Adaptive Modeling of Physiological Signals

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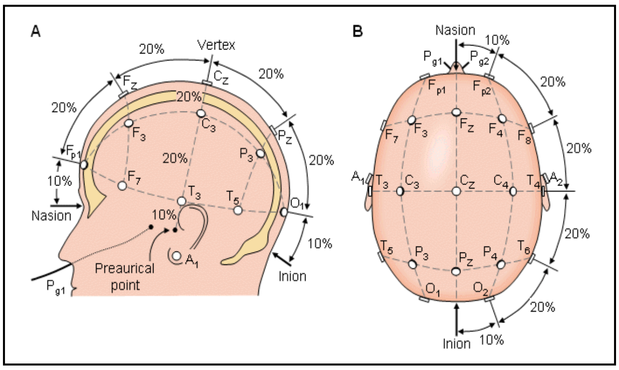
***Abstract*— There is a great amount of studies on EEG signals to determine the subject's behavior while performing certain tasks. EEG signals collected are always impure, with certain amount of noise due to multiple factors that are unavoidable. In this study, we extract the underlying source signals using Independent Component Analysis (ICA) and Fast Fourier Transform (FFT) from the high-resolution EEG signals in an attempt to use noise free data to a model that predicts stress level. The ICA approach lead to the extraction of a significant pattern in the source signals that represents eye-blink of the subject. Further, Time Series or Memory based models to be applied on this study.**

Keywords—EEG signals;Feature Extraction; ICA; Memory based models;FFT

I. Introduction

Extracting characteristic patterns from the EEG signals to infer insightful details is a complex task, when individuals (subjects) are put through a series of sessions. For this study, two subjects were put through 48 trials each and were asked to perform two types of tasks viz. tracking and surveillance. Each subject performed 8 trials in a session, each trial lasted for 4 – 6 minutes. After each trial the subjects were asked to give feedback on the difficulty level of the task. This feedback was scaled to a continuous value (0 to 100) and considered as a label



for the study. Each trial has a single label value. These subjected were fitted with an international 10-20 system of electrodes to gather the EEG signals along with the ECG signals and eye movements in vertical and horizontal direction. With data collected at every 1000^{th} fraction of a second, 4-minute trial generated a high resolution of data of about 400 hundred thousand data points.

II. Feature Extraction

These EEG signals are in time space with finite details that could lead to meaningful insights. Different approaches such as Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Fast Fourier Transform (FFT) were considered to extract characteristic patterns. An exploratory study was carried to choose the variables that will be used for extracting features.

A. Correlation Study

With multiple signals contributing towards the same output, a linear correlation between variables was suspected. A "Pearson" pairwise correlation test at a significance level of 0.7 across all the trials lead to a conclusion that the following variables were linearly correlated with each other.

TABLE I.

	F7	**F8**	**Fz**	**O2**	**Pz**	**T3**	**VEOG**
F7	1	-	-	-	-	0.73	-
F8	-	1	-	-	-	-	0.72
Fz	-	-	1		0.71	-	0.8
O2	-	-		1	0.74	-	-
Pz	-	-	0.71	0.74	1	-	-
T3	0.73	-	-	-	-	1	-
VEOG	-	0.72	0.8	-	-	-	1

B. Using ICA

A single label value cannot predict the state of mind of the subject through the variations in a 4-minute trial. A higher resolution of information is required for fitting a model to the collected data. Multiple labels for each trial were generated using ICA. ICA allows to separate the EEG signal into its components of Source Signals, Mixing Matrices and Noise Signals. With an understanding from an earlier research that the alpha and theta bands are highly correlated with subject's behavior [6], signals in the frontal and parietal lobe captured on the midline (Fz and Pz) were chosen to be further decomposed into its subcomponents using ICA. ICA separates the signal into the following subcomponents

- S Matrix of source signal estimates
- M Estimated mixing matrix.
- W Estimated un-mixing matrix
- Y Whitened data matrix.
- Q Whitening matrix.
- R Orthogonal rotation matrix.

ICA package [7] in R language was used for this analysis. These two signals (Fz & Pz) were separated assuming that there are two sources. The plot of the two signals is shown in Figure 1. The signal in orange represents signal from the first source whereas the signal in blue is from the second source. The downward spike on the blue signal is considered as the eye blink captured by the source.

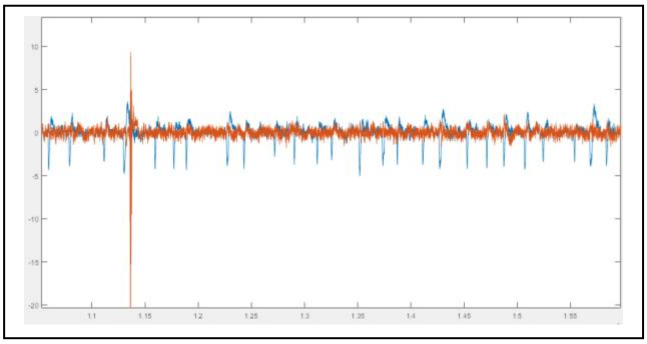


Fig. 1. Plot of Source Signals

The above result is a proof that the source signals of the 10-20 system extracted through ICA (EEG signals) could lead to finer details related to cognitive state of mind. Further using this approach, the rest of the source signals (O_2, F7, F8 along with Fz and Pz) could be studied and analyzed for more insightful details.

C. Using FFT

Using FFT the time series, data points were converted into amplitude to a frequency space. A Fast Fourier Transform converts a wave from the time domain into the frequency domain. There is a set of sine waves that, when summed together, are equal to any given wave. These sine waves each have a frequency and amplitude. A plot of frequency versus strength (amplitude) on an x-y graph of these sine wave components is a frequency spectrum, i.e., the trajectory can be translated to a set of frequency spikes. [5]. An R function *fft* that returns amount of frequency as a complex number X_k on each data point was used.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i.2\pi kn/N}$$

Where X_k is the amount of frequency k in the signal; each k^{th} value is a complex number including strength (amplitude) and phase shift; N number of samples; n current sample, $n \in \{0...N-1\} n \in \{0...N-1\}$; k current frequency, between 0 Hz to N-1 Hz; $1/N$ gives the actual sizes of the time spikes; n/N is the percent of the time passed through; $2\pi k$ is the speed in radians/second; e^{-ix} is the backwards-moving circular path. The X_k values generated are complex numbers and need to be converted for easy operation. So an R function *convert.fft* [5] was applied, to extract the strength (amplitude) & angle for each X_k value.

The advantage of using the amplitude value is that it

- eliminates the presence of negative values that were in source data points
- enables the possibility of stretching the time series line into a straight line by summating the strengths
- enables the possibility of capturing two nearby data points that were positive and negative when trimmed at a certain threshold. This approach is shown in the figure below.

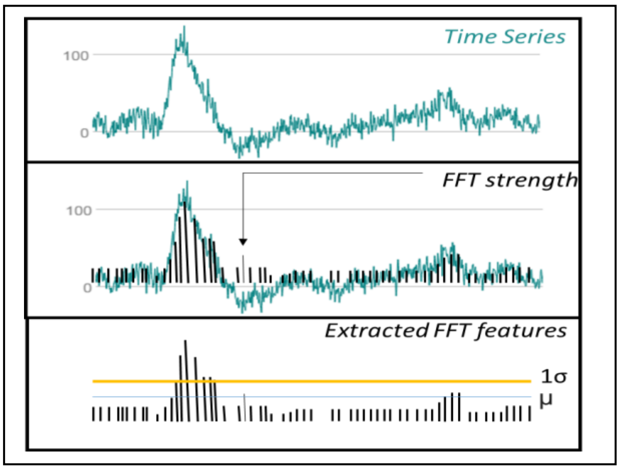


Fig. 2. A representative picture on Feature Extraction using FFT (1) EEG signal variable as time series. (2) Overlap of FFT converted strengths over variable in time series. (3) Extracted FFT feature in frequency space.

1) Using the sum of FFT strengths (F1): The total sum of the FFT strengths (amplitude) would nearly represent a straight line of the variable, when it is stretched. It was taken in to consideration that the sum of strengths of two neighbouring points is not equivalent to its separting distance. But the length of the line (sum value) would still represent a characteristic of stretching compartively among the variables.This approach helped to reduce the 400 thousand datapoints for one session to single record of values for one trial.

2) Using Mean of FFT Strengths(F2): The second outcome from the FFT strengths could the mean values of each variables per trial.

3) Number of occurences above threshold(F3): The number of occurrences of FFT strength values that are above its mean and one standard deviation were counted. This approach also helped reduce the number of datapoints for each trial to one record.

D. Features by fusing EEG and ECG channels

Along with ECG channel, a set of EEG channels - F7, F8 & Fz from Frontal Lobe, Pz from Parital Lobe and O2 from Occipital lobe were chosen as channels were chosen based on its functions in the TABLE II below, such that the generated features represent the subject's different brain activities (verbal, visual & emotional) during mental intensive tasks.

TABLE II.

EEG Channels	Function
F7	Verbal Expression
F8	Emotional Expression (Anger, Joy & Happiness)
Fz	Working Memory / Absent Mindedness
Pz	Cognitive Processing
O2	Visual Processing

The above set of EEG & ECG channels were used to extract 27 features that consist of SFT (Single Feature Tracking?? - sft1, sft2, sft3 & sft4), katz feature (1 feature), Band Powers (All, Beta, Alpha, Delta & Theta), Auto-Regressive features (AR1, AR2, AR3, AR4 &AR5 – 5 features to the order of 5) and 12 EEG features on each window (mean, bandpower & std.dev of Alpha, Beta, Delta & Theta)

Window Selection : The source files have 1000 data points per second. A window size of 1000 data points (equivalent to 1 second) and an offset of 500 data points (equivalent of half a second) was applied to extract features. First 6 windows & the last 6 windows were dropped out of study to drop noise / idle time signals of each trial, which resulted in generating 505 windows of 27 features for each channel.

Building Features as Images : Every window (1 * 27) of each channel was arranged vertically to construct 6 * 27 matrix, which then normalized at each column to develop 505 images per trial. These images were used in Convolutional Network prediction models.

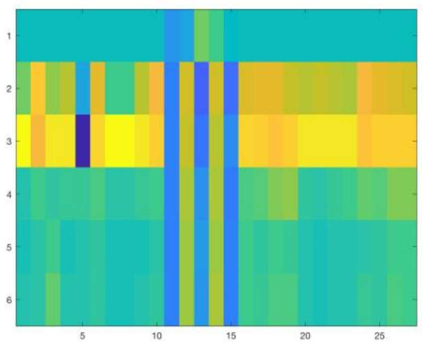


Fig. 3. x-axis – 27 features, y-axis (1-ECG, 2-F7, 3-F8, 4-Fz, 5-Pz & 6-O2)

E. Label Generation

Label generation using VEOG : The labels are genarated from the VEOG signal (a signal that captures the vertical eye movement). The labels try to give the average blinks of the subjects per second. This label is extracted using the windowing function which is the same as the one performed for the feature extraction and only differs in the window size. The window size is 7000 for generating the labels, but effectively is 1000, where a window of 3000 samples is applied before and after the effective window for bosltering it.

Label generation using PCA (slope + cont %) : With mutiple features having similar underlying properties, Principal component analysis yeilded the principal components that were clearly able to show the similar features having all their variation alligned in one dimension. Using these tuned principal components for label generation, the selection of the best label is left to choice for the author. The selection needs consideration of the property each PC exihibits and the total variation in data it can explain. The increased eye blink rate along with time seems to be an indicator of increased activity in the trial. The product of the gradient of response with repsect to time and the coverage of PC with repect to entire data decides the label to be used for further modeling.

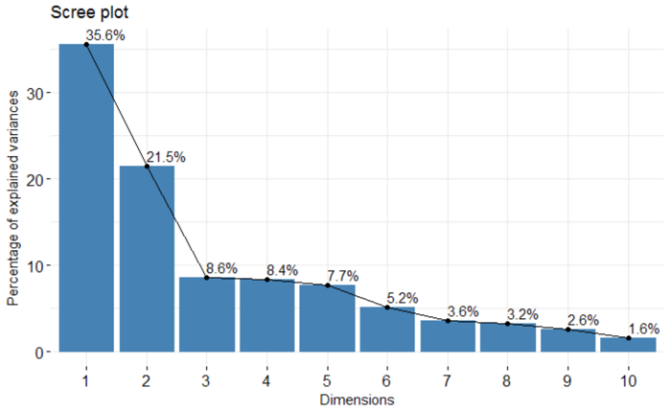


Fig. 4. Percentage variation in each Principal Component

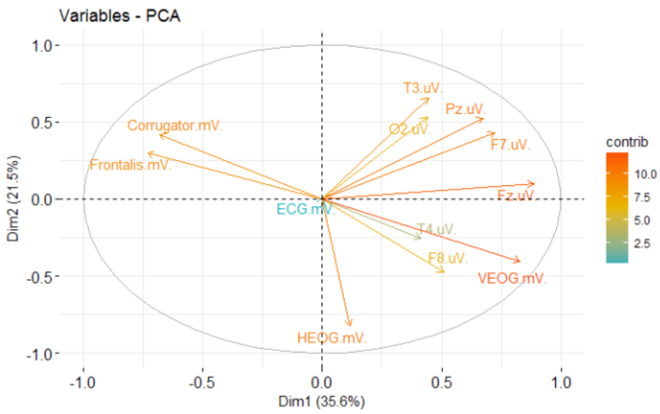


Fig. 5. Biplot of variables.

III. Predictive Models

With the two set of extracted features from ICA and FFT approach, they were analyzed using separate models.

A. Linear Regression Model uisng ICA extracted features

The source signals extracted from signals Fz and Pz, were considered as labels for the rest of the data. Since they were extracted from Fz and Pz, leaving these two variables from the study was a reasonable choice. As ICA assumes the nature of the signal as additive while decomposing it into its subcomponents, using the source signal as label and the original signal as a predictive variable does not seem to be a good statistical model due to high linear correlation involved. In this case, we consider the two signals as label generators. We run this linear model for the rest of the data sets. For the first subject of the study, the regression model performs well when the second source signal was used as the label compared to the first sources signal or the sum of the two source signals

TABLE III.

ICA Generated Labels	Source Signal 1 (S1)	Source Signal 2 (S2)	∑ (S1+S2)
R-square	0.5922	0.6699	0.6166

B. Classification Models on FFT extracted features

The FFT approaches taken for feature extraction reduced the numerous records to a single record for every trial. As the original study was focused on arriving at predicting a difficulty level, the authors applied an approach of reducing the label of the trial (composite TLX) to a qualitative value by factoring as shown in the TABLE III.

TABLE IV.

Composite TLX (0 to 100)	Difficulty Level (Factorized)
Above 75	A
51 to 75	B
26 to 50	C
0 to 25	D

The FFT extracted were applied on to different classification models to predict the difficulty levels the individuals experienced. Neural Network classifier using the occurrence (F3) gave the highest accuracy. The details are in TABLE IV.

TABLE V.

Models	Accuracy		
	F1	*F2*	*F3*
NN	96%	96%	100%
SVM	54%	54%	54%
Random Forest	42%	42%	50%
Naïve Bayes	71%	71%	92%

C. Models applied in second part

1) NARXNet: Within each trial the windows of features and labels are applied on a time series model using NARX(Nonlinear Autoregressive with External (Exogenous) Input) Neural Network in MATLAB. Using VEOG influenced labels on windows of F7 feature on trial 2 with 10 hidden layers & 4 delays, the R values were close to .80.

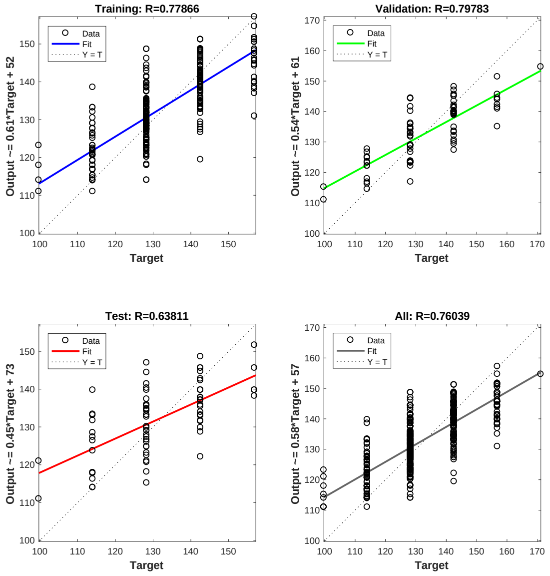


Fig. 6. Trial 2, Regression plot for F7 features

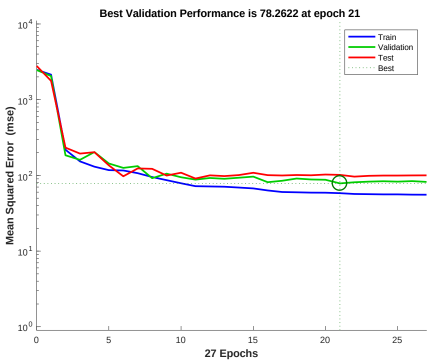


Fig. 7. Trial 2 – Performance plot

2) Convolutional Neural Network : Convolutional Neural Network is popularly used for classification of images. It could also be used for regression based on images. A 6 x 27 matrix of features for 505 windows in temporal space is a candidate for ConvNet models. An attempt was made to predict behavioral labels using the features representing brain intensive activities.

IV. Conclusions

ICA Approach: Extracting the source signals of two EEG variables and visual inspection of the source signal plots provided confidence to the study with a characteristic pattern that represents the eye-blink. Additional variables could be applied in this study to extract more characteristic patterns that could symbolize a significant clue towards a specific cognitive state of mind.

FFT Approach: Though the approach enabled reducing the sample size, loss of finer details within sub segments of EEG signals could not be ruled out due to the approximation imposed by feature extraction. A combined approach of ICA, FFT and other stated methods above to be tried to bring more clarity to the model.

V. Next Steps

1) In the current FFT approach, raw data points were used.Instead ICA transformed source signals to be used in the FFT approach.

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