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SIGNAL PROCESSING APPROACH IN P300 EVENT DETECTION AND CLASSIFICATIONFROM SINGLE TRIAL EEG FOR ATTENTION ASSESSMENT STUDIES

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Abstract-To detect P300 Event Related Potential(ERP) in Brain Computer Interface (BCI) experiments is a challenging task because of its poor Signal to Noise Ratio (SNR) and trial to trial variability. The second major challenge is the choice of electrodes that varies from subject to subject which involves more computation time for better classification accuracy in a dense electrode array system. The proposed work is intended to improve the extraction and classification of P300 from the standard mid-line electrodes F_Z, P_z, C_z that are subject independent with improved signal to noise ratio and reduced computation complexity . Five classifiers namely, Weighted KNN(W-kNN), Quadratic Discriminant analysis(QD), Bagged Trees(BT), Guassian Naive Bayes(G-NB) and Logistic Regression(LR) performance were compared in classifying the target and non target P300 ERPs from single trial. The time domain markers peak and latency of P300 and correlation coefficient obtained by template matching are the three features used. The bagged tree classifier outperformed with classification accuracy of 87.9% and AUC 0.95 which is comparatively good with other existing baseline approaches that uses 3 electrodes. With better pre-processing the proposed method will reduce the computational load for a portable BCI application in attention assessment studies that uses peak and latency features.

Key words- Supervised Learning, Discrete Wavelet Transform, Template Matching, Time Domain Approach, Feature Extraction

I. INTRODUCTION

BCI system is an alternative and augmentative communication tool for the people suffering from locked in syndrome, where the signal from the brain is used for control and communication. P300 Brain computer interface system is widely preferred among other EEG based BCI as it requires no user training. The P300 is an event related potential generated when users respond to infrequent stimuli in an oddball paradigm. This potential is of very low amplitude with latency between 250-550ms embedded in background EEG activity that differs in patterns and also depends on other factors such as, motivation, level of attention, fatigue, mental state and learning [17] .Extracting it from the background EEG activity requires an efficient signal processing algorithm. The conventional approach is to average multiple trials under the assumption that the observed signal is a zero mean stationary random process. It is a time consuming process and there is variability in amplitude and latency for each trail within the subject and across the subject.

The two main characteristics of P300 are the amplitude and latency. The amplitude is measured in microvolts(μV). It is defined as the difference between mean pre-stimulus base line voltage and the largest positive going peak of ERP[14]. The latency is the time from stimulus onset to the point at which the ERP amplitude is positive maximum. It is measured in milliseconds(ms).This P300 is used as a cognitive marker for healthy subjects and patients as these characteristics are associated with cognitive performance such as attention. The latency is short in duration for higher attention processes. The amplitude of P300 depends on various factors like probability of stimulus, inter stimulus interval, habituation effects, task difficulty, attentional and motivational issues [6],[9],[3].

The motivation of BCI is to provide a communication channel for people withsevere physical and speech impairment. For such people, the optimal P300 BCI should be simple to operate, affordable, accurate and efficient for communication on a daily basis[12]. Though the visual BCI system is proven to be good for people with ALS, stroke and spinal cord injury, they are still in initial clinical settings because of limitations in performance like poor information transfer rate and target detection accuracy. Modern BCI systems use dense array electrodes for data collection which involves high system cost and setup time. Computation in

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classification algorithms for signals acquired over many channels will be more intense and will be infeasible for portable applications in home environments or clinical setup. Hence the proposed work concentrates on portable BCI systems with standard 3 channel data that is subject independent. The analysis focuses towards extraction and classification of ERP as target or non- target by averaging equal number of epochs for both the cases which is novel in this BCI study with a suitable pre-processing stage with improved SNR. Whereas the conventional procedure is to, average few targets and more non-target ERPs.

II. DATABASE AND EXPERIMENT PROTOCOL

The data for this research work is obtained from Physionet website which is a research resource for complex physiological signals[5]. The ERP BCI database consists of EEG data obtained from 64 channels sampled at a rate of 2048 Hz, collected from 12 subjects. Each subject has 20 short records and each record corresponds to a single target character. This data set was generated by [4], as a part of study aimed at identifying the factors limiting the performance of brain computer interface systems based on event related potentials. The EEG signal recorded in response to a single character in speller matrix visual stimuli is considered as a single trial EEG. Each short record shows the intensification of a target character in a randomly flashed rows and columns of speller matrix. About 85,000 samples are recorded for single character intensification. All the datasets are annotated to indicate the start of a run, stimulus sequence and end of the event. For each character selection, i.e., for each single trial, all the rows and the columns were intensified 20 times and corresponding EEG response was recorded. The signal is downloaded from the database in .mat format and imported to the MATLAB environment for further processing.

III. PROPOSED METHOD

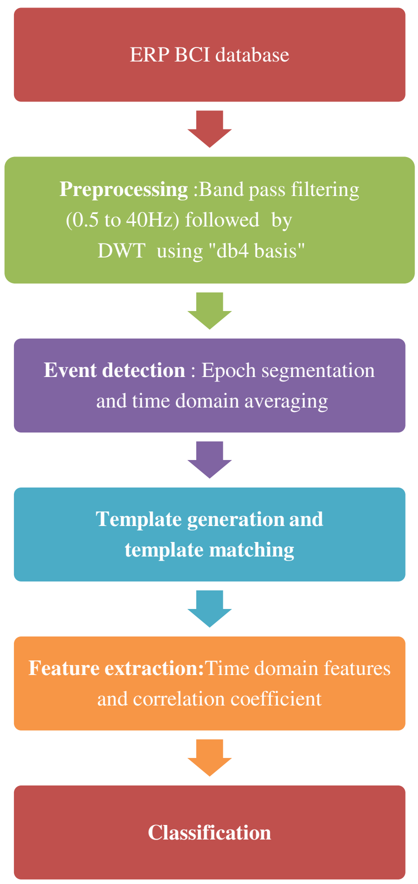

Fig. 1. Proposed algorithm structure

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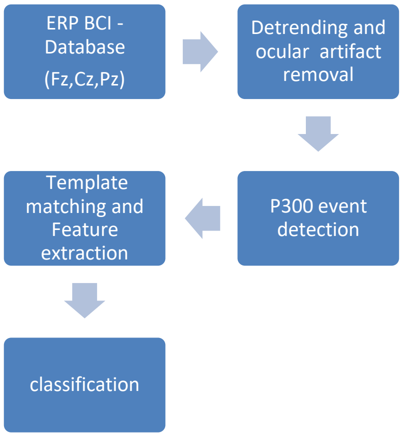

Fig. 2. Algorithm flow diagram

Detection of target events from a single trial EEG from the midline electrodes avoiding subject independent channel selection procedure is a major challenge in the P300 BCI systems used for AAC applications. This work aims to develop suitable techniques that address the challenge. An overview of the proposed work is shown in Fig.1. and algorithm flow in Fig.2.

A. Pre-processing

The EEG signal is contaminated with ocular artefacts and randomnoise. To detect the event P300, the EEG has to be noise free.

1) Detrending and ocular artifact removal:

The signal is band pass filtered with cut off 0f 0.5Hz to 40Hz using 100th order FIR filter using Kaiser window to eliminate high frequency noises. The band-passed signal is decomposed to 9 levels using Discrete Wavelet Transform(DWT) and soft threshold in all levels. The 9th level approximation components is reconstructed and subtracted from the actual recorded EEG to remove trends and artifacts in the signal as shown Fig.3 .The"db4" wavelet is used since it has morphological feature same as that of ocular artefact and resulted in better signal to noise ratio as discussed [13].The signals were baseline corrected and artefact removed at this stage. The result of denoising process shown in Fig.4

Fig. 3. Artifact cancellation process

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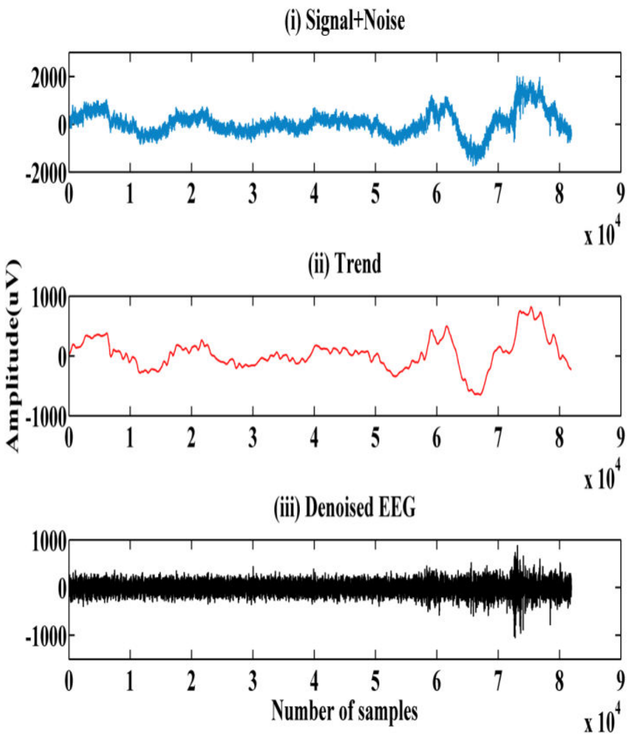

Fig.4. Removal of artifacts and trends in EEG

Table 1 Wavelet decomposition for signal sampled at a rate of 2048Hz

Approximate component:	Frequency band 0 to $2^{-(j+1)} * f_s$ Hz	Detail component	Frequency band $2^{-(j+1)}f_s$ to $2^{-j}f_s$Hz
A1	0-512	**D1**	512-1024
A2	0-256	**D2**	256-512
A3	0-128	**D3**	128-256
A4	0-64	**D4**	64-128
A5	0-32	**D5**	32-64
A6	0-16	**D6**	16-32
A7	0-8	**D7**	8-16
A8	0-4	**D8**	4-8
A9	0-2	**D9**	2-4

2) Segmentation, Averaging and event detection:

To remove random noise in non-stationary signals when multiple realizations are available, ensemble averaging is the best suited time domain approach. Similarly, when random noise has to be cancelled from single realization of signals, moving window average is the appropriate time domain signal processing approach .

Ensemble averaging or synchronized averaging is a time domain averaging technique that can separate a repetitive signal or event from noise without distorting the signal [16]. Let y_k be the observed signal given by

$$y_k(n) = x_k(n) + n_k(n) \quad (1)$$

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where $x_k(n)$ is the original signal without noise and $n_k(n)$ is the noise in the k^{th} copy of the signal. If M number of copies of signal are added at each instant of time n, then the resultant equation is given by,

$$\sum_{k=1}^{M} y_k(n) = \sum_{k=1}^{M} x_k(n) + \sum_{k=1}^{M} n_k(n) \qquad (2)$$

If the repetitions are identical and time aligned then,

$$\sum_{k=1}^{M} x_k(n) = Mx(n)(3)$$

If the noise is random and has zero mean and variance σ^2, on averaging multiple events $\sum_{k=1}^{M} n_k(n)$, the noise reduces to zero as M increases, with a variance of $M\sigma^2$. Thus synchronous averaging will increase the SNR by a factor of $\sqrt{M}$, where M is the number of epochs. More the epochs averaged, the better will be the SNR. The advantage of this method is that it preserves the signal content by producing no loss in spectral component.

The temporal averaging is another time domain approach for elimination of random noise discussed by [16]. It involves averaging of data samples over a predefined window length. The number of time points in the window decides the effects of averaging. Minimum number of samples in the window for averaging will not be sufficient to eliminate the random noise. If more time points are taken for averaging, it over smoothens the signal resulting in loss of information. There always exists a trade off between number of time points and information loss. Since the temporal averager acts like a frequency domain low pass filter, it results in spectral loss. Moving window averager is a FIR filter given by the equation,

$$y(n) = \frac{1}{N+1}\sum_{k=0}^{N} b_k x(n-k) \qquad (4)$$

where x(n) and y(n) are the input and output of the filter in time domain, N is the order of the filter, b_k is the filter coefficients, k=0,1,2..N

The event detection procedure is shown in Fig.5.For a single trail record, the row and column were intensified 20 times. The intersection of row/ column elicits a larger P300 for a target character. So the segments corresponding to both row and column intensification were manually segmented for duration of 600ms which is equal to 1230 samples. 17 such EEG segments were extracted leaving the target segments that are highlighted immediately after first intensification to avoid attention blinks. The segments were time aligned and synchronously averaged to reduce signal variability . To extract the ERP , the averaged data is passed though an 300 point moving average window which is used to identify the trends in the EEG. The above procedure is repeated for non

target EEG segments also. The first 2 stages were repeatedforall 3 mid- line electrodes of 8 subjects and the target and non –target ERPs were extracted.

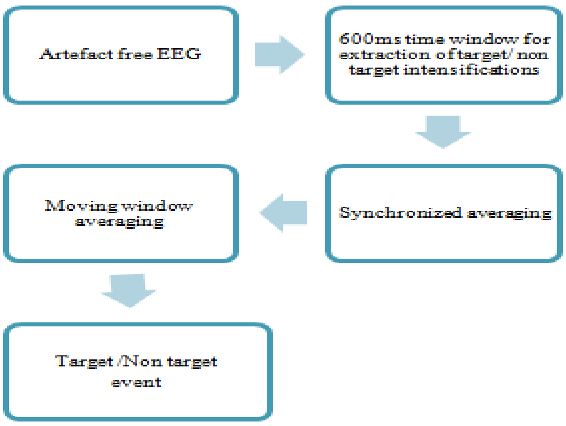

Fig. 5. Event detection algorithm

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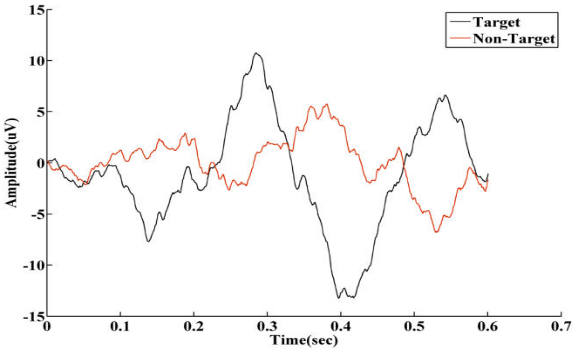
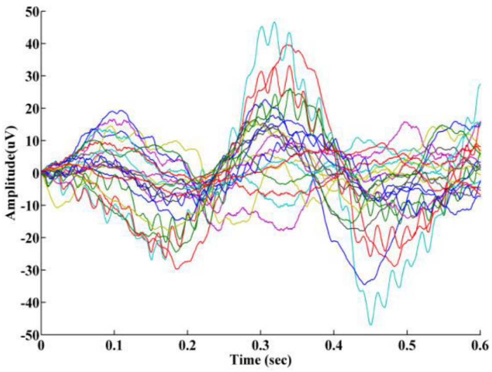


Fig. 6 . Event related potential grand average from single electrode site

B. Template matching and feature extraction:

1) Template generation: Template is a reference signal generated for pattern matching.To generate a template, the ERP obtained from 3 midline electrode sites from 8 subjects are averaged as the ERP signal has no ground truth. It is generated by averaging (17x3x8=408) 408 target ERP epochs segments obtained for 17 row/column intensifications from 3 electrodes namely mid frontal, central and parietal positions from 8 subjects. Fig.7(a) and(b)shows the response from midline electrodes of 8 subjects for target character intensification and non targetintensification.Fig.7(c) represents the template generated by averaging all target responses from 3 electrode sites.



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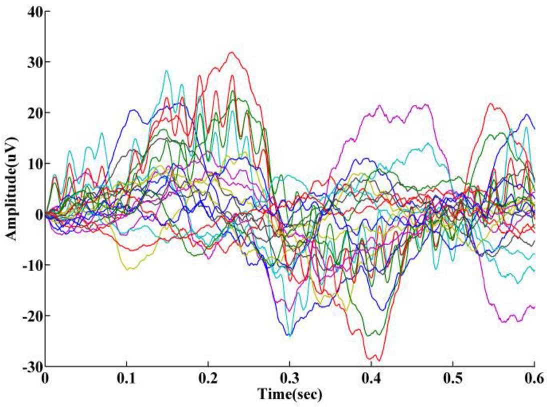

(b)

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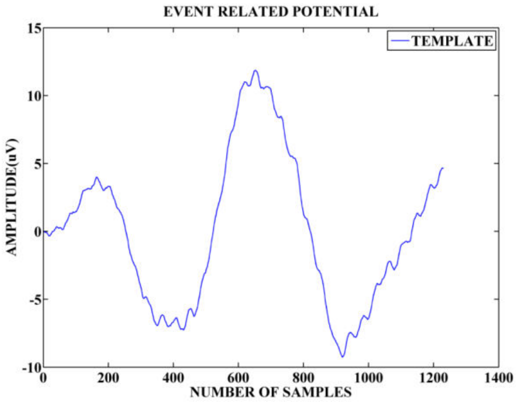

(c)

Fig. 7. (a) Target ERPs (b)Non target ERPs (c)Template from grand average of 3 electrode sites of 8 subjects

2)Feature Extraction

Features are the main attributes for representing a signal without loss of any information. It is one of the techniques used to reduce multiple dimensions of data. For ERP based BCI experiments, the main time-series data is the ERP signal obtained as a result of averaging multiple trials of a time aligned event. Since this signal varies from trial- to-trial within a subject and across multiple subjects, detection of ERP-P300 for a target stimulus is a challenging task. Hence, this work focuses on extracting features of ERP-P300 from a single trial EEG signal.

For feature extraction, from single trial data for each electrode position, correlation coefficient is estimated by template matching [2] and is defined as

$$R = \frac{\sum_n (X_n - \bar{X})(Y_n - \bar{Y})}{\sqrt{\sum_n (X_n - \bar{X})}\sqrt{\sum_n (Y_n - \bar{Y})}} \qquad (5)$$

WhereXn represents the target/non target epoch signal to be analyzed, and $\bar{X}$ denotes the mean; Yn represents the template, and $\bar{Y}$represents the mean of the template. The correlation coefficient R represents the similarity between the epoch and the template. It is used as one of the features for classification.

The features extracted from ERPs are peak and latency calculated from the results obtained in the time domain analysis using the equations of [7],[1] and the values obtained for 3 electrode positions from 5 subjects for single character intensification are tabulated as shown in Table 2.

i. Peak Value (AMP, *y*max) - the maximum signal value:

$$y\max = \max\{y(n)\} \qquad (6)$$

ii. Latency (LAT, *ty*max) - the ERP's latency time, i.e. the time where the maximum signal value appears in the time window of 0- 600ms:

$$ty\max = \{t|y(n) = y\max\} \qquad (7)$$

Table 2Features extracted from Target and non-target events

El ect	Single character	Target stimulus	Non target stimulus

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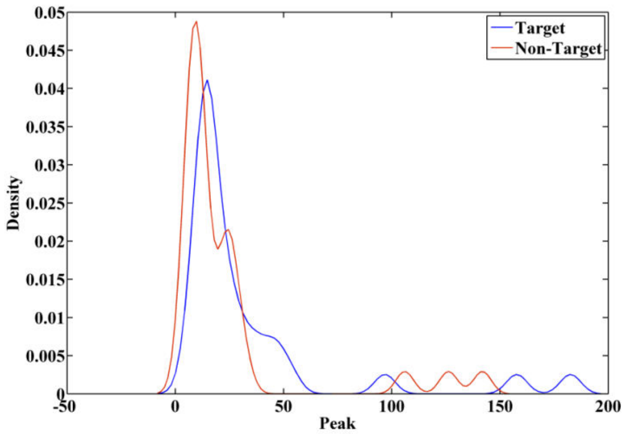
	Subject	Peak Value (μV)	Latency (s)	Correlation coefficient	Peak Value (μV)	Latency (s)	Correlation coefficient
Fz	**A**	27.89	0.10	0.03	38.03	0.55	-0.40
	B	71.50	0.15	0.21	23.57	0.40	-0.31
	C	39.63	0.33	0.84	31.92	0.22	-0.42
	D	49.75	0.31	0.81	30.43	0.14	-0.51
	E	16.59	0.09	-0.2	21.71	0.46	-0.30
Cz	**A**	14.14	0.31	0.84	15.07	0.14	-0.35
	B	22.67	0.30	0.61	11.04	0.39	-0.34
	C	25.69	0.34	0.77	22.84	0.23	-0.27
	D	34.37	0.31	0.82	29.89	0.18	-0.52
	E	15.71	0.59	-0.05	14.06	0.46	-0.40
Pz	**A**	6.18	0.30	0.66	8.29	0.14	-0.34
	B	16.52	0.29	0.66	7.15	0.38	-0.18
	C	16.28	0.33	0.86	11.24	0.24	0.01
	D	25.93	0.33	0.85	25.04	0.23	-0.53
	E	9.73	0.08	-0.25	7.39	0.34	0.56

3)Density plot

The feature distribution is studied using a density plot. Fig8 shows the density plots, using kernel smoothing density estimate, which uses normal distribution. From Fig7(a) an overlap of curves for both the target and non target with peaks mostly distributed between 10-15uv. Similarly from Fig7(b), it is seen that the latency features of both cases overlap, with target having maximum samples closer to 0.28ms-0.35ms.From Fig7(c) of both the approaches, it is observed that the curve is not much overlapping, showing the targets have correlation closer to +1.In the peak and latency density plot, there is an overlap of feature curves.

(a)



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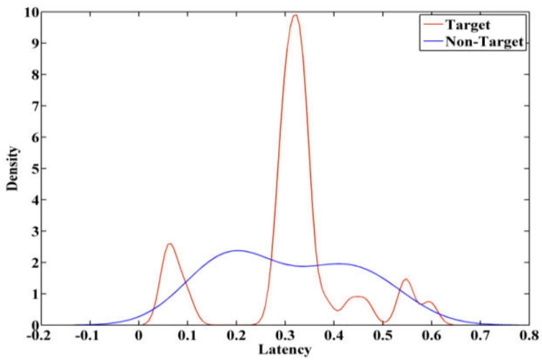

(c)

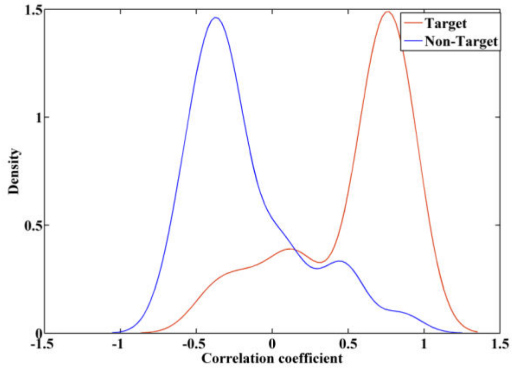

Fig.8. Feature density plot (a) Density Vs Peak (b) Density Vs Latency (c) Density Vs Correlation coefficient

C. Classification

Classification is an important stage in a BCI system, in which the signal patterns are classified to make decisions to control the external devices. The feature vectors obtained from events detected are evaluated for feature dependence. Before applying to classifiers they are labelled. The steps involved are discussed as follows,

1)Feature Selection

Pearson's correlation coefficient(r) is one of the techniques used to quantify the linear dependency between two variables X and Y. The Pearson's correlation is obtained by dividing the covariance of the two variables by the product of their standard deviations. It has a value between ± 1. Where +1 is the maximum positive linear correlation, 0 is no linear correlation and -1 is max negative linear correlation. The Pearson's correlation coefficient value for the 3 features is computed for both the approaches to check the feature dependence.

2)Creating Training and Test Data Set

For identifying target and non target events in a single trial EEG signal with perfect features that are closely related to the class the samples/data required for classification is very less. Here sample size of equal probability is taken. Target and non target ERPs are appropriately labelled and fed to the machine learning algorithms for classification. Since the size of the available dataset is small, the data is not split into training and test sets, but a cross validation technique is used.

3)Validation Technique

For evaluating the machine learning models on a smaller data set, cross validation technique, which is a resampling procedure is applied. This procedure involves a single parameter k that indicates the number of groups that a given data sample to be split into. For subject dependent data like EEG, k-fold cross validation is carried out for smaller data sets obtained . In the proposed work, 10 fold cross validation technique is used.

4)Machine learning algorithms

Both supervised and unsupervised algorithms were used to evaluate the performance of signal processing approach.. Five classifiers namely, Weighted KNN(W-kNN), Quadratic Discriminant analysis(QD), Bagged Trees(BT), Guassian Naive Bayes(G-NB) and Logistic Regression(LR) were tested.

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5)Classifier performance metrics

The performance measures to evaluate the classifiers are as follows:

Sensitivity represents the number of correctly classified target epochs. It is given by

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \quad (8)$$

Specificity represents the number of correctly classified non target epochs. It is given b

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative+False Positive}} \quad (9)$$

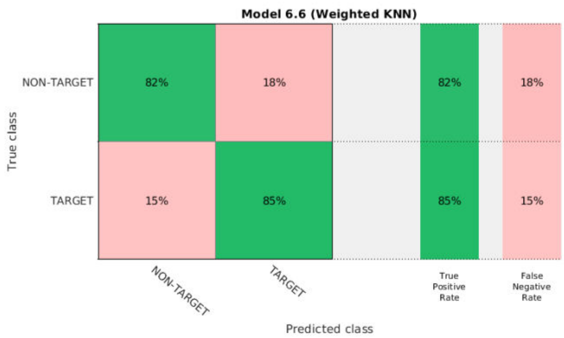
Finally, accuracy is the best measure for a binary classification problem with limited data sets having equal number of samples in both the classes.

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{True Positive+True Negative+False positive+False Negative}} \quad (10)$$

IV RESULTS AND DISCUSSION

1)Time domain analysis:

The average of 17 intensifications of target and non-target ERP segments per trial from a single electrode site of a subject is shown in Fig.6. This clearly depicts that the amplitude of target stimuli is greater and has a maximum peak at 300ms. From the Fig.7(a), It is seen that the amplitude of grand average for each electrodes of all subjects were greater than that of the non target and latency varied between 250-450ms.For non target stimuli, the grand averages of each electrode for all the 8 subjects have peaks and latencies that are not well defined as shown in Fig.7(b).The grand average of all the electrodes is the template shown in Fig.7(c) with peak of 12uV and latency of between 290-350ms. From the pattern it could be analysed that the target ERPS will have comparatively higher correlation with the template. The features peak ,latency and cross correlation between the template and ERP of each subject is shown in Table 2 From the table it is observed that a peak lying in the interval of 290-350ms had higher correlation with the template. It is also observed that the most of the target ERP has positive correlation and non targets have negative correlation with the template.



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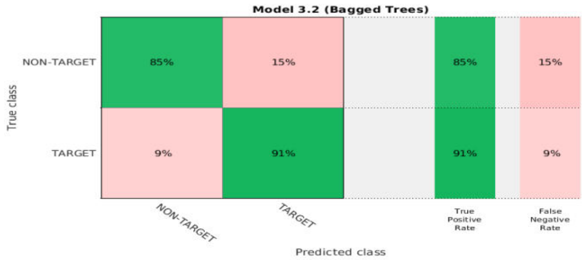

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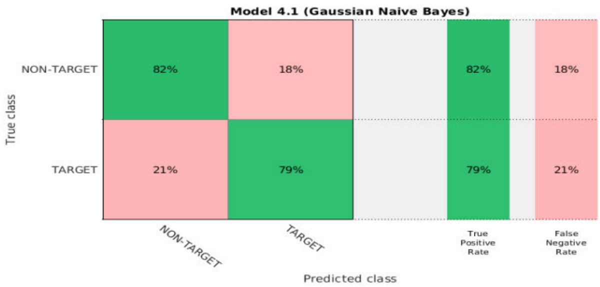

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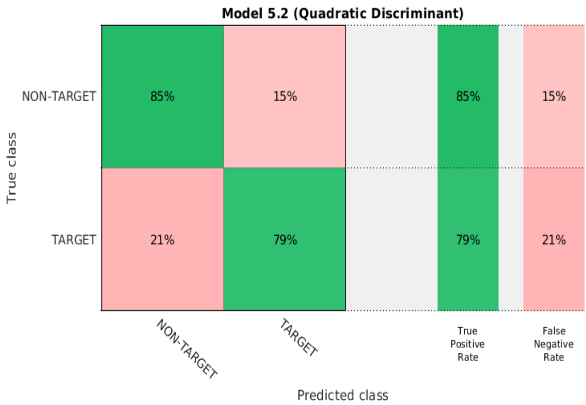

(e)

Fig.9.Classifier performance-confusion matrix (a) w-kNN(b) BT(c)LR(d)G-NB(e)DQ

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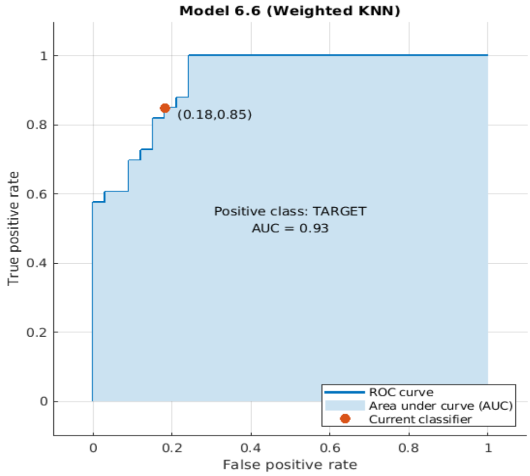
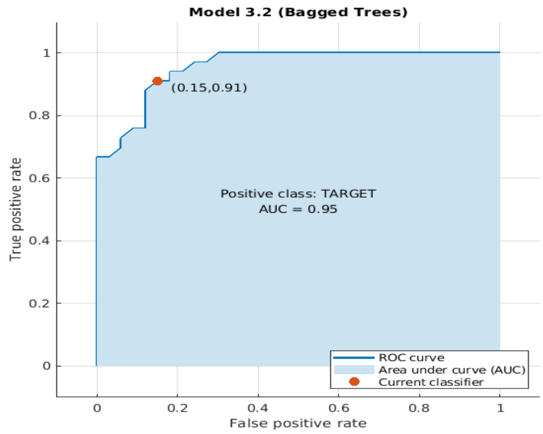


(a)



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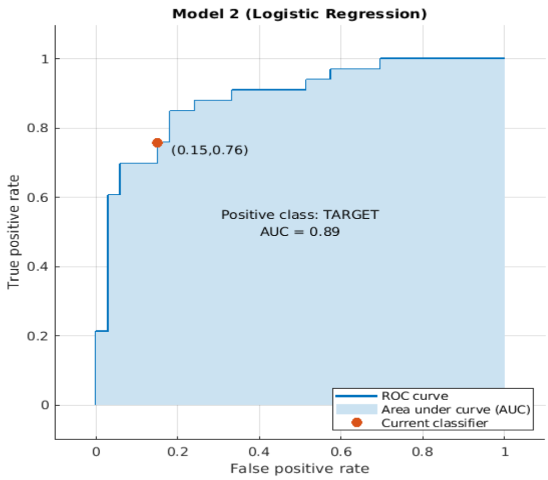

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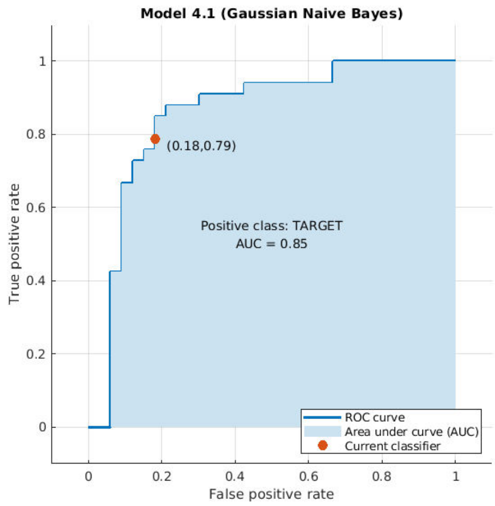

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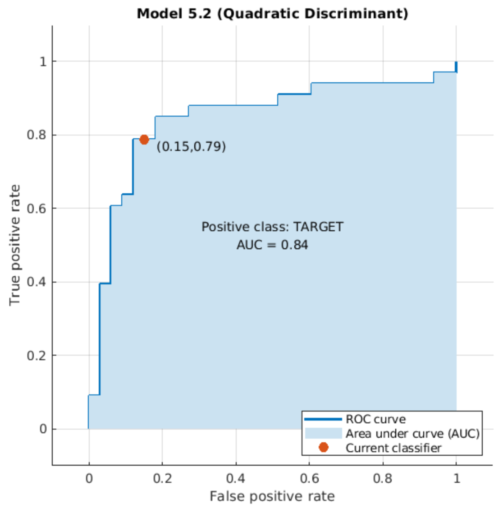

(e)

Fig.10. ROC plot (a) w-kNN(b) BT(c)LR(d)G-NB(e)DQ

Table 3 Comparison of classifier's performance

Classifiers	Sensitivity/ TPR /Recall	Specificity (1-FPR)	Accuracy	AUC
Weighted KNN	0.85	0.82	83.3	0.93
Bagged trees	0.91	0.85	87.9	0.95
Logistic regression	0.76	0.85	80.3	0.89
Gaussian Naïve Bayes	0.79	0.82	80.3	0.85

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Quadratic Discriminant	0.79	0.85	80.3	0.89

Table 4 Comparison of P300 extraction methods based on number of channels

Author	**P300extraction Methods**	**No.of channels**	**Number of trial**	**Accuracy**
Krusienski, D J et al.(2008)	Channel set selection	3 (Fz,Cz,Pz)	15	65
Khan, O.I., et al(2012)	Constrained ICA(averagingof ERP's)	3	15	78
		10	15	85
		64	15	97
Proposed method	DWT+Time domain averaging +template matching	3 (Fz,Cz,Pz)	1	87.9

Table 5Performance comparison of the classifier with other approaches

Authors	**Electrodes**	**Classifiers**	**Database**	**Accuracy (%)**
Lafuente, V., et al 2017	Cz , CPz	ML matched filter **(classifier- 1)**	Goldberger et al. (2000)	36.11
Lafuente, V., et al 2017	Cz , CPz	ML matched filter + Correlation with P 300 **(classifier -2)**	Goldberger et al. (2000)	72.22
Lafuente, V., et al 2017	Cz , CPz	ML matched filter + Correlation with P 300+ weighted scorer **(classifier- 3)**	Goldberger et al. (2000)	83.33
Lafuente, V., et al 2017	Cz , CPz	ML matched filter + Correlation with P 300+ weighted scorer + window selection and contextual analysis **(classifier- 4)**	Goldberger et al. (2000)	86.11

Lafuente, V., et al 2017	Cz , CPz	ML matched filter + Correlation with P 300+ weighted scorer + window selection and contextual analysis+artefact cancellation **(classifier5 - unsupervised approach)**	Goldberger et al. (2000)	91.66
Citi et al. (2010)	Pz,POz, PO7	Weighted average of the responses produced by a SVM during multiple stimulus presentations.	BCI competition	87.50
Rakotomamonjy& Guigue (2008)	64 (channel optimizati-on)	Ensembles of SVM averaged in sequence	BCI competition	96.00
Proposed	Fz, Cz, Pz	Bagged trees	Goldberger et al. (2000)	87.9

2) Classifier's performance

To prove the efficacy of the proposed method in detecting the target event from a single trial with 17 intensifications for a particular target character, five different classifiers performance were analysed. The performance measures sensitivity, specificity, accuracy, and ROC as shown in Table 3. The classifiers DQ,LR,G-NB are found to have the same accuracy in identifying the target events. It is also observed that out of all the 5 classifiers the bagged tree classifiers has sensitivity0.91 and specificity of 0.85 and ROC area 0.95.The confusion matrix shown in fig.9 is the table of form of both actual and predicted class of ERP's. Accuracy is the best measure for a binary classification problem with limited data sets of equal number of samples in both the classes. From Table 3 it is observed an accuracy of 87.9% is achieved by bagged trees.

Table 4: Describes the comparison of P300 extraction methods based on number of channels and trials. It is observed [8] has used 15 trails and also increased the number channel to average ERP's from 3 to 10 using constrained independent component analysis to improve the accuracy from 78 to 85% and achieved the classification accuracy of 97% by averaging the 64 channel independent ERP components .[10] has reported a classification accuracy of 65% for the classical 3 channel set (Fz,Cz,Pz). The proposed methodology has achieved better accuracy of 87.9% with the three standard midline channels.

Table 5 shows the comparison of performance of classifiers tested on the database of [5] and other baseline approaches. Five classifiers were proposed by [11] for the 2 electrode positions Cz,CPz based on " leave one out" cross validation for error estimation. The proposed method has comparatively high accuracy than first four classifiers for 3 electrode positions Fz, Cz, Pz and closer to classifier five. The performance of the proposed method in detecting the target event is same as that of [4] where they required a training data set and validation to avoid over -fitting whereas, the proposed method is based on 10-fold cross validation.

V.CONCLUSION

It is worth to concluding that an algorithm with a better artefact cancellation approach eliminates the need for baseline correction. Witha smaller data set can the proposed framework yield better classification accuracy of 87.9% from the single trial event of Donchin speller experiment . The bagged tree classifier on 10 fold cross validation provides better classification accuracy when compared to other classifiers in BCI study by [4],[15]eliminating the risk of overfitting and closer performance to unsupervised classifier of [11] which involves complex stages for extraction of P300. Finally, for portable BCI applications such as studies in attention assessment, our proposed method is simple and efficient to implement without the need for channel optimization for each subject.

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