

# A Review on Classification and Future Extraction Techniques for EEG Signal Processing

Manini Monalisa Pradhan<sup>1</sup>

<sup>1</sup> Lecture, Utkalmani Gopobandhu Institute of Engineering, Rourkela

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## Abstract

Current situation of world most of people affected mental diseases. Depression is most common mental illness. It is vital cause of sickness. Suicide is the main cause of depression. Assessment methods of mental diseases are diagnosing depression exclusive on patient-report clinical judgments of symptom severity. In modern techniques Electroencephalogram (EEG) base emotion recognition is a new arena of this area with challenging issue concerning the induction of emotion state diagnosis. In this paper we conclude the different technology for analysis mental diagnosis which helps to further clinical assessment. The techniques are eye gaze signal tracking, facial expression signal tracking, and Brain Computer interface technologies between humans and machines. EEG signal for tag relevance assessment and effective neuromodulator therapies etc. It is based on statistics tools like Artificial Neural Networked models for brain computer interface and proper detection of emotion classifications reorganize-ation etc.

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## 1. Introduction

Present situation most of people affect mental disease. Unhappiness is major cause of usual emotional disarrays. A report assessed by the World Health Organization (WHO) that cause of disability in the world due to depression by 2020[1]. Latest research by Bromet et al. [2] published that about 121 million persons worldwide must have been assumed by this problem and near about 8,50,000 deaths are reported every year due to depression [2]. The health inhabitants are fundamental concept and also contributing suitable progress in all areas of the world. Medical sciences remain contributed to preservation person health on practice of medicine. On develop of science and new technology in medical application will help for improve of human health care condition. To check the human health condition with accurate used improve of medical care method and latest technology. It can assist people better treatment. The development of the new analysis method and modern medical instrument can be added advantage to progress the medical care effectiveness. For treatment of brain and mental condition several techniques have proved as tools study tracking brain works. The methods are

## 2. Eye movement data classification

Track brain and mental condition eye gaze tracking has important tools in the analysis of care in depressed individual Li et al [3]. The classification of eye movement data is novel approach of finding depression. Eye tracking paradigm lead a perceptive study which noticed on eye movement data of dual group of peoples (depressed subject and normal controls) by Eizenman [4] and Kellough [5]. Their goal is to distinguish the mental depressed and mental non depressed theme using eye movement factor built on classification methods. The eye movement data are classified by k Nearest Neighbour (kNN), Native Bayes (NB), Logistic Regression (LR), Support Vectors Machines and Random Forest techniques are its feature based on fixation saccades, under study scope and negative preferences.

*Fixation:* Fixations are predefined as alternate eye look locations concentrated within an area of on optical measure for a time of 100 ms or more [6]. Fixation data normally used for feature extraction on fixation duration, fixation count etc. As per measurement in eye faction figures are signifying in different attention unfairness form with respect to different

kind of stimuli with taking in fixation duration. Fixation amounts is the sum of fixation points throughout an experimental more fixation point in an experimental the move attentiveness the topics determined on the subjects [3].

**Saccade:** Saccade is described in the consistent of endpoints fixations. To distinguish by the saccades, considering long-term duration, amplitude rate and location of the saccades based on viewpoints of individual saccades. For purpose of direction in view of only total value of saccade method, overlooking the track of the movement [3].

**Pupil size:** It is a measurement a group of features originated from pupil thickness collected through the task. It's taken as the median value from total of the experimental for each subject [3].

**Negative Preference (NP):** It is considered as the location of the emotive picture by way of ROI (region of interest), then the sources of fixations that are located in the ROI NP frequency is computed as Eq.1 [3]

Silent Data	Measurements	
Classifier	Accuracy	Precision
kNN	0.86	0.84
NB	0.59	0.72
LR	0.72	0.69
SVM	0.73	0.66
RF	0.09	0.77
Emotional Data	Measurements	
Classifier	Accuracy	Precision
kNN	0.83	0.80
NB	0.73	0.72
LR	0.75	0.71
SVM	0.76	0.76
RF	0.79	0.78

$$NPF = E / (S + E) \dots\dots\dots Eq.1$$

Table.1. Classification Result on Eye Measure Data from the Silent and Emotional Block

According to Li et al. eye movement data depression detection rate are high and believe that method could boost existing method [3]. The assumption EEG and eye movement data from fifteen experiments in the unspeaking picture block, in 35 studies from each experiment. The normal accuracy reduced about 10% indicating that an increase of observation by using kNN method from each problem may prime to more accurate calculation result.

### 3. Emotion classification by facial expression

Emotions are the reaction or perception has specific situation. Affective feature of multimedia is individual source of information for multimedia indexing and approval [7]. There is trouble of accumulating emotive self-report to multimedia from user's emotion recognition. Feedback in response of multimedia for purpose of indexing is effective way of collecting user's emotion [8]. Emotion recognition could be done from the text, speech, facial expression or gesture. The person emotional feel and appearance on scientific level and

to developed benchmarks method, for natural recognition, scientists are in need of rich set of data of repeatable experiment. Human emotional expensive poses both a technological challenge [9]. According Soleymani et al. the power spectral features as of signal also facial point is used as feature detected valence level for each frame continuously [10]. They analyzed the correlation between feature as of EEG and also facial expression by continuous valence. In this case as experiment basis taking EEG signal are available at 256 Hz sampling rate. The undesirable trend, artifact, noise filtered by EEG lab, EEG signal re-reference average situation are improving the signal-to-noise proportion. An effective model is facing tracking employed to track 40 points [11]. The points of face remained removed after action the appearance to a normalize face and revising the head post. The 33-point position including eye bow, eyes, lips and iris etc. distance to calculate and average to be used in feature [10]. The 10 folding cross validation are used for analyzing continuous emotion detection. Here considered each fold the trials are separated in three sets. The 10% are taken by mean of the test set 6 and remaining of samples (54% of the whole) are taken for the training set and the excess are used as the validation set [10]. Here Multi Linear regression (MLP), Support Vector Regression and Continuous Condition Random Field (CCRF) and LSTM-RNN tools applied on person correlation coefficient ( $\rho$ ) averaged linear error and distance (Dist.).

Model	MLR		SVR	
	$\bar{\rho}$	Dist	$\bar{\rho}$	Dist
EEG	.31 .35	.053± .034	.31± .34	.057 ± .033
FACE	.38± .51	.056± .038	.38± .59	.065 ± .044
FLF	.40± .47	.043± .034	.49± .46	.060 ± .037
DLF	.49± .50	.050± .033	.59± .49	.053 ± .033

(a)

Mode l	CCRF		LSTM-RNN	
	$\bar{\rho}$	Dist	$\bar{\rho}$	Dist
EEG	.36± .54	.058± .054	.38± .43	.050± .032
FAC E	.32± .46	.053± .029	.28± .42	.043± .027
FLF	.44± .54	.053± .037	.40± .47	.051± .032
DLF	.44± .56	.050± .035	.43± .48	.048± .033

(b)

Table.2 Calculate the finding performance from altered modalities and also fusion schemes the person i) coefficient (p), ii) averaged linear error or distances (Dist). a) Reported measures are averaged for all the sequence of i) Multi Linear Regression (MLP), ii) Support Vector Regression (SVR) of i) EEG, ii) Face, iii) Feature Level

Fusion, iv) Decision Level Fusion b) i) Continuous Conditional Radom Fields (CCRF)ii) LSTM Recurrent Network (LSTM-RNN) of i) EEG, ii) Face, iii) FeatureLevel Fusion, iv) Decision Level Fusion

According to Soleymani e.al 35.7% did not show any facial expression of their experiment and LSTM-RNN find that on EEG modality functioning remains not lower toward the one of facial appearances [10]. The analysis of relationship between EEG signals with the ground fact showed that upper rate component of signal brings more significant data gaze at the satisfaction of emotion as well as the informative features.

However, we found fake facial expression or change tone of speech and these signals are not always obtainable and the vary from physiological signals which occur always and hard to conceal Electroencephalogram (EEG) is the base of recording electrical activity of the scalp [13].

### 4. Brain computer interfaces

Brain-computer Interface (BCIs) also called Brain Machine Interface, which is communication structure that helps human relating to electroencephalographic motion control signal with not linking exterior nerves and muscles. Human’s intention to external devices corresponding speech synthesizer’s computer assistive appliances and neural prostheses is created a new non-muscular channel by BCI. On artificial intelligence systems the recognized patterns set in brain signals are in five phases i.e., preprocessing, signal acquisition, signal enhancement, classification, feature extraction and control interface as depicted [12] Figure.1 shows Brain computer interface.

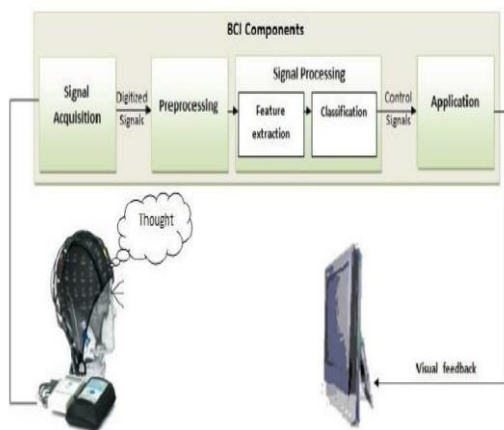


Fig.1 Brain computer Interface

In this method first reduction noise and then processing of artifact signal of capture brain signals. An additional dispensation require for preprocessing makes signals in appropriate form. In feature extraction recognized on brain signals and discriminative data are recorded. Once measure a signal is mapped in to a vector. That have real and separate feature from observed signals. Which is mapped a vector to raster and having effective and separate feature experimental signal [12]. EEG signal detail shows in Figure.2.

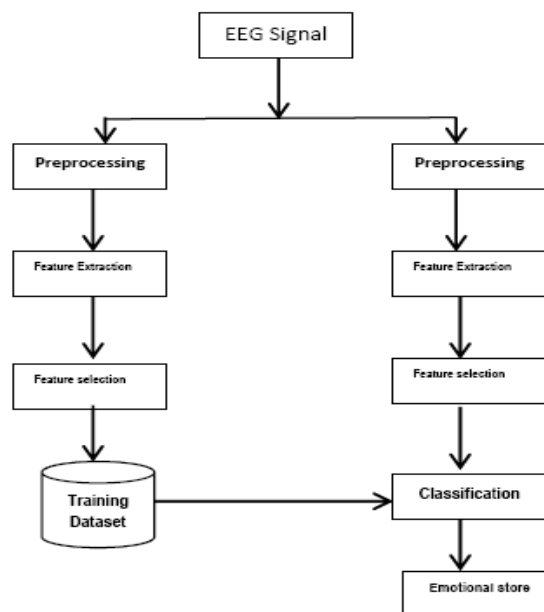


Fig-2 Procedure of Classification [13]

a). Feature extraction Combination of Auto Regression and Fast Fourier Transform and Classification used Support Vector Machines.

Preprocess data are using feature extraction. For feature extraction a lot of methods are used combination AR (Auto Regression) and FPT (Fast Fourier Transform). The SVM method is used for classification. As compare to other classifier SVM has provided good generalization and its more performance. In emotion detection SVM has given 89% accuracy whereas ANN runtime performance is on large training set. Experiment results indicate that the normal accuracy result of 88.52% for classifying emotion states it can be achieved by using frequency domain feature and support vector machine [13].

b) Feature extractions held by using technics ‘Walsh Hadamard Transform’ (WHT), and feature selection done through techniques of ‘Principal Component Analysis’ (PCA), PSO ‘Particle Swarm Optimization’ (PSO) classification, through Bagging and decision tree [14]. In this technique methodology of classification is indications in Figure 3

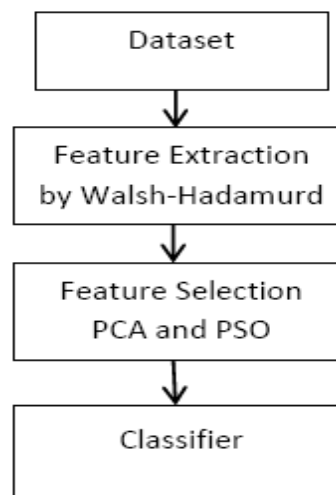


Fig-3 Flowchart of Methodology

Feature Extraction by ‘Walsh Hadamard’ transforms are a ‘Non-Situational Orthogonal’ transformation technique decomposing signal to basic functions which as Walsh function rectangular or square wave with value of +1 or -1. ‘Walsh Hardamad’ transform returns sequence value. Each Walsh function has sequence value [14].

### *Feature selection*

We are applied to raw data as a classifier in feature extraction which outcomes in the use of unrelated info existence assisted to the classifier. This is not allowing the classifier for simplification, so feature selection techniques are used to extract subset of feature for classification. In particular removed from EEG are carefully chosen using of PCA proposed a PSO based feature selection. The valuable results are finding in applied of linear algebra and PCA. It is used both analysis of neuroscience and computer graphics as simple accessible by non-parametric techniques to extract related information from complicating data sets. The orthogonal linear transformation to changing data in PCA and their new coordinate system similar highest variance by data projection on first coordinate. The second greatest variance is considered as second coordinate as son. PSO is used to find the optimal feature subset of ‘Eigen’ features extracted by PCA. In proposed method we find an optimal feature subgroup with least number of features and high classification accuracy. In PSO all particle files in search space are a rate adjusted by own flying memory and confidant’s flying experience. The particles of the PSO signify the features subgroup where if a bit is given value 1 the feature is selected and if given 0, it is not selected. The particles fly through the feature space and during the iteration of the algorithm coverage to optimal position. The On-classification accuracy and the number of features is evaluating base on fitness function of particles [14]

$Fitness = \alpha * accuracy + \beta * number\ of\ features$

Classification done through i) Bagging techniques, ii) Alternate Decision Trees (ADTrees), iii) REPTree, iv) Native Baysian Tree Learner (NBTREE), v) LADTree.

In this analysis of classification, the extreme and standard power are used as feature to classify the example. On this experiment out of 64 features in PCA technique 45 features are considered. Among selected 38 features of PSO classification working out set was made up to 60% of the data and remaining 40% was used as test set. Classification

performances are based on the 10-fold cross validation for more accuracy. A high classification accuracy of 95.68% is bagging with Native Bayes classifier [14].

c) Feature extraction and classification of EEG Signals using ‘Wavelet Transform’, SVM and ‘Artificial Neural Networks’.

In this case EEG artifact has exact activities and scalp structure that remain more easily recognizable in the rate of recurrence domain. For purpose of chronological muscle creations typically induce relative strong 20-60 Hz activity at chronological electrodes while saccadic eye signals produced unusually strong (1-3Hz) low frequency activity at frontal electrodes. Software routines for performing the artifact detection method described above are available within the EEGLAB toolbox [15].

For feature extraction use of the power spectrum variance and mean of the Haar mother wavelet. Finally, it’s useful classification a feed-forward ‘Multi-Layer Perception’ (MLP). Aimed at features extraction from the raw EEG data many used in method such as time domain, frequency domain meanwhile the EEG is non-stationary in general [16]. In this situation most appropriate to use time-frequency domain methods like ‘Wavelet Transform’ (WT) as a mean for time-frequency representation of a signal by agree to the use of mutable sized windows. In WT long time windows are used to a finer low-frequency resolution and short time widows are used to get high-frequency information. This marks the WT for the proper analysis of irregular data patterns, such as impulses following at various time instances. The EEG recordings are decomposed into various frequency bands through fourth-level ‘Wavelet Packet Decomposition’ (WPD). The decomposition filters are usually constructed from the Haar or other sharp mother wavelets, when the data has discontinuities [17].

In this works classification through neural network the different techniques are used

i) ‘Multilayered Perception Neural Networks’ for minimizing errors and raised the number of neuron in concealed layer.

ii) ‘Probabilistic Neural Network’ (PNN) pattern recognition of statistics is used probabilistic approach to neural network.

If PNN derivative from ‘Radial Basis Function’ (RBF). It is many times faster than ‘Back Propagation’ (BP) network.

iii) The SVM is a comparatively new classification procedure developed by Vapnik [18]. Table shows training and testing of different classifier

Accuracy classifiers	Training	Test
MLP	98%	88%
PNN	99%	84%
SVM	99%	81%

Table-3. Classification result.

On the datasets 70% are training and the balance used for test classifier. Generally training is higher than the accuracy of testing set in classification Table 3 indicate the result of classification accuracy during training and test stage for both data set.[17].

## 5. Eeg signal for tag relevance assessment.

In this is techniques used EEG signals at 256Hz. EEG point which is detached by deducting the affecting average signal with a 5 second (1280 point) window. The noise decrease is done by put on a low pass filter with the cut-off frequency of 10Hz, since the ERP responses are own frequency [19]. EEG signals are again re-reference to the average referent. Here the ERP response to perform in 400ms to 600ms after showing the tag. Therefore, the EEG signals of the one second period after displaying overlaid tags under the images are sampled 16 times and used as feature for every test. The tests in which the contributors' responses contradict the relevant tag are unwanted as complicating examples, e.g. a contributor arranged with an unrelated tag [20]. For classification build a contributor subject to intra contributor classification. For each contributor one of the 54 experiments are taken as test set and the rest are used as the training set in the leave-one-out of cross validation strategy. If applying principal component analysis feature vector is reduced and keeping the basis with 79% of variance. In used of 'Linear Discriminant Analysis' (LDA) classifier to discriminate between the responses to relevant of non-relevant tags. In order to aggregate multiple participants responses their EEG signal are averaged after normalization. The resulting features are classified using same classifier and validated by the same cross validation strategy [20].

The relevant tags associate with target tag of contributor look like P300 pin are used as BCI speller [21]. The response associated with mismatch. The F1 pin scores are designed for every contributor and also finding 0.56 in standard deviation and maximum 0.79. In order to verify the statistical significance of the results, a one sided on sample t-test with 0.0005 significance level was applied in this case. The t-test rejected so assumption that the detection rates are equal or inferior to the chance level [20].

## 6. Eeg signals biomarkers of vns theoraphy.

The aim of this work it is objective estimate the efficiency of neuromodulator therapies special, Vagus Nerve Stimulation is reducing the severity of seizures in patient with medically

refractory epilepsy methods [22]. On combination feature obtain EEG and signals around seizure events in 16 patients who underwent implementation of closed-loop of VNS Therapy System namely AspiresSR®, VNS therapy is FDA accepted neuromodulator treatment that is used as an adjunctive therapy to pharmacology. It has been demonstrated to reduce seizure frequency in multicenter, randomized controlled test as well as is subsequent single center test [23][24]. On experiment 212 patient (105 are pre-treatment and 107 post-treatment). We find 85.85%. total performance in Fuzzy-C-Mean (FCM). The total performance 90.20% are FMC classification using only complex partial and secondary generalized seizures (54 pre-treatment and 48 post treatment seizures) [22]. According VNS therapy EEG management decreases heart-rate (HR%) shorter tachycardia duration following VNS treatment compared to their pre-treatment values.

## 7. Conclusion

Here we present a review study of No of papers from eye gaze pattern to VNS therapy measure their performance. General BCI computer interface is based on ERPs. BCI procedures usually include multiple incentives to improve their accuracy [21]. The result of VNS therapy on management has been examined in few studies in this past [25] [26] where all used the synchronicity of interracial EEG activities. Total reviewing the all papers taken the No of patient experiment in different slots and situation which helps for clinical further diagnosing. Further research work need for find physical cause of mental depression.

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**Manini Monalisa Pradhan** completed B.Tech and M.Tech from the Biju Pattanaik University of Technology, Her research interests lie in the area of Medical Image Processing, Signal Processing, Pattern recognition and Robotics.

**Email:** maninimonalisa2012@gmail.com