

A STUDY ON SCHIZOPHRENIA DIAGNOSIS WITH EEG SIGNALS

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Abstract: Electroencephalogram (EEG) signal complexity quantifies the brain dynamic and yields many different features to diagnose many psychotic disorders. The aim of this work is to analyze EEG to detect schizophrenia in comparison with normal subjects using EEG signal complexity, at various conditions such as amplitude dynamics of electroencephalogram (EEG) oscillations. Neuronal oscillations reflect the activity of neuronal ensembles engaged in integrative cognition, and may serve as a functional measure for the cognitive impairment in schizophrenia. This project aims to reveal the abnormal amplitude dynamics of electroencephalogram (EEG) data acquisition process feasible and quick for most patients. The highest classification accuracy 88.5% is obtained when features of both stimulus are considered together. This work suggests that the EEG signal oscillations in schizophrenia patients on multiple time scales. This article presents the Dyadic wavelet transformation, a novel approach for schizophrenia detection showing great success in classification accuracy with no false positives. The methodology is designed for single electrode recording, and it attempts to make the complexity during mental activity can be used to identify schizophrenia subjects.

Keywords: Schizophrenia cortical thickness, individual hierarchical network, multiple kernel learning,classification.

I.INTRODUCTION

One of the most important organs of human body is brain. Brain is the vertebrate central nervous system that is enclosed within the cranium, spinal cord and also composed of gray and white matter. Brain is the prime centre for regulation and controls the functioning of the human body including heart bit and respiration. It is an extremely complex system in the entire body and exhibits rich spatiotemporal dynamics. And it is often affected by some disorder and malfunction. One of the most common brain disorders is Epilepsy. Today about 60 million people are affected by this disorder. Machine learning approaches for mining neurophysiological data are rapidly gaining popularity and justifiably so, as they provide a level of analysis not possible with conventional method. commonly used systems for acquiring such brain activity data non-invasively include electroencephalography(EEG) ,which provides an estimate of electrical currents produced by the brain and functional magnetic resonance imaging (fMRI), where local blood flow changes are quantified. The analysis of neurophysiological data relies on descriptive statistical. Schizophrenia is a mental disorder that usually appears in late adolescence or early adulthood. Characterized by delusions, hallucinations, and others cognitive difficulties, schizophrenia can often be a lifelong struggle. Patients with SCZ may seem like they have lost touch with reality. To obtain a more accurate characterization for SCZ/HC classification, the correlation between ROIs has to be taken into account. Artificial intelligence is a useful predictor of schizophrenia where the disease can be diagnosed and accessed

II.LITERATURE REVIEW

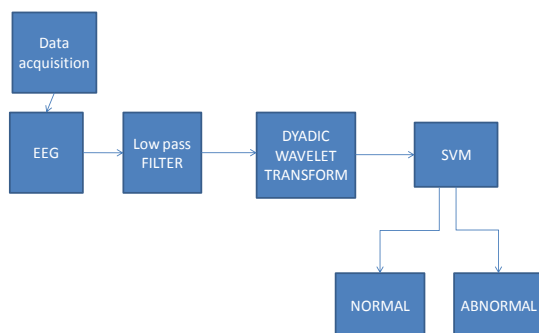
- In 2017 Ericson; Kavitha P. Thomas; A. P. Vinod has proposed biometric recognition of persons are widely explored nowadays to develop robust and trustworthy security systems. The stimuli set consist of a number of self-face images and that of subject's relatives, which are expected to elicit brain activity in a subject-specific manner. [5]
- In 2017 Arko Barman; Shishir K. Shah has proposed person re-identification in video-based surveillance where the goal is to identify the same person in different camera views. Aggregating the results from multiple algorithms for person re-identification is a relatively less-explored area of research.[7]
- In 2014 Patrizio Campisi; Daria La Rocca has proposed brain signals within the medical field to study brain diseases like epilepsy, spinal cord injuries, Alzheimer's, Parkinson's, schizophrenia, and stroke among others.[14]
- In 2011 Haichao Zhang; Nasser M. Nasrabadi; Thomas S. Huang; Yanning Zhang has proposed the multi-view face recognition problem as that of classifying among several multi-input (views) regression models by using a novel joint dynamic sparse representation method.[17]
- In 2011 P. Campisi; G. Scarano; F. Babiloni; has proposed the use of brain waves as a biometric identifier is investigated. Very different protocols have been used to acquire the electroencephalogram signal

(EEG) of an individual. This analysis has been performed for three different frequency bands for each of the ten different triplet under analysis. [20]

III. PROPOSED SYSTEM

EEGs were recorded from channel scalp electrodes mounted in an elastic cap including two pairs of vertical and horizontal electrooculography (EOG) electrodes. The electrode-scalp impedance was kept below 5 kΩ for each electrode. The signal acquired from EEG electrode process with dyadic wavelet transform. A LSSVM apply to detect normal and abnormal brain activity. The advantage of the proposed system is that it can analyze recurrent schizophrenic patterns in patients.

System design



This figure shows the proposed architecture of this project.

SUBSYSTEM

Support vector machine(SVM): Support vector machine (SVM) is a classical supervised machine learning model with associated learning algorithm based on statistical learning theorem, which is widely used for classification. Given a set of training samples, each marked for belonging to one of two categories, the SVM training algorithm constructs a non-probabilistic binary linear classifier to assign new testing samples into one category or the other. In the SVM model, each sample is represented by a point in a high-dimensional space, where a hyperplane separates the samples into two categories. New samples will be mapped to the same space and tagged as one category according to which side of the hyperplane they fall on. A good classifier is obtained by a hyperplane that has the largest functional margin making a least generalization error. SVM aims to improve the generalization ability of the learning via seeking for a structural risk minimization, which makes it perform well in spite of the small sample size. This is why we choose SVM for classification due to a small number of subjects and large quantities of features.

The linear SVM is supplied by MATLAB toolbox. The performance of the classification is evaluated by accuracy, false positive rate (FPR) or Sensitivity (measuring the hit rate in tinnitus group) and false negative rate (FNR) or Specificity (measuring the hit rate in normal group), where the normal controls are labeled as 1 and tinnitus patients are labeled as -1. The formulas are displayed as follows:

$$\begin{aligned}
 \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\
 \text{FPR} &= \frac{FP}{FP + TN} \\
 \text{Sensitivity} &= \frac{TN}{FP + TN} \\
 \text{FNR} &= \frac{FN}{FN + TP} \\
 \text{Specificity} &= \frac{TP}{FN + TP}
 \end{aligned}$$

Where TP stands for the number of normal controls who were correctly classified; TN stands for the number of tinnitus patients who were correctly classified; FP stands for the number of tinnitus patients who were misjudged to be normal controls; and FN stands for the number of normal controls who were misjudged to be tinnitus patients.

Wavelet transform : Wavelet transform is a new multiresolution time- frequency analysis method. WT possesses well localization feature both in time and frequency domains. It acts as a group of band-pass filters to decompose mixed signal into signals at different frequency bands.

The complex valued function $V(x)$ is said to be a wavelet if its Fourier transform 'T' satisfies:

$$\int_0^{+\infty} \frac{|\Psi(\omega)|^2}{\omega} d\omega < +\infty$$

Let $s(x) = (1/s) V(x/s)$ be the dilation of $V(x)$ by the scale factor s . The wavelet transform of a function $f(x)$ of $L^2(\mathbb{R})$ is defined by $Wf(s, x) = f(1/s) s^{1/2} V(x/s)$

Mallat fast algorithm of wavelet transform is used to decompose and reconstruct EEG signals. Adopting this algorithm, signals are decomposed to wavelet coefficients in different scales. Some coefficients related to noises are discarded, and the remained signals are reconstructed by inverse WT, then noises can be removed. Mallat proved that the average density of modulus maxima of a white noise is inversely proportional to the scale s of WT. If the Lipschitz exponent of $f(x)$ is α , there exists a constant K and

$$|Wf(s, x)| \leq K s^{-\alpha}$$

If let the scale $s=2^j$, then we have

$$|Wf(2^j, x)| \leq C 2^{-j\alpha}$$

Since EEG has singularities with positive Lipschitz exponent and the Lipschitz exponent of noise is negative, WT of EEG and noises present different inclination with the increase of scale. Energy of noises concentrate on 2^j scale and decrease significantly when the scale increases, while EEG concentrates mainly on scales 2^2-2^7 . By eliminating wavelet coefficients of small scales, denoised EEG are reconstructed by other scales, and the useful signals of EEG are well reserved while noises are removed effectively.

EEG

- Measures electrical activity generated by the synchronized activity of thousands of neurons (in voltage)
- Provides excellent time resolution, allowing you to analyze which brain areas are active at a certain time – even at sub-second timescales

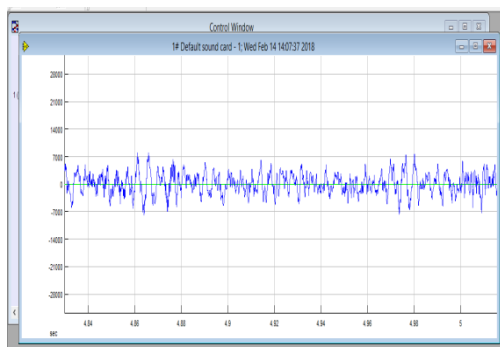
Since the voltage fluctuations measured at the electrodes are very small, the recorded data is digitized and sent to an amplifier. The amplified data can then be displayed as a sequence of voltage values.

Price differences in EEG systems are typically due to the number of electrodes, the quality of the digitization, the quality of the amplifier, and the number of snapshots the device can take per second (this is the sampling rate in Hz). EEG is one of the fastest imaging techniques available as it can take thousands of snapshots per second (256 Hz or higher). 100 years ago the EEG time course was a plot on

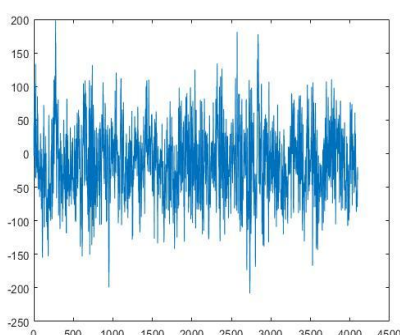
$$Wf(u, 2^j) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{2^j}} \psi\left(\frac{t-u}{2^j}\right) dt = f * \psi_{2^j}(u),$$

with

$$\bar{\psi}_{2^j}(t) = \psi_{2^j}(-t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{-t}{2^j}\right).$$



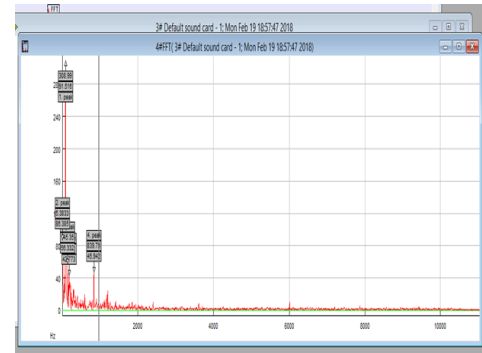
DYADIC WAVELET OUTPUT



paper. Current systems display the data as continuous flow of voltages on a screen.

IV.RESULTS

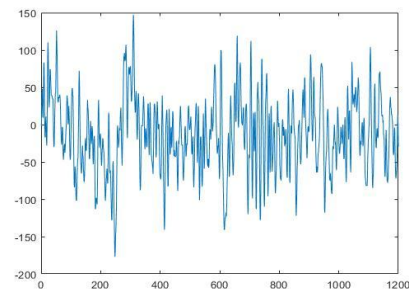
Sigview is a real-time and offline signal analysis software package with wide range of powerful signal analysis tools, statistics functions and a comprehensive visualization system.



By applying fourier transform, the frequency and amplitude is obtained.

DYADIC WAVELET INPUT

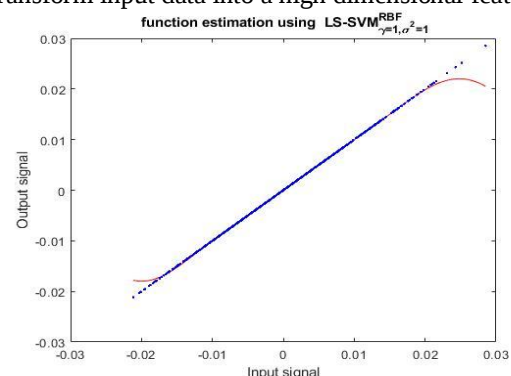
Dyadic wavelet transforms are scale samples of wavelet transforms following a geometric sequence of ratio 2.



The coefficients output from the function 'wavedec' are the artifacts from the convolution of the input signal (vector) and the wavelet/scale functions.

SUPPORT VECTOR MACHINE

The SVM is one of the most popular supervised learning algorithms for solving classification problems. The basic of SVM involves the adoption of a nonlinear kernel function to transform input data into a high dimensional feature space



V.CONCLUSION

The brain activity at different conditions such as at rest and at meditation and at stress are recorded for comprehensive analysis.

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