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Identification and Detection of Brain Tumours By Continuously Monitoring EEG Signals

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Abstract: In the present world, most of the human beings are suffering with brain tumors and mental disorders like false beliefs, unclear or confused thinking, auditory hallucinations, reduced social engagement and emotional expression, and inactivity because of their mental tensions. The disorder can be diagnosed by differentiating affected patients and normal persons. This can be done by analyzing the EEG signal. So in order to achieve this support vector machines (SVM), independent component analysis (ICA) algorithms are to be analyzed and a new algorithm is to be developed. In general EEG signal consists of alpha, beta, delta, theta out of which each component has separate frequency. Whenever there is any mental disorder these frequencies will be changed. So in this project a new hybrid algorithm based on wavelets and Karhunen-loeve transform (KLT) will be developed to identify the variations in frequencies of each component.

Keywords: Electroencephalogram (EEG) signal, Fast Fourier transforms (FFT), wavelets transform (WT), and support vector machines (SVM), Independent component analysis (ICA), Principal component analysis (PCA) and Karhunen-loeve transform (KLT).

I. INTRODUCTION

Human brain consists of millions of neurons which are playing an important role for controlling behavior of human body with respect to internal/external motor/sensory stimuli. These neurons will act as information carriers between human body and brain. Understanding cognitive behavior of brain can be done by analyzing either signals or images from the brain. Human behavior can be visualized in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. These states are related with specific signal frequency which helps to understand functional behavior of complex brain structure. Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponds to various states from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies.

FREQUENCY BAND OF EEG SIGNAL:

The brain waves recorded from the scalp have small amplitude of approximately 100µV. The frequencies of these brain waves range from 0.5 to 100 Hz, and their characteristics are highly dependent on the degree of activity of the cerebral cortex. Generally, in normal persons, the brain waves may be classified as belonging to one of four wave group.

1. **Delta (δ) -**The Delta waves which include all the waves in the EEG below 3.5 Hz. They occur in deep sleep, in childhood, and in serious organic brain disease.

2. **Theta (θ) -**The Theta waves have frequencies between 4 and 7 Hz. These occur mainly during the childhood, but they also occur during emotional stress in some adults.

3. **Alpha (α) -**The Alpha waves are rhythmic waves occurring at a frequency range between 8 and 13 Hz, which are found in all normal persons when they are awake in a quiet, resting state of cerebration.

4. **Beta (β)** - The Beta waves are very low amplitude, and high frequency range between 13 and 30 Hz.

They are affected by mental activity.

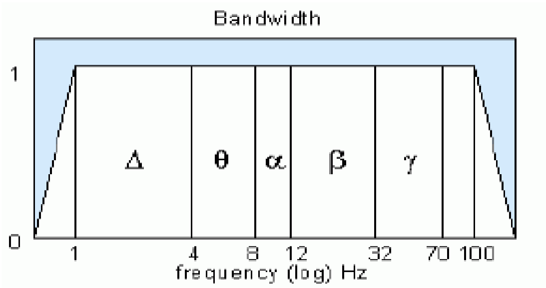

Fig. Frequency Bands of EEG signal

Electroencephalograms (EEGs) are becoming increasingly important measurements of brain activity and they have great potential for the diagnosis and treatment of mental and brain diseases and abnormalities. With appropriate interpretation methods they are emerging as a key methodology to satisfy the increasing global demand for more affordable and effective clinical and health care services. Developing and understanding advanced signal processing techniques for the analysis of EEG signals is crucial in the area of biomedical research. So in order to achieve this support vector machines (SVM), independent component analysis (ICA) algorithms are to be analyzed, and a new algorithm Karhunen-loeve transform (KLT)' is to be developed.

II. EXISTING MEOTHDS

Various denoising techniques have been implemented for removal of artifacts from EEG signals. Some of the techniques are: ICA(independent component analysis),PCA(principal component analysis), Wavelet transform.

a)Principal Component Analysis (PCA):

Principal component analysis involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) Number of uncorrelated variables called principal Components. PCA is sensitive to scaling. The mathematical technique used in PCA is called Eigen analysis: we solve for the eigen values and eigen vectors of a square symmetric matrix with sums of squares and cross products.

b) Independent Component Analysis (ICA):

ICA components of many signals are sparse, so that one can remove noise in the ICA domain.ICA carries all the information in single component and mostly contain non-artifactual information which can result in information loss. The limitation of this method is that the signals can only be analyzed in time domain not in the frequency domain.

c) Support Vector Machine (SVM):

Support Vector Machine (SVM) is one of the popular Machine Learning techniques for classifying the Electroencephalography (EEG) signals based on the neuronal activity of the brain. EEG signals are represented into high dimensional feature space for analyzing the brain activity. Kernel functions are helpful for efficient implementation of non linear mapping.

III. PROPOSED METHODS

i)FAST FOURIER TRANSFORM (FFT):

This method employs mathematical means or tools to EEG data analysis. Characteristics of the acquired EEG signal to be analyzed are computed by power spectral density (PSD) estimation in order to selectively represent the EEG samples signal.

Advantages:

(i) Good tool for stationary signal processing

(ii) It is more appropriate for narrowband signal, such as sine wave

(iii) It has an enhanced speed over virtually all other available methods in real-time applications

Disadvantages:

(i) Weakness in analyzing non stationary signals such as EEG

(ii) It does not have good spectral estimation and cannot be employed for analysis of short EEG signals

(iii) FFT cannot reveal the localized spikes and complexes that are typical among epileptic seizures in EEG signals

(iv) FFT suffers from large noise sensitivity, and it does not have shorter duration data record

ii)WAVELET TRANSFORM (WT):

Wavelet transforms are signal-processing algorithms similar to Fourier transforms that are used to convert complex signals from time to frequency domains. However, unlike Fourier transforms, wavelets are able to functionally localize a signal in both time and frequency space, thus allowing transformed data to be simultaneously analyzed in both domains (frequency and time).

The wavelet transform of the noisy signal generates the wavelet coefficients which denote the correlation coefficients between the noisy EEG and the wavelet function. Depending on the choice of mother wavelet function (which may resemble the noise component), larger coefficients will be generated corresponding to the noise affected zones. Ironically smaller coefficients will be generated in the areas corresponding to the actual EEG. The larger coefficients will now be an estimate of noise.

Appropriate threshold limit is to be found which separates the noise coefficients and the signal coefficients.

A proper thresholding function is to be chosen to discard the noise coefficients appropriately.Thresholding functions decide upon which coefficients should be retained and what should be done to them.

Hence discarded coefficients would result in the removal of noise, and the retained coefficients represent the wavelet coefficients of the de-noised EEG signal.

On taking the inverse wavelet transform, the de-noised signal is obtained. Hence the selection of threshold and thresholding function plays a crucial role in EEG denoising.

Advantages:

(i) It has a varying window size, being broad at low frequencies and narrow at high frequencies

(ii) It is better suited for analysis of sudden and transient signal changes

(iii) Better poised to analyze irregular data patterns, that is, impulses existing at different time instances

Disadvantages: Needs selecting a proper mother wavelet.

iii) KARHUNEN LOEVE TRANSFORM:

Karhunen-Loeve Transform (KLT) which was built on statistical-based properties. The outstanding advantage of KLT is a good de-correlation. In the MSE (Mean Square Error) sense, it is the best transform, and it has an important position in the data compression technology

KLT has four characteristics:

1. De-correlation. After transform the weight if vector signal Y unrelated.

2. Energy concentration. After transform of N-dimensional vector signal, the maximum variance is in the former of M lower sub-vector.

3. Under measuring of the MSE, the distortion is less than other transform. It is the sum of the sub-vectors which were omitted.

4. No quick algorithm and the different signal sample collection has different transformation matrix. (it is the shortcoming of KLT)

Differences between the KLT and Fourier Transform:

Now-a-days, the Fourier transform is of paramount importance in signal processing. The main advantages of KLT as compared with the Fourier transform are:

- Karhunen-Loeve Transform (KLT) works well for both wideband and narrowband signals, whereas the Fourier transform suitable for narrow band signals only.
- KLT works for both stationary and non-stationary input stochastic processes, whereas FT works for stationary input stochastic processes only.
- KLT is more flexible transform because its basis function can be of any form which gives better decomposition of the signal, whereas FT is very limited because its basis functions are strictly limited to sines and cosines.
- KLT defined for any finite time interval, whereas FT is afflicted by the windowing problems.

Development of Algorithm:

As we know that any periodic signal can be expressed in terms of a Fourier series is as follows:

$$x(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty}[a_n \cos(w_n t) + b_n \sin(w_n t) \quad \text{--------} (1)$$

Where the angular frequencies are defined by $w_n = n(2\pi/T)$ with the period of the signal being $T = t_2 - t_1$.

Applying the KLT methodology to a stochastic process X(t) over the finite time interval $0 \le t \le T$ can be represented by the equation:

$$X(t) = \sum_{n=1}^{\infty} Z_n(t)\phi_n(t) \quad \text{----------------} (2)$$

The deterministic functions $\varphi_n(t)$ are called *eigen vectors or eigen functions.* Z_n are random scalar variables.

Unlike the FT, the coefficients Z_n of the KL expansion of a stochastic process X(t) are pure random variables.

Computation of the random variables Z_n is given by,

$$Z_n = \int_0^T X(t)\phi_n(t)\,d(t) \quad \text{--------} (3)$$

The above equation describes the eigen functions with integral boundaries are finite and cover the entire signal duration$0 \le t \le T$; thus KLT well suitable for non-periodic signals.

The Eigen value λ_n corresponds to $\varphi_n(t)$ and represents the expected power of the corresponding eigen function and is important for the filtering capabilities that can be used to find out the feeble signals.

To compute the unknown eigen values and eigen functions the equation is as follows:

$$\int_0^T E\{X(t_1)\,X(t_2)\}\varphi(t_1)\,dt_1 = \lambda_n(\varphi_n(t_2)) \text{-----} (4)$$

Where, $E\{X(t_1)\,X(t_2)\}$ represents auto correlation of a stochastic process X(t) at instants t_1 and t_2 which is a known variable in this equation.

From the above equation, we can find out the Toeplitz auto correlation matrix of size N x N with the equation,

$$\sum_{k=1}^{N} E\{X_k\, X_l\}\,\phi_{nk}\,\Delta t = \lambda_n\,\phi_{nl} \quad \text{--------} (5)$$

Practical implementation steps:

1. Calculate discrete auto correlation of data and normalize by eliminating by the energy of the signal.
2. Place the auto correlation values into a matrix as follows:

$$\begin{pmatrix} 1 & a & b & c & d & .. & .. \\ a & 1 & a & b & c & .. & .. \\ b & a & 1 & a & b & .. & .. \\ c & b & a & 1 & a & .. & .. \\ d & c & b & a & 1 & .. & .. \\ .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. \end{pmatrix}$$

Where **'a'** is an auto correlation values with one unit delay **'b'** for 2.

Calculate the eigen values and the eigen vectors of the particular matrix for nxn matrix there will be 'n' eigen vectors. Each of these eigen vectors will contain 'n' values and these 'n' eigen vectors will make the orthogonal basis.

Jointly algorithm combined WT and KLT:

The principle of this joint algorithm is very simple. Just need them to do what they are good at. Firstly, discussing what KLT will do in the combination algorithm. This part is mainly use KLT to compute the covariance matrix and then use it to rebuild after de-noising by WT. One point need to announce here firstly is that in this part the PCA function is used to instead of the whole KLT codec which is much easy to realize in the MATLAB. It will not influence the result, because the PCA and KLT actually is the same in this paper. And the principal components analysis is also a main function of KLT. The PCA, in this part, will compute the covariance matrix. The process is to transform a given data set **X** of dimension *M* to an alternative data set **Y** of smaller dimension *L*, where **Y** is the KLT of matrix **X**. From the process we can find that the PCA can be judged as the same as KLT in this paper. The reason for implemented the KLT in the KLT cases following the steps given in the KLT mathematics description, because of needing to verify the mathematic describable work. After that, believing it actually works, so the PCA function offered in the MATLAB is the best and most reliable way to implement the jointly transform.

In the last, introduce the mainly steps of the whole jointly algorithm. Firstly, transfer the EEG signal into vector matrix then the KLT will calculate the covariance matrix to show its significant ability of de-correlation. After that, the matrix will be given to the WT to do the de-noising. In the end, the de-nosing matrix will be reconstructed to the picture by KLT.

Jointly algorithm compare with FFT:

The meaning of the jointly algorithm is that it offered a new way but maybe not the best way to process EEG signals. This is a good try. And according to the mathematics of the jointly algorithm, it has the following advantages:

1. Because the jointly algorithm is based on the WT and KLT, which means it has more widely range than FFT. The reason is the FFT of the signal must exist and it also needed to design the filter to fit the condition. The KLT is based on the statistics, it do not need some special terms. And the WT is just deal with the matrix that be processed by KLT.

2. Turn to the wavelet part, it was much faster than FFT.

3. Turn to the KLT, KLT applies to both stationary and non-stationary processes, but the FFT works only for stationary input stochastic processes.

4. This algorithm mainly can offer special requirements of signal processing. For example, we need analyze or denoise part of the signal, this is what FFT cannot.

5. FFT needs more data to rebuild the signal but our WT&KLT do not.

IV. EXPERIMENTAL RESULTS

Output representation of brain tumor classification from EEG signal.

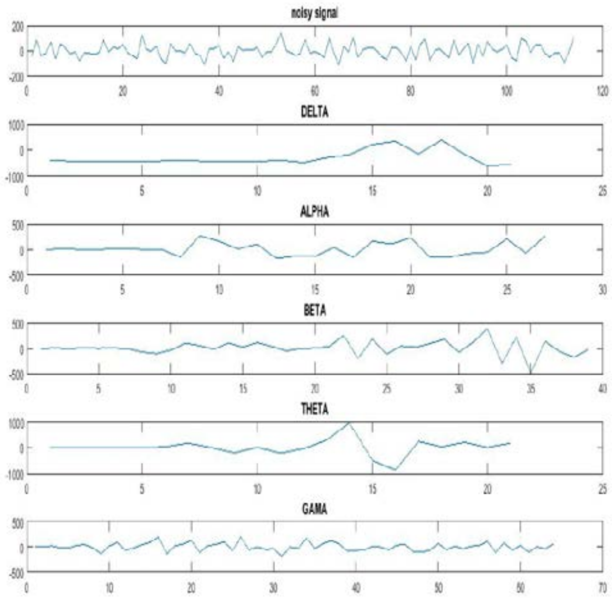

Fig1: Reconstructed Signal of EEG

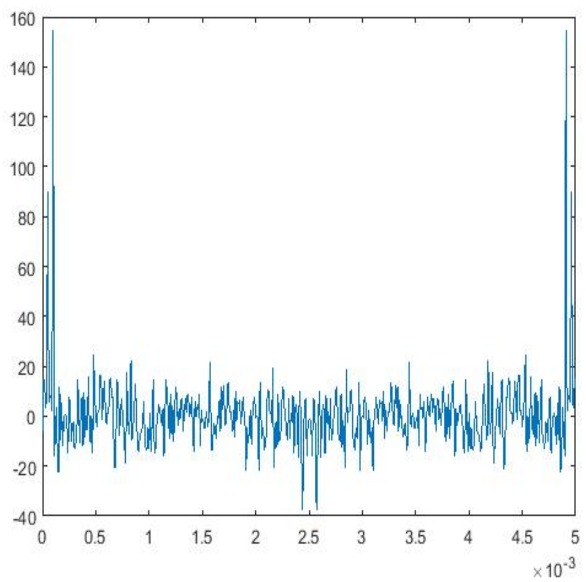

Fig2: Spectral Analysis Using FFT

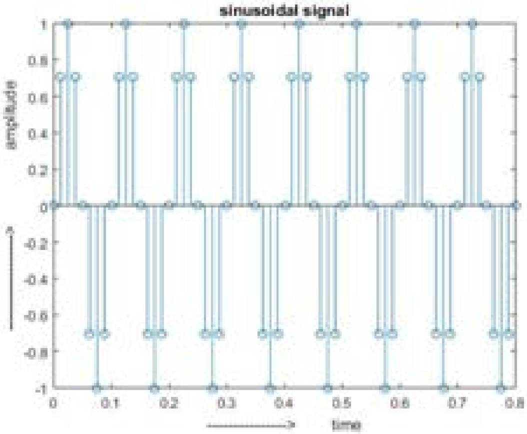

Fig3: sinusoidal signal

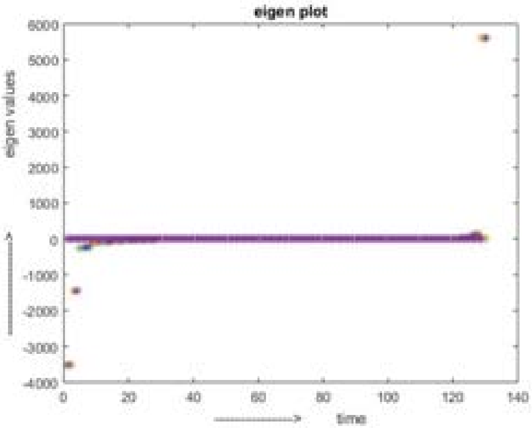

Fig4: Eigen plot

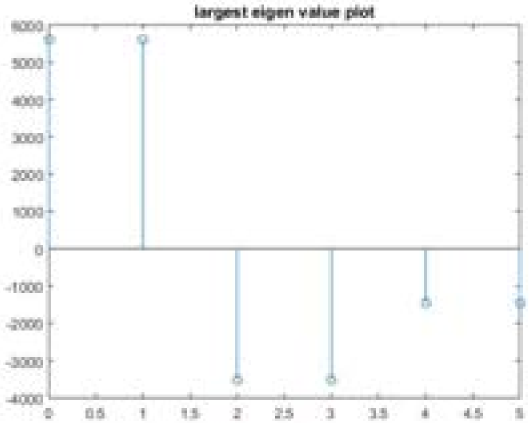

Fig5: Largest eigen value plot

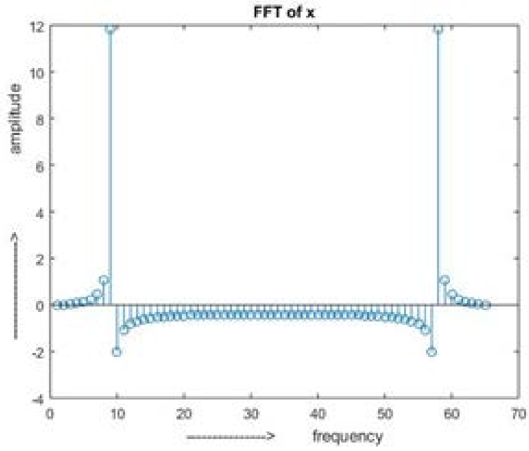

Fig6: Fast Fourier transform of x

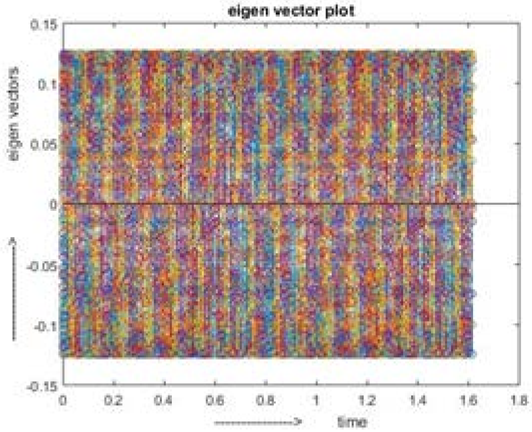

Fig7: Eigen vector plot

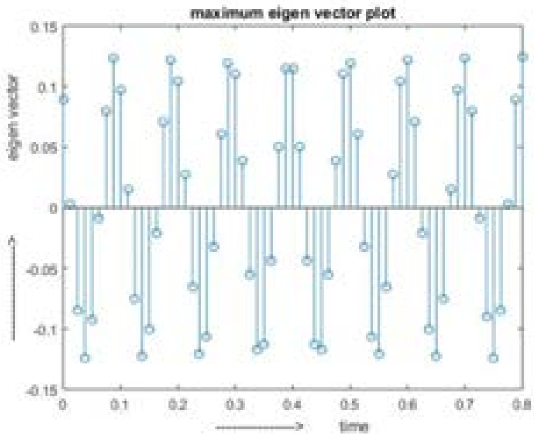

Fig8: Maximum eigen vector plot

V. CONCLUSION AND FUTURE SCOPE

In the thesis, EEG signal processing algorithm is KLT. The thesis through comparing of KLT, DCT (discrete cosine transform) and DFT (discrete Fourier transform) of signal rebuild, to compare to each other between the KLT and the ability of re-establish signal. Under the few frequencies, the KLT is the best one. This is also proves the KLT has a good de-correlation and a high energy concentration.

In the thesis, we achieve the WT and KLT joint de-noising. The paper also gets the emulation result as we needed. The emulation result shows that this proposal is feasible.

EEG waves classification is achieved using an accurate and highly distinguishable technique WT and KLT.

This method offers more efficiency than previous works, which it can be easily distinguished between EEG waves.

WT and KLT are all have a wide application area, we believe that in the near future, these two algorithms will have a more excellent performance than main stream algorithm (Fourier transform) now.

REFERENCES

[1] Jeena Joy, Salice Peter et al., “Denoising Using Soft Thresholding,” International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol 2, issue 3,pp. 1027-1031, March 2013.

[2] Geeta Kaushik et al., “Biomedical Signal Analysis through Wavelets : A Review,” International Journal Of Advanced Research in Computer Science And Software Engineering, vol. 2, issue 9, pp. 422-428, September, 2012.

[3] Priyanka Khatwani, Archana Tiwari, “A Survey on Different Noise Removal Techniques Of EEG Signals,” International Journal of Advanced Research in Computer and Communication Engineering, vol. 2,issue 2, pp. 1091-95, February 2013.

[4] Gnonnou. C, Smaoui. N, “Segmentation and 3D reconstruction of MRI images for breast cancer detection” Image Processing, Applications and Systems Conference (IPAS), 2014 First International on 5-7 Nov. 2014

[5] Abbasi. S, Tajeri Pour. F, “A hybrid approach for detection of brain tumor in MRI images” Biomedical Engineering (ICBME), 2014 21th Iranian Conference on 26-28 Nov. 2014.

[6] X.G. Xia and B.W. Suter, “On vector Karhunen-Loeve transform and optimal vector transforms,” IEEE Trans. CSVT, Vol. 5, pp. 372-374, Aug. 1995.

[7] A. Subasi, “EEG signal classification using wavelet feature extraction and a mixture of expert model,” Expert Systems with Applications, vol. 32, no. 4, pp. 1084–1093, 2007. View at Publisher · View at Google Scholar · View at Scopus.

[8] J. R. Panda. , " Classification of EEG signals using wavelet transform and support vector machine for epileptic seizure activity", Proceedings of International Conference on Systems in Medicine and Biology, 2010.

[9] Claudio Maccone, "advantages of Karhunen-Loeve transform over fast Fourier transform for planetary radar and space debris detection", International academy of Astronautics, Via martorelli 43, Torino(TO) 10155,Italy. Available online 27 October 2006.

[10] Jolliffe, I. T., *Principal Component Analysis*, 2nd edition, Springer, 2002.

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