Study of Various Techniques of EEG Feature Extraction

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Abstract : Now a day, Electroencephalography (EEG) in very popular in research field. Although researchers are doing research in EEG and designed their own technique for feature extraction like independent component analysis (ICA), discrete wavelet transform, fast fourier transform, power spectral density (PSD), empirical mode decomposition (EMD), Cluster analysis, Hilbert-Huang transform, Principal Component Analysis and Local Discriminant Bases still illustration by specialist is required. To locate the artifacts and extract them from real EEG signal by the use of proficient algorithm is challenge for researchers and doctors. This paper discusses the various techniques along with restrictions of EEG feature extraction techniques.

***IndexTerms* - Electroencephalography, Feature Extraction Techniques, Independent Component Analysis, Discrete Wavelet Transform, Cluster Analysis**

I. Introduction

The electroencephalogram is to determine the electrical potential of neurons inside the nervous system on scalp through a number of electrodes. This paper discusses the various techniques of feature extraction. The most important confront in Brain Computer Interface research are in what manner the features are extracted in time varying EEG signals. The features can be extracted in EEG signals by various techniques. These techniques are discussed in Section2

II. RELATED WORK

Many technique are used by researchers for feature extraction like discrete wavelet transforms (DWT), power spectral density (PSD), empirical mode decomposition (EMD), independent component analysis (ICA), fast fourier transform, Cluster analysis, Hilbert-Huang transform, Principal Component Analysis and Local Discriminant Bases.

Monika Prucnal et al., 2017, uses an artificial neural network to relate the competence of three techniques for feature extraction i.e. discrete wavelet transforms (DWT), power spectral density (PSD), and empirical mode decomposition (EMD) in the automatic cataloging of sleep phases. From the database of PhysioNet, a 30 second EEG epoch which represents five different sleep stages was converted into feature vectors by the use of abovementioned methods and principal component analysis. The result shows that the characterised by a cataloging precision of 81.1% was produced once the features were ready by the use of average powers of the frequency subbands of PSD &a neural network was provided as the classifier. The analysis illustrates that the competence of PSD is superior to EMD and DWT in this precise cataloging problem.

The limitations in their study:-

1) By uniting selected estimation and detailed coefficients there is a probability of removing the distinctive frequency sub-bands from DWT and that should be tested.
2) With the use of Hilbert transform, EMD coefficients will be tested.
3) Analyzing additional classification approaches like the support vector machine and decision trees will give improved cataloging accuracy than achieved in this study.

Shuli Huang, et al., 2011, uses cluster analysis technique for feature extraction. Cluster analysis technique has the benefit that it does not determined by well-defined class of learning and training. Analyzing the motor imagery EEG the feature abstraction step is designed through test. Analysis of EEG indicates that cluster analysis is very respectable for the brain signal analysis

Wan Amirah et al., 2014, reviewed various techniques on signal analysis for feature extraction of EEG signal. For achieving robust cataloging of signal, a noble method for feature extraction is essential. This paper reviewed the commonly used techniques for schizophrenia i.e. Hilbert-Huang transform, Independent Component Analysis, Principal Component Analysis and Local Discriminant Bases. These techniques have their own shortcomings still they can be useful depending on purpose of a research, parameters and the collected data but the modifications are needed to overwhelmed the inadequacies of these algorithm. The improved algorithm Local Discriminant Bases is presented here as alternative feature extraction method for EEG signal in examining schizophrenia. Since LDB is not frequently used in EEG signal, but this method is very obliging in schizophrenia. More exploration is required in extracting the features of EEG signal in schizophrenia.

Lei Zhang, 2017, offers a Field Programmable Gates Array (FPGA) strategy for feature extraction of real time Electroencephalogram (EEG) signals which is used for implementation of Short-time Fourier Transform (STFT) and remove 20 feature components of frequency for cataloging. These features are distributed into 5 sets consistent to5 dissimilar brainwaves groups. Every feature is the ordinary power spectrum of a number of adjacent frequency components. With the use of Xilinx System Generator, a model is designed and applied on a Xilinx Zedboard with clock rate of 50MHz and the model is capable of 128-channel EEG signals feature removal at sample rate of 250 Hz. The designed model is capable for BCI applications.
The limitations in their study:-

1) Design model is not evaluated on widely existing EEG data sets to extract the features & to train artificial neural network for EEG signals
2) For EEG signals pattern recognition, implement FPGA for ANN cataloging algorithms as this may provide better performance and lower consumption of power.
3) The hardware of the designed model is cumbersome for the implementation of huge number of features.

Manisha Chandani et al., 2017, Electroencephalogram (EEG) is a method to identify neurological disorder like brain cancer, epilepsy etc. Here, classifier based on neural network analysis classifier was used to identify epileptic seizure movement from surroundings EEGs. In this analysis, two types of EEG signals were selected (i.e. well subject with open eye condition, epileptic). With the use of DWT signal were reprocessed, decaying until 5th level of decaying tree. For cataloging of signals, different features (Standard deviation, mean, median, kurtosis, skewness and entropy) were computed. The results indicates that the cataloging precision of almost 100% in recognition of irregular signal from regular EEG signals with less computation time of NNA classifier.

Naveen Verma, et al., in 2010, proposes a low-power SoC to perform acquisition and feature extraction of EEG which is essential for incessant detection of seizure onset in patients of epilepsy. The SoC combine an instrumentation amplifier, digital processor and ADC. Here, unprocessed bio-potentials are processed to remove physiologically significant information and signify this as a feature vector. As processing and communicating complete data from the system inflict too much power cost while ultra low power local processing is decisive to build the overall system feasible. It is significant to utilize targeted analog processing to keep away from the restrictions forced by environment, electrode and physiological disturbances. The offered SoC achieved acquisition of EEG, digitization, and feature vector removal.

Xiang Liao et al., 2007, introduce a spatial filtering algorithm discriminative spatial pattern (DSP) for enhanced removal of the variation in the amplitudes of movement-related potentials (MRPs) and it is incorporated with common spatial patterns (CSP) to remove the features from the recorded EEG signals through intended tasks of left against right finger movement. A support vector machines (SVM) based structure is planned as the feature classifier. The outcome demonstrates that, for MRPs and event-related desynchronization (ERD) features, the joint spatial filters comprehend the single-trial EEG cataloging superior than DSP and CSP alone. In this paper, a DSP algorithm and a BCI system was designed based on EEG for the cataloging of single trial left/right finger tapping. As in the planned algorithm no precise data preprocessing is fretful thus permit it to be use in real-time investigation on a wide set of BCI testing.

Amjed S. Al-Fahoum et al., 2014, discuss various methods which are recently used to remove the features from an EEG signals like time frequency distributions (TFD), eigen vector methods (EM), fast fourier transform(FFT), wavelet transform (WT) , auto regressive method (ARM) etc. They discuss these methods, assess their performances for definite task, and lastly on the basis of performance, recommend the most suitable technique for feature extraction. Out of these five well-known discuss methods; it's very tough to approve any one method according to their capability. The conclusion shows that every method has its specific advantages and disadvantages to say it is suitable for particular type of signals. Frequency domain technique may not give high-class recital for several EEG signal while time-frequency technique may not give comprehensive information on analysis of EEG as given by frequency domain technique. It is critical to create apparent of the signal to be evaluate in the application of the technique, whenever the recital of evaluating technique is discussed. This concludes that the best technique for any application might be dissimilar.

Su Yang et al., 2017, seeking effective measures to characterize the chaotic patterns of EEG signals for seizure diagnosis is a long-term endeavor in the literature. We propose to count the number of zero-crossing (ZC) points on Poincare surface as a feature when the time series of interest is embedded into the reconstructed state space. The experiments show that Poincare surface can act as a platform to observe the chaotic patterns of EEG signals and the ZC feature on Poincare surface is a promising pattern descriptor to discriminate different categories of EEG signals. When used alone for EEG classification, the ZC feature achieves 100%, 99.27%, and 94.68% accuracy in 2-class, 3-class, and 5-class classification on a widely used benchmark. This study reveals that Poincare surface provides a useful means to capture the intrinsic chaotic patterns of EEG signals. The number of zero-crossing points on Poincare surface is effective in distinguishing different categories of EEG signals. As far as we know, it is a unique nonlinear feature that can be used independently to achieve over 94% accuracy in the 5-class EEG classification problem.

Ling Zou et al., 2010, discuss that in BCI one of the significant concerns is precise cataloging of right and left hand motor imagery and for that in this research initially discrete wavelet transform was applied to remove the features of right and left hand motor imagery in EEG. After that, Fisher Linear Discriminant Analysis was applied with two dissimilar threshold calculation techniques and excellent misclassification rate was achieved. . In first threshold technique, threshold value was the mid-point of class center projection of two types. The other threshold was the weighted average based on the class frequency of two class centers. The Support Vector Machine was also used to evaluate the performance with Fisher Linear Discriminant Analysis and the concluded cataloging outcome shows that fake classification rate was lowest by Support Vector Machine and achieves an ideal cataloging results.

III. CONCLUSION

In this paper extensive literature has been reviewed to explore different technique of EEG feature extraction. Various methods are discrete wavelet transforms (DWT), power spectral density (PSD), empirical mode decomposition (EMD), independent component analysis (ICA), fast fourier transform, Cluster analysis, Hilbert-Huang transform, Principal Component Analysis and Local Discriminant Bases. The restrictions of previous accessible work in this area has been highlighted which shall act as a basis for advance research. The already offered algorithms can be proficiently executed for numerous applications that involve a feature extraction real-time EEG signal.

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