2007. CME 2007*, pages 1499–1502, May 2007.

[15] Dimitris G. Manolakis John G. Proakis. *Digital Signal Processing: Principles, Algorithms, and Applications*. Prentice-Hall India, 3rd edition, August 2000.

[16] N. Kannathal, Min Lim Choo, U. Rajendra Acharya, and P. K. Sadasivan. Entropies for detection of epilepsy in EEG. *Computer Methods and Programs in Biomedicine*, 80(3):187–194, December 2005.

[17] Alexander Ya. Kaplan, Andrew A. Fingelkurts, Alexander A. Fingelkurts, Sergei V. Borisov, and Boris S. Darkhovsky. Nonstationary nature of the brain activity as revealed by EEG/MEG: Methodological, practical and conceptual challenges. *Signal Processing*, 85(11):2190–2212, November 2005.

[18] Zhenhu Liang, Yinghua Wang, Xue Sun, Duan Li, Logan J. Voss, Jamie W. Sleigh, Satoshi Hagihira, and Xiaoli Li. EEG entropy measures in anesthesia. *Frontiers in Computational Neuroscience*, 9:16, 2015.

[19] Kip A. Ludwig, Rachel M. Miriani, Nicholas B. Langhals, Michael D. Joseph, David J. Anderson, and Daryl R. Kipke. Using a Common Average Reference to Improve Cortical Neuron Recordings From Microelectrode Arrays. *Journal of Neurophysiology*, 101(3):1679–1689, March 2009.

[20] Shravani Sur and V. K. Sinha. Event-related potential: An overview. *Industrial Psychiatry Journal*, 18(1):70–73, 2009.

[21] Lei Wang, Guizhi Xu, Shuo Yang, Miaomiao Guo, Weili Yan, and Jiang Wang. Motor Imagery BCI Research Based on Sample Entropy and SVM. In *2012 Sixth International Conference on Electromagnetic Field Problems and Applications (ICEF)*, pages 1–4, June 2012.