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A Review on Classification and Feature Extraction Techniques for EEG Signal Processing

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ABSTRACT
In the current world, many people are affected by mental diseases. Depression is the most common mental illness. It is a vital cause of sickness. Suicide is the leading cause of depression. Clinical diagnosing symptoms is not a reliable assessment of mental depression disease reported by doctors. In modern techniques, Electroencephalogram (EEG) based emotion recognition is a new arena in this area with challenging issues concerning the induction of emotion state diagnosis. In this paper, we conclude the different technology for mental diagnosis analysis, which helps 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 reorganization etc.

Keyword: *EEG, kNN, NB, CCRF, SVM, RF*

INTRODUCTION

In the current world, many people are getting affected by mental diseases. Unhappiness is a significant cause of usual emotional disarrays. A report assessed by the World Health Organization (WHO) that the cause of disability in the world due to depression by 2020[1].

The latest research by Bromet *et al.*[2] published that these problems must have assumed about 121 million persons worldwide, and nearly 8,50,000 deaths are reported yearly due to depression [2]. Health inhabitants are fundamental and contribute to suitable progress in all world areas. Medical sciences have helplessly contributed landmark for preserving a person's health in the practice of medicine due to accurate assessments of mental status.

Developing science and new technology in the medical application will help improve human health care conditions. Enhanced medical care methods and the latest technology to check the human health condition accurately. It can assist people in better treatment. The development of the new analysis method and the modern medical instrument can be an added advantage to the progress of medical care effectiveness. Several techniques have proved to be used to treat brain and mental conditions as tools to study tracking brain works.

Organization of paper section 2 has discussed the classification of eye movement data. Section-3 is classification by facial expression of data. Section 4 covers the brain-computer interface. Section 5 discusses EEG signal tag relevance assessment and section 6 discusses EEG biomarker of VNS therapy.

EYE MOVEMENT DATA CLASSIFICATION

Track brain and mental conditions eye gaze tracking is an essential tool in analyzing care in depressed individuals Li *et al.* [3]. The classification of eye movement data is a novel approach to finding depression. The eye tracking paradigm led to a wise study that noticed eye movement data of the dual group of people (depressing subject and normal controls) by Eizenman [4] and Kellough[5]. They aim to distinguish the mental depression and mental non-depressed themes using eye movement factors built on classification methods.

The eye movement data are classified by k Nearest Neighbour (kNN), Native Bayes (N.B.), Logistic Regression (L.R.), Support Vectors Machines (SVM), and Random Forest (R.F.) techniques are its feature based on fixation saccades, under study scope and negative preferences. Support Vector Machine (SVM) is gaining popularity for its capacity to group noise and high dimension data. SVM is a statistical learning calculation that arranges algorithms to classify a subset o training sample subset.

The art of neural architecture for categorizing the LSTM model has been used for binary emotion classification. This model's applicability and accuracy have been validated using the DEAP dataset for emotion recognition. RNN neural network is derived from the basis of deep learning algorithms. In this network, we assume all input is an output independent of each other, i.e., the parameter of the particular neuron is not affected due input-output sequence. LSTM-RNN model is combination LSTM and RNN model. Two fusion strategies are adopted for the general classification of brain images, i.e., feature level fusion and decision level fusion (DLF). DLF is used on a percent of the eye closer and calculates data recorded by eye tracking classes indicator driver fatigue level.

Fixation

Fixations are predefined as alternate eye look locations concentrated within an area of optical measure for 100 ms or more [6]. Fixation data is generally used for feature extraction on fixation duration, fixation count, etc. As per measurement in eye faction, figures are signifying different attention unfairness forms concerning another type of stimuli with fixation duration. Fixation amounts are the sum of fixation points throughout an experimental more fixation point in a practical the move attentiveness the topics determined on the subjects [3].

Saccade

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

Pupil size

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

Negative Preference (N.P.)

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

***Table 1:** Classification Result on Eye Measured Data from the Silent and Emotional Block [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)..............Eq.1

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

As a result of Table1, we found emotion data measurement accuracy and silent data measurement accuracy. Here kNN classifier models 0.03 more accuracy on quiet data. In dynamic data measurement, N.B., L.R., and SVM classifier models are more precise than 0.14, 0.03, and 0.03. In R.F. classifier models, emotional data found 0.70 more accuracies.

EMOTION CLASSIFICATION BY FACIAL EXPRESSION

Emotions are the reaction or perceptions has a specific situation. The valuable feature of multimedia is individual sources of information for multimedia indexing and approval [7]. There is trouble accumulating emotive self-report to multimedia from the user's emotion recognition. Feedback in response to multimedia for indexing effectively collects users' emotions [8]. Emotion recognition could be done from the text, speech, facial expression, or gesture. The person's emotional feel and appearance on a scientific level and to develop benchmarks method, for natural recognition, scientists need a rich set of data of a repeatable experiment—human emotional expensive poses both a technological challenge [9]. According to Soleymani et al., the power spectral features as of signal also the facial point is used as component detected valence level for each frame continuously [10]. They analyzed the correlation between EEG parts and facial expression by continuous valence. In this case, EEG signals are available at a 256 Hz sampling rate as an experiment basis. The undesirable trend, artifact, and noise filtered by EEG lab, an EEG signal re-reference average situation improves the signal-to-noise proportion. A practical model is facing tracking employed to track 40 points [11]. The points of the face remained removed after action, the appearance to a normalized face and revising the head post. The 33-point position includes eye bow, eyes, lips, iris, etc., and the distance to calculate an average used in the feature [10]. The ten folding cross-validations are used for analyzing continuous emotion detection. Here considering each fold, the trials are separated into three sets. The 10% are taken by mean of the test set 6, the remaining samples (54% of the whole) are taken for the training set, and the excess is used as the validation set[10]. Here Multi Linear regression (MLP), Support Vector Regression, and Continuous Condition Random(SVR) Field (CCRF), LSTM-RNN tools were applied to person correlation coefficient (ρ) averaged linear error and distance (Dist.).

Table 2: *Calculate the finding performance from altered modalities and also fusion schemes the person i) coefficient ($\bar{\rho}$), 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 Neural Network(LSTM-RNN) of i) EEG, ii) Face, iii) Feature Level Fusion, iv) Decision Level Fusion.*

(a)

Model	MLR		SVR	
Matric	$\bar{\rho}$	$Dist$	$\bar{\rho}$	$Dist$
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

(b)

Model	CCRF		LSTM-RNN	
Matric	$\bar{\rho}$	$Dist$	$\bar{\rho}$	$Dist$
EEG	.36± .54	.058± .054	.38± .43	.050±.032
FACE	.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

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

However, we found fake facial expressions or changed the tone of speech. These signals are not always obtainable and vary from physiological signals, which always occur and are hard to conceal. An electroencephalogram (EEG) is the base for recording the scalp's electrical activity [13]. According to Table-2 EEG signal data, four models (i.e., MLR, SVR, CCRF, LSTM-RNN) have found approximate 0.05 differences in co-relation and coefficient result.

BRAIN-COMPUTER INTERFACES

Brain-computer Interface (BCIs), also called Brain Machine Interface, is a communication structure that helps humans relate to electroencephalographic motion control signals without linking exterior nerves and muscles. Human's intention to external devices corresponding to speech synthesizer's computer assistive appliances and neural prostheses are created a new non-muscular channel by BCI. In 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 the Brain-computer interface.

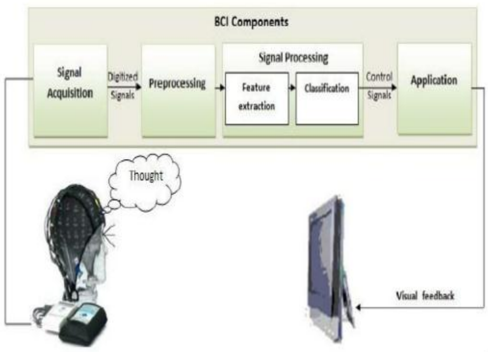

Fig. 1: *Brain-computer Interface.*

This method first reduces noise, and then the processing of artifact signals captures brain signals. An additional dispensation requires for preprocessing to make signals in appropriate form. In feature extraction, recognized brain signals and discriminative data are recorded. Once measured, a signal is mapped into a vector. That has a natural and separate feature from observed signals, which is mapped a vector to raster and has adequate and different feature experimental signal [12]. EEG signal detail shows in Figure.2.

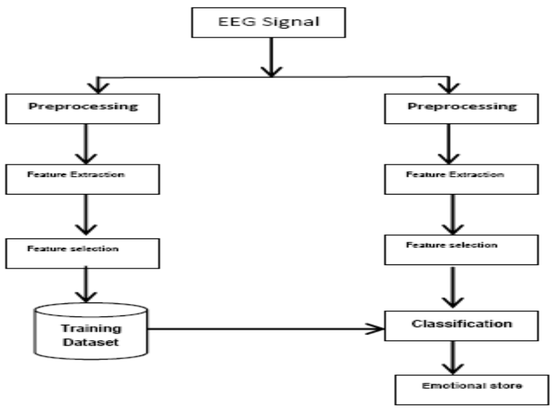

Fig. 2: *Procedure of Classification [13].*

- Feature extraction Combination of Auto Regression, and Fast Fourier Transform and Classification using Support Vector Machines.

Preprocess data using feature extraction. Many methods are used for feature extraction: A.R. (Auto Regression) and FPT (Fast Fourier Transform). The SVM method is used for classification. Compared to other classifiers, SVM has provided good generalization and more performance. In emotion detection, SVM has given 89% accuracy, whereas ANN runtime performance is on an extensive training set. Experiment results indicate that the typical accuracy result of 88.52% for classifying emotion states can be achieved using the frequency domain feature and support vector machine [13].

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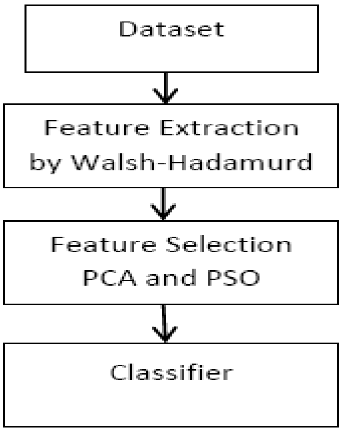

Fig. 3: *Flowchart of Methodology.*

Feature Extraction by 'Walsh Hadamard' transforms is a 'Non-Situational Orthogonal' transformation techniques decomposing signal to essential functions which as Walsh function rectangular or square wave with the value of +1 or -1. 'Walsh Hardamard' transform returns sequence value. Each Walsh function has a 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 the classifier. This does not allow the classifier to simplify, so feature selection techniques are used to extract a subset of the feature for classification. In particular, removed from EEG are carefully chosen using PCA's proposed PSO-based feature selection. The valuable results are found in applied of linear algebra and PCA. It uses both neuroscience and computer graphics analysis as simple accessible by non parametric techniques to extract related information from complicated data sets.

The orthogonal linear transformation to changing data in PCA and their new coordinate system is similar highest variance by data projection on the first coordinate. The second most significant variance is the second coordinate is s on. PSO is used to find the optimal feature subset of 'Eigen' features extracted by PCA. We see an optimal feature subgroup with the least number of features and high classification accuracy in the proposed method.

In PSO, every particle files in search space are a rate adjusted by own flying memory and the confidant's flying experience. The particles of the PSO signify the features subgroup where if a bit is given value one, 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 an optimal position. The On classification accuracy and the number of the feature are evaluated base on the fitness function of particles [14]

Fitness =
$\alpha \times \text{accurac} \times \text{number of feature}$
…………..Eq.2

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

In this classification analysis, extreme and standard power is used as a feature to classify the example. In this experiment, out of 64 elements in the PCA technique, 45 characteristics are considered. Among selected 38 features of PSO classification working out, the set comprised 60% of the data, and the remaining 40% was used as a test set. Classification performances are based on the 10-fold cross-validation for more accuracy. High classification accuracy of 95.68% is bagged with Native Bayes classifier [14].

- Feature extraction and classification of EEG Signals using 'Wavelet Transform,' SVM, and 'Artificial Neural Networks.

In this case, the EEG artifact has exact activities and scalp structure that remain more easily recognizable in the rate of recurrence domain. The purpose of chronological muscle creation typically induces relative vigorous 20-60 Hz activity at chronological electrodes, while saccadic eye signals produce 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 the Haar mother wavelet's power spectrum variance and mean. Finally, it's valuable classification as a feed-forward 'Multi-Layer Perception' (MLP). Aimed at feature extraction from the raw EEG data, many are used in methods such as time domain and frequency domain, while the EEG is non-stationary in general [16].

In this situation most appropriate to use time-frequency domain methods like 'Wavelet Transform' (W.T.) as a means for time-frequency representation of a signal by agreeing to the use of mutable-sized windows. In W.T., long-time windows are used for a more acceptable low-frequency resolution, and short-time windows are used to get high-frequency information. This marks the W.T. for properly analyzing irregular data patterns, such as impulses following at various instances. The EEG recordings are decomposed into frequency bands through fourth-level 'Wavelet Packet Decomposition' (WPD). When the data has discontinuities, the decomposition filters are usually constructed from the Haar or other sharp mother wavelets [17].

In the classification of this work through the neural network, different techniques are used

- Multilayered Perception Neural Networks' for minimizing errors and raising the number of neurons in a concealed layer.
- 'Probabilistic Neural Network' (PNN) pattern recognition of statistics is used as a probabilistic approach to the neural network. Suppose PNN is derivative from 'Radial Basis Function' (RBF). It is often faster than the 'Back Propagation' (B.P.) network.
- The SVM is a comparatively new classification procedure developed by Vapnik [18]. The table shows the training and testing of different

classifiers of the data sets, 70% are training, and the balance is used for the test classifier. Generally, activity is higher than the accuracy of the testing set in classification.

Table 3: *Classification result.[18]*

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

Table 3 indicates the result of classification accuracy during the training and test stage for both data sets.[17]. MLP data sets are shown 98% on training and 88% on testing. Whereas PNN shows 99% training and 84% on testing, SVM shows 99% training and 81% testing.

EEG SIGNAL FOR TAG RELEVANCE ASSESSMENT

In this technique used, EEG signals at 256Hz. EEG point is detached by deducting the average affecting movement 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 their frequency [19]. EEG signals are again re-reference to the average referent. Here is the ERP response to perform in 400ms to 600ms after showing the tag.

Therefore, the EEG signals of one second after displaying overlaid tags under the images are sampled 16 times and used as a 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 the intra-contributor category.

For each contributor, one of the 54 experiments is taken as a test set, and the rest are used as the training set in the leave-one-out cross-validation strategy. If applying principal component analysis feature vector is reduced and keeping the basis with 79% of the variance. We used 'Linear Discriminant Analysis (LDA) classifier to discriminate between the responses to relevant of nonrelevant tags. Their EEG signals are averaged after normalization to aggregate multiple participants' responses. The resulting features are classified using the same classifier and validated by the same cross-validation strategy [20].

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

EEG SIGNALS BIOMARKERS OF VNS THERAPY.

This work objectively estimates the efficiency of special neuromodulator therapies; Vagus Nerve Stimulation reduces the severity of seizures in a 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 adjunctive therapy to pharmacology. It has been demonstrated to reduce seizure frequency in a multicenter, randomized controlled test and a subsequent single-center test [23][24] on experiment 212 patients (105 are pre-treatment and 107 post-treatment).

We find 85.85%—of total performance in Fuzzy-C-Mean (FCM). The complete version of 90.20% is FMC classification using only complex partial and secondary generalized seizures (54 pre-treatment and 48 post-treatment seizures) [22]. According to VNS therapy, EEG management decreases heart rate (%) and shorter tachycardia duration following VNS treatment compared to their pre-treatment values.

CONCLUSION

In our research studies, no's of techniques (i.e., eye gaze tracking to VNS therapy) for mental depression status. B.C. computer interface is based on ERPs developed multiple corners to improve their accuracy [21]. The result of VNS therapy on management has been examined in a few studies in this past [25] [26], where all used the synchronicity of interracial EEG activities. All research work depends on the selected no of the patient in a different slot. Situational analysis helps for further clinical diagnosing mental status. Other research works need to find physical causes of mental depression.

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