ISSN 2349-6193
Impact Factor: 2.805

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International Journal OF Engineering Sciences & Management Research

Review on classification of EEG data for different Applications

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Keywords: EEG signals, Brain Computer Interface, Rehabilitative application, Clinical Application,Motor Cortex, Algorithms.

ABSTRACT
This paper discusses different paradigms of analyzing EEG signals which can provide useful insights of cognitive state of mind, it may be either clinical conditions like Epilepsy, Alzheimer or rehabilitative purposes like Brain Computer Interface. This paper provides extensive review on both the above approaches which uses different kind of algorithms to predict cognitive state. Analysis is done on different components of algorithm like feature extraction and classification. The paper also explores various new paradigms of research in EEG.

INTRODUCTION
EEG signals are the most complicated to understand since these signals are superimposition of activities of underlying brain structures. And furthermore the no. of channels are vast (i.e. 32, 64 or 128), so in order to analyze such large data with superimposition of different sources firing simultaneously is the most challenging task. Most of the information from EEG signal can be primarily classified into two categories according to their usages. Currently this data usage can be classified as both Clinical purpose (i.e. Epilepsy [4], Alzheimer [5]) and Rehabilitation purpose (i.e. BCI [2], Augmentative and Alternative Communication [3]). Furthermore EEG's could also be used for personal identification but we will discuss only clinical and rehabilitative usages only.

In the paper we will discuss different approaches taken for clinical and rehabilitative applications. These applications requires generalized algorithm for improved and robust performance. For proper generalization large amount of data sets are required otherwise it would difficult to get generalized algorithm. But as we take large data the algorithm complexity will also increase. So in order to resolve the problem different researchers have adapted different techniques like data reduction (i.e. PCA, ICA)[33] or filter based (i.e. FFT, Wavelet) [30], [31]. These techniques will either reduce the size of data or detects the changes in the signals. These reduced data or changes in EEG signal can be used as extracted features. After getting reduced data it requires to classify the data for particular purpose. Classification can either done by statistical means (i.e. Different Discriminant techniques, SVM) [34] or by Neural network [2]. Accuracy of classifier depends on its ability to classify nonlinear data, since EEG are mostly nonlinear due to superimposition of sources.

Algorithm designed for both the purposes are distinct because in rehabilitation applications the signals of interest tend to vary their frequency and amplitude whereas in clinical application occurrence of particular event is required to be captured.

REHABILITATIVE APPLICATIONS
Most of the time algorithm designed for rehabilitative purpose are more focused on particular frequency band (so-called *mu*(8–12 Hz) and *beta* rhythms (18–25 Hz) in EEG, which have been present in the central part of the brain) [31], [4] or synchronous activity of brain in response to some external event, to predict the activity of certain part of brain (motor cortex). Which means the algorithm contains components which focuses on frequency analysis like Fourier transform or most probably wavelet transform. Both the above analysis approaches provides total frequencies present and respective power densities in the signal.

In most of the studies which uses above methods, frequency's power-based features such as signal's maximum or average powers extracted from its power spectrum density (PSD) have been used[30],[32], and [4]. One of the major drawback of the Fourier Transform is that it cannot provide time of occurrence of frequency of interest, which is very important for Rehabilitative application. Interestingly wavelet has the capability to provide information on time of occurrence of particular frequency which is very useful in analysis. The signals from time window provided by wavelet spectrum analysis can be used for further analysis which lead to prediction of particular event [4]. Generally Discrete Wavelet Transform (DWT) proved to be most useful because it can provide optimal time-frequency resolution for analysis which is generally dominated by low frequencies [31]. DWT can be produced with different scaling and translation properties which gives us

IJESMR
International Journal OF Engineering Sciences & Management Research

different shapes. These shapes can detect underlying neuro-electrical event. In case of EEG numbers of channels are more so the complexity will increase which will increase computational load as well.

On the contrary most of the data reduction techniques before their application filtering of signal is required to be done. Particularly CSP algorithm finds spatial filters that exploit variance for one class and that at the same time diminish variance for the other class. Initially CSP's were used for classification of two classes (i.e. left hand v/s right hand movement) but four classes classification was also used by using producing individual filter for each class [37]. Some other commonly used spatial filter's[38], local temporal common spatial patterns, L1-norm-based CSP, regularized CSP and stationary CSP [39].CSP can also be used in conjunction with Wavelet by creating time-frequency-space localized signal using multiple decomposition level of signal[40].

After preprocessing of signal mentioned above generally PCA or ICA can be applied so that we get features from frequency of interest only. In the case of ICA, under assumption that measured EEG data are combination of signals of interest, noise, other brain activity unrelated to the task and artifacts. Blind source separation technique like ICA is used to separate sources of interest from other interfering signals [33]. Assuming statistical independence between mixed sources, ICA tackles the problem of source separation on the basis of improving an objective function that is appropriate even with partial assumptions on source statistics, including, non-whiteness, non-Gaussianity, or nonstationarity. Whereas with PCA the dimension of EEG evidence (feature) vectors obtained upon concatenation of data from each channel can be reduced using PCA, which projects the feature vectors to the subspace spanned by the largest eigenvectors of the feature covariance matrix in order to preserve high power bands. For reduction of large data set, only Eigen vector with Eigen value above some threshold are preserved which can be treated as features for classification.

Feature Classification is another important domain where plenty of work is already done starting from simple Linear Discriminant Analysis (LDA) to highly nonlinear approaches like Artificial Neural Network (ANN) and Support vector machine (SVM). Proper generalization and robustness can be achieved by properly choosing classification frame work. For our application the algorithm must allow multiple class classification with highly nonlinear, non-stationery data. Here another challenge is to deal with large data set which heavily influence the overall accuracy of the algorithm.

LDA basically searches for project axes which gives maximum difference with other classes and minimum with same class data. The optimal prediction of LDA is computed by using an Eigen-decomposition on the distributed matrices of the training data [34]. The above method assumes nonsingular matrices of data which is not true in the case of EEG data. So modifications were done in the form of by incorporating singular value decomposition with LDA. This further enhances by application of regularization which reduces the discrepancy ensuring good generalization ability for previously unseen data. Another improvement is Spectral Regression Discriminant Analysis (SRDA) approach [34]. Spatial-Temporal Discriminant Analysis method doesn't use concatenation of multiple channels in temporal points but instead temporal features placed in columns and spatial features placed in row form [35].In recent wake of time up gradation of Regularized LDA is done in form of Stacked Regularized Linear Discriminant Analysis (SRLDA), which combines multiple models to produce a higher-level classifier with improved performance and generalization [36].

Support Vector machine (SVM) is used in many application due to its ability to provide nonlinear, multi-dimensional separation of data. So SVM can be used for problem of 2-class and multiclass classification problem of EEG data. Basically SVM tries to find out an optimal hyper plane which splits multiple classes by maximizing the margin between them. For the case of nonlinear data separation algorithm actually projects the original data to a high-dimensional feature space which uses kernel function in order to project them. This will return nonlinear hyper plane which separates the nonlinear data [41]. In a research LS-SVM implemented which uses Radial Bias Function (RBF) as a projection function which is non-linear in the nature. LS-SVM is differing from natural SVM algorithm because this method has close relationship with Gaussian processes, regularization networks and kernel fisher Discriminant analysis. This method is fast as compared to normal SVM and it finds global optimum instead of local optimum [42].

Artificial Neural Network (ANN) widely used due to their capability of nonlinear classification. Convolution Neural network has attracted many researchers because this type of network can adapt to variation in signal over time and persons. CNN contains Multilayer perceptron with more than one hidden layer so network can extract Discriminant features on its own. Another development was online neural network based classifier based on the

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principles of Schrodinger wave equation and quantum mechanics (QM) known as recurrent quantum neural network (RQNN), which will estimate time varying probability density function [10]. The approach taken here is based on estimation and filtration of noise from raw EEG signals by means of stochastic filtering. Four class Classification was done using sub-band decomposition of event related potential. In the said approach each sub-band is examined using combined factorized feature extraction (CFFE) with culminative average power (CAP) and Culminative mean (CM) as main features. Other neural network method like neural-time-series-predication-preprocessing (NTSPP) framework predicts filter to be used and in order to increases data separation by mapping the original signals to a high dimensional space. This technique uses Neural Network based predictive/regression models which is specialized (trained) on EEG signals connected with specific brain tasks [2].

Even several attempts were done using hybrid approach like combined neuro-fuzzy, neural network based on particle swarm optimization model etc. There is one online method uses combination of neural networks and fuzzy theory(S-dFasArt) is used to classify impulsive mental activities from electroencephalogram signals [8]. This algorithm can be interpreted as a fuzzy logic system based on rules connecting fuzzy categories and optimized by adaptive neural learning. This method is accompanying by voting strategy which can eliminate rules generated from confused data. Recently fuzzy particle swarm optimization with the cross-mutated operation (FPSOCM) was utilized for three class classification purpose [7]. In their approach Hilbert–Huang transform (HHT) was used as feature extractor and for classification purpose, ANN’s cost function was optimized using FPSCM in order to get global minima. Another approach that uses recurrent self-evolving fuzzy neural network (RSEFNN)[9], this structure utilizes combination of Fuzzy Neural Network (FNN) and Recurrent Neural Network (RNN) in order to increase adaptability.

Even some researchers have implemented new paradigm of source reconstruction approaches [43] - [46]. They can be divided in two main classes: First is imaging models, which explain the data with a dense set of current dipoles distributed over different brain locations; and equivalent current dipole models, which assume a small number of focal sources at locations to be estimated from the data. Imaging techniques (LORETA, Beam former) provides detailed map of neural activity the parametric models represent a direct mapping from scalp topology to a small number of parameters. Dipole solutions provide more intuitive interpretations that explain the sensor data. Furthermore, it is easy to report statistics of dipole parameters over different subjects. Summarizing distributed brain activity with a small number of active dipoles simplifies the analysis of connectivity among those sources. Popular deterministic parametric solutions include the multiple signal classification (MUSIC) algorithm and its modified versions, the methods for inverse problems [43].

CLINICAL APPLICATIONS

Mostly EEG analysis applied in the case of Epilepsy and early diagnosis of Alzheimer’s disease. Epileptic seizures is basically temporary disruption of electrical activity of brain which causes uncontrolled movements depends on affected brain parts and certain times epilepsy attributed by loss of consciousness [11]. Normally these episodes lasts for 2-5 minutes and analysis done on 20 minutes pre epilepsy period recordings. This period can be efficiently diagnosed by pattern recognition algorithm like SVM, ANN or feature extractor like discrete wavelet Transform, ICA and Fourier transform followed by k-Nearest neighbor, Naïve Bayesian and Gaussian mixture model type classifier.

Epileptic seizures phenomena is basically disrupted EEG signals which are having different time-frequency representation and can be quantified as non-stationery and non-linear dynamics of EEG. Several attempts to detect epilepsy from recording were made using EEG signal’s time, frequency domain analysis or combination of both. Samiee et al. have used discrete short time Fourier transform (DSTFT) based on the fact that, high frequency rhythmic spikes and subtle amplitude changes are present in beta and alpha frequency sub-band affected by seizures [13]. Based on above fact they have used a rational function based orthogonal polynomials as feature extractor to detect seizure in given short time window of EEG signal. These features later on classified by feed forward multilayer perceptron trained with back propagation algorithm. Above method has a short coming in terms of localizing particular frequency in time since method uses short time periods rather than over all signal. The issue can be addressed by using continuous or discrete wavelet transform which can localize frequency with respect to its occurrence. Yinxia Liu et al. has proposed approach where they have used discrete wavelet transform (DWT) which gives enhanced low frequency resolution for longer time interval and shorter for high frequency, and that’s why it is better to use DWT for feature extraction purpose [14]. Daubechies wavelet family chosen as it is having similar shape and frequency characteristic of Seizures. Seizure normally

IJESMR
International Journal OF Engineering Sciences & Management Research

occur at broader frequency but generally they found in 3-29 Hz frequency band [15] and thus db4 coefficient having maximum information. Using db3 to db5 coefficient's relative energy, amplitude and fluctuation index as feature and classified by SVM. A. Sharmila et al. have also used DWT and Daubechies-4 coefficients and extracted features are classified using naïve bayes and k-nearest neighbor [16]. They have confirmed that naïve bayes are better classifier with highest accuracy.

Alam et al. have used Empirical mode decomposition (EMD) since it is well suited for non-stationery and non-linear signals like EEG. EMD is a process of extracting frequency and amplitude modulated oscillatory pattern from raw EEG data, these patterns are also known as intrinsic mode function (IMF). The paper presents the idea of using high order statistical features such variance, kurtosis and skewness in EMD domain as feature [17]. These features are further classified by a feed forward neural network on the basis of band-limited signals. Wang et al. have proposed approach which uses information flow between brain parts as a tool for detecting seizure, which is done by partial directed coherence (PDC). PDC used for extracting intensity and direction of information flowing between brain regions [18]. In the paper researcher proposed approach where raw EEG signals information was segmented by multivariate autoregressive model (MVAR) and simultaneously PDC gives outflow information which are treated as features. Classification was done by SVM and Back Propagation (BP) ANN and experiment shows SVM based classifier performed better. Yang et al. have proposed Fuzzy logic System (FLS) because it can perform better when test data set is different than training data set [19]. FSL learning was done by transductive transfer learning method where the membership function is defined by fuzzy c-mean (FCM) clustering algorithm whereas fuzzy Interference rules are based on L2-norm penalty for training of algorithm. Final outcome of algorithm is based on solving dual problem by optimization theory. They have developed and tested two algorithm TSK-TL-FLS regression and TSK-TL-FLS binary classification and found out that binary classification is better in classifying epilepsy seizures. Apart from these approaches Sanjay et al. have tried cloud computing approach for early detection and advance alert to patient of epilepsy occurrence [20]. They have used Fast Walsh Hadamardtransform (FWHT) for feature extraction and these features are further reduced by higher order spectral analysis and classified using Gaussian process algorithm. Normally FWHT converts time domain signal to frequency domain representation which detects transient events that can occur before seizure onset. Whereas higher order spectral analysis uses higher cumulant of power spectrum of EEG signal which also contains incoherence values of signals. Final outcome is shared with physician and relatives of patient in case of pre-Epilepsy seizure (ictel event) event is detected. Another Researcher uses multilayer perceptron with logistic regression model to identify epilepsy [21].

In general Alzheimer's disease (AD) detection is done by imaging technology like MRI, Positron Emission Tomography [22]-[24].But several researcher have used EEG as low cost and widely accepted tool for screening Alzheimer developing patients. Mostly these researcher have utilized higher order signals attributes of EEG by means of differentiating healthy subject's EEG with AD patients. Morabito et al. have used compression of EEG signal without sampling them which will yield low sample number [25]. The research suggested that AD patients EEG have high data compressibility as compared to healthy patients EEG. They have also compared the results with Discrete Wavelet Transform and found their compressibility algorithm satisfactorily reduced data than wavelet. The compression technique here done firstly using thresholding which discards sample below certain level,secondly these signals are projected onto other basis which in turn find lowered coefficients. Samantha et al. have utilized concept of Entropy which gives degree of disorder in the system using quadratic sample entropy (QSE) algorithm [26]. QSE was developed as a modification of sample entropy because this entropy heavily depends on input parameters. QSE is different because unlike probability based regularity it gives density statistic, the results of algorithm was compared with LDA. Labate et al. have used multiscale multivariate complexity analysis of permutation entropy, sample entropy and Lempel-ziv complexity analysis done [27]. The analysis done for different parts of brain (i.e. frontal, occipital and mixed) region. The results suggest that Permutation entropy is best suited to detect slowing effect related to AD.

Unlike above approaches Kang et al. have used Principal Dynamics Mode (PDM) modeling approach. This approach determines associated nonlinear functions (ANF) using volterra kernels with Laguerre expansions [28]. In order to reduce the complexity they have used singular Value decomposition (SVD) of rectangular matrix that contains all ANF's and from all available ANF minimum set of ANF were selected based on adequate representation of input-output dynamics. Apart from these techniques source localization method used by Aghajani et al. have also used for rehabilitative purpose [29]. Basic idea behind source localization is done by firstly forward modal generation and then projecting the EEG signal back to forward modal in order to get mapping of affected region. Forward modal created using Boundry Element method (BEM) based on MNI152

 ISSN 2349-6193
Impact Factor: 2.805

IJESMR

International Journal OF Engineering Sciences & Management Research

template yields multi sphere head model. The projection of EEG data done by standardized low-resolution brain electromagnetic tomography (sLORETA) which approximates current density. The projection was done for different EEG bands (i.e. delta, theta, alpha & beta) in order to get effect on brain regions and concluded that alpha band has maximum accuracy.

CONCLUSION

Above discussion related to clinical and rehabilitative purpose have covered all the aspects of EEG analysis. There are potentially newer paradigm available which can increase the robustness and reliability. One of them is use of source reconstruction which can substantially reduce number of channels and give precise mapping of EEG signal to brain region of signals origin. This technique can be clubbed to other non-linear classifier that can make real time implementation possible and it is possible to customize algorithm for individual basis.

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