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Curvelet Transform Based EEG Signal Analysis Using Pca

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***Abstract**: The knowledge of Brain-Computer Interface (BCI) provides a direct exchange of information from the human brain and external devices. In BCI design structure, electroencephalography (EEG) identifies to be the major deliberately calculate the recordings of brain activity. Our proposed method is used to extract and analyze the characteristics of the EEG signal. They organize signal for BCI can be discriminate against and serve up human emotions. The projected method recognizes EEG information retrieving and computing feature extraction and classification. These signals have dissimilar frequency stages for Data waves, theta, alpha and beta. The combination of curvelet transforms (CT) and the principal component analysis (PCA) compute the dimensionality minimize and optimal characteristic extraction. The categorization of EEG signals, ANN (Artificial Neural Network) impact on this process of classification. This paper also provides a similarity between the projected two tools PCA and CT, with a combination of ANN.*

***Keywords** : BCI, EEG, Curvelet Transform, PCA, ANN.*

I. INTRODUCTION

The brain's regular outcome procedures of peripheral nerves and muscles, communiqué systems do not base on BCI [1]. This method enters to manage brain electrical activity through electroencephalogram signals [2]. The BCI schemes depend on the inquiry of impulsive EEG signals. The BCI structure is taken as a prototype identification process, the EEG identification system mostly using for the characteristic mining and classification of signals [3]. The majority of existence BCI methods using for extracting impulsive EEG signals. This process based on autoregressive models for signal analysis. The autoregressive models working with the combination of different transform techniques like short-time wavelet transform, fast Fourier transform and Fourier transform. The autoregressive models cannot imprison the passing features in an input signal. The parameters of these models are not present in the proper way for analysis of signals. The statistical information analysis of the PCA technique used feature mining and data reduction for signal classification [7].

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The rest of the paper is preparing as follows. Section 2 presents the EEG Signal recovery with an informative description. Section 3 is stating EEG characteristic extraction techniques. Section 4 represents ANN classification of the signal, section 5 provides simulation outcome is discussed, and finally, section 6 concludes the paper.

II. EEG DATA RECOVERY

In this paper, the analysis of EEG signals can use a data set denoted as A – E. Every data set containing 100 single-channels EEG signals of the 24.5 S [5]. In this processing, the sampling rate of information is 174.31s evaluated. The time series attainment scheme gain 0.6 Hz to 86 Hz. In this process, the initial step of analysis of the low-pass filter is 41 Hz. The following sets A and B EEG recordings are taken from the surface of 5 good elements with open and closed eyes. The remaining two sets calculated five patients in the epileptogenic zone (D). The high camp arrangement shows conflicting hemisphere of the brain (C). The set E consists of an attack action, and it chosen from all recording sites exhibit actual action [4]. Among these data sets, A and B recorded as extra cranial and C, D, E recorded as intracranial. [6].

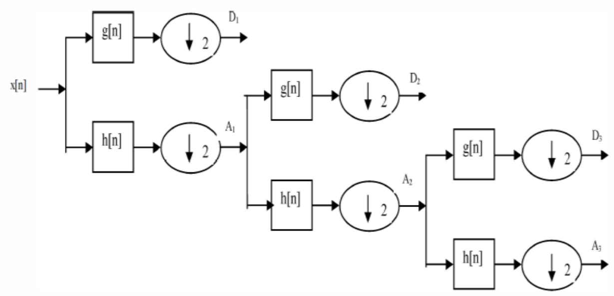

Figure l. Decomposition of discrete curvelet transforms sub band

III. EEG CHARACTERISTIC EXTRACTION TECHNIQUES

III.A. Curvelet Transform

Discrete Curvelet transform has good signal properties, it is applicable for many real signals, and it is also computationally efficient. For these reasons, it is applicable for multi-purposes, including pattern recognition image compression, numerical integration and noise reduction [10].

A lesser amount of orthogonal functions can express the main part of the signal. The main unit signal in the new field is understandable. A curvelet transform takes apart from the further co-relational family of wavelet transforms by the degree of localization of dissimilar scales. The fine-scale functions are extending ridges; the basic form of a scale at j is 2^{-j} by $2^{-j/2}$.

These good scales are angular ridges with a tremendously strong-minded orientation of a result [9].

The discrete curvelet transforms using different filtering methods in digital signal processing concerning time and space. This process, based on a variety of cutoff frequencies with multiple scales, applied to process the signal. These filters carry out the functions for processing the raw signal to avoid noise. Different scales recognized for using slow and fast sample techniques. Therefore, the applied high and low pass filters in excess of a digitized input signal [8].

The following function helpful to signify an image with passion values in discrete curvelet transform f (x_1, x_2), $x_1 = 0, 1,..., M_1 - 1$, $x_2 = 0, 1,..., M_2 - 1$, based on this function, we define the discrete Fourier transform

$$\overline{f}\,(m_1, m_2)\,,\ \sum_{y_2=0}^{M_2-1}\sum_{y_1=0}^{M_1-1} f(y_1, y_2)e^{-2\pi i\left(\frac{M_1 y_1}{M_1}+\frac{M_2 y_2}{M_2}\right)} \quad \ldots\ldots (1)$$

The following function for discrete curvelet transform not integrated with curvelet coefficients.

$$f\,(m_1,m_2)= \sum_{j=1}^{j}\sum_{l=0}^{L_j-1}\sum_{k_1=0}^{K_{jl,1}-1}\sum_{k_2=0}^{K_{jl,2}-1} c_{jlk} s_{jlk}\,(y_1,y_2) \quad \ldots\ldots (2)$$

Where $k= (k_1, k_2)$, s is the curvelet on point j with direction l and spatial shift k.

$$\sum_{jlk} |C_{jilk}|^2 = \sum_{y1,y2} + |f(y_1, y_2)|^2 \ldots\ldots (3)$$

The following function for discrete curvelet transform not integrated with curvelet coefficients of the signal f into J whole stages, i.e.

$$\sum_{jlk} |C_{jilk}|^2 = \sum_{y1,y2} + |f(y_1, y_2)|^2 \ldots (4)$$

The following function for discrete curvelet transform not integrated with curvelet coefficients of the signal f into J whole stages, of the curvelet s is described through its discrete transform as

$\bar{s}_{jok}(m_1,m_2) = U_j(m_1,m_2) \quad e^{-2\pi i}(k_1m_1 / K_{j0,1}+ k_2m_2 / K_{j0,2})$ and $\bar{s}_{jlk} = S^T\theta_1\bar{s}_{jok}$ ………………………….. (5)

Here, S_θ is term as shear matrix, which stands for lattice on the curvelet is assessing by an angle $\varnothing_l$.

III. B. PCA Technique

The principal component analysis is a good technique for optimal feature construction for the classification of signals. Due to the best computational capability of PCA, it constructs the best feature set with fast processing capability. Let vector of input samples taken from the training set and determine an optimal feature set at zero means. The generated mean value subtracts from every feature of the signal. This process mutually uncorrelated features is [8]

$F[b (i) b (j)] =0$, for $i \neq j$;

Let

$$b=B^Ta \quad \ldots\ldots (6)$$

We assumed that $F[a] = 0$, now eagerly seen that $F[b] = 0$. We get from the correlation matrix,

$$R_A \equiv F[bb^T] = E\,[B^T a\, a^T B] = B^T R_a B \quad \ldots\ldots (7)$$

R_A is expected matrix as provide the middling set of training vectors.

$$R_a \approx \frac{1}{n}\sum_{k=1}^{n} a_k a^T{}_k \ldots\ldots (8)$$

R_x is a symmetric matrix, then the Rx and then Ry is diagonal.

$$R_b=B^TR_aB=\Lambda \quad \ldots\ldots (9)$$

Where Λ is the diagonal matrix the respective Eigenvalues $\lambda_{i,\,i} = 0, 1,\ldots\ldots M-1$, of R_a.

For 0 mean variables, the association matrix R parallel with the covariance matrix $\sum$. The definition is as,

$$\textstyle\sum_a=R_a-F[a]F[a]^T \quad \ldots\ldots(10)$$

In case 0 mean guessing is not valid, then state for not associated variables follows

$F[(X(i) - F[(X(i)])\,(X(j) - F[X(j)])] = 0$, for $i \neq j$; ……………..….(11)

The issue outcome in the Eigen breakdown of the covariance matrix is

$$\textstyle\sum_b =B^T\sum_a B=\Lambda \quad \ldots\ldots(12)$$

The MSE calculation is given as

$a=$ $\mathbf{c}_i$ and $b\,(i) =\mathbf{c}^T{}_i a$ ……….........…....(13)

In m dimensional subspace a vector is defined as follows

$$\mathbf{a}^\wedge=\sum_{i=0}^{m-1} b(i)\mathbf{c}_i \quad \ldots\ldots(14)$$

We estimate x by its outcrop $x^\wedge$ and outcome MSE is generated as

$$F[\|a - a^\wedge\|^2]=F[\|\sum_{i=m}^{N-1} b(i)a i\|^2] \ldots\ldots(15)$$

From the equation (15), we have

$$F\ [\|\sum_{i=m}^{N-1} b(i)ci\|^2] = F\ [\ \textstyle\sum_i \sum_j\ (X(i)\mathbf{c}^T{}_i\ )(X(j)\ \mathbf{c}_j\ ) = \sum_{i=m}^{N-1} F[X^2(i)]=\sum_{i=m}^{N-1} F c_i{}^T{}_i F[xx^T \ldots\ldots(16)$$

From equation (16), we finally get

$$F[\|a - a^\wedge\|^2]=\sum_{i=m}^{N-1} c^T{}_i\lambda_i\mathbf{c}_i=\sum_{i=m}^{N-1}\lambda_I \ldots\ldots(17)$$

To discover the best m-directional subspace and the MSE estimation is

$$X^\wedge=\sum_{i=0}^{m-1} b(i)\mathbf{c}^\wedge{}_i+\sum_{i=m}^{N-1} bi\,\mathbf{c}^\wedge{}_I, \qquad b\,(i) \equiv \mathbf{c}^\wedge{}_i{}^T \ \cdots\ (18)$$

The outcomes orthogonal contain eigenvectors of the covariance matrix, the equivalent PCA Eigenvalues of $\sum_a$. The PCA constants are similar to

$b_i = F[y(i)]= \mathbf{c}^\wedge{}_i{}^T F[x]$, i =m,……M-1

The new developed algorithm is presented, it is utilized to a best characteristic set discovery procedure quicker is presented below [10].

```
Algorithm: PCA
Input: D1, Dataset;
Output: the best characteristic assortment.
begin
 function [eeg signals, PCA_1, Y] = pca (D1)
{
    [R, S] = size (D1);
     avg =mean (DATA, 2);
      D1    = D1 – r (avg, 1, S)
     covariance = 1 / (Q-1) * D1 * D1';
     [PCA_1, Y] = eig_vect (covariance matrix);
    X = diag(Y);
    [junk, r1] = sort eig_vect (-1*Y);
Y = Y (r1);
    PCA_1 = PCA_1 (:, r1);
    signals = PCA_1' * D1;
  }
```

feature vector = max (PCA_1);
end

IV. ANN CLASSIFICATION

ANN domain connected to biological networks; it looks like the human brain structure of connections [3]. The significant properties of the artificial neural network with its capability and learn from previous states, to generate a particular outcome when feeding with positive given input. After learning, modification of their associated weights and their complete throughput correlate to a preferred throughput defined by the set of training samples in neural networks. The previous output support generates new out coming output from previous input. In the training network selected suitable previous one and generated optimal output. If the generated output is not correct, then change the training values based on an algorithm. This training continued for another training model; it will continue until the network reached to the stable state [4].

Table 1. Characteristics extracted from five data sets

Data set	Featured Extracted	D1	D2	D3	D4	A4
Set A	Standard Deviation	5.698	20.336	53.57	89.37	116.70
	Mean	-0.04931	0.13589	-0.7432	1.1128	28.2345
	Maximum Coefficient	27.86	67.234	155.062	211.487	389.321
	Minimum Coefficient	-20.123	-69.762	-153.23	-244.12	-425.21
Set B	Standard Deviation	6.98	24.35	64.21	99.42	144.23
	Mean	-0.02356	-0.00546	1.0923	2.9786	19.5486
	Maximum Coefficient	35.234	104.765	238.765	120.644	642.932
	Minimum Coefficient	-32.023	-86.876	-236.543	-249.654	-352.768
Set C	Standard Deviation	3.12	10.23	35.47	89.76	170.65
	Mean	0.0345	0.042	0.2943	-4.5432	-73.432
	Maximum Coefficient	93.456	31.908	116.432	250.654	371.234
	Minimum Coefficient	-12.432	-41.34	-110.43	-354.76	-283.453
Set D	Standard Deviation	3.0987	8.1243	20.456	38.976	103.45
	Mean	-0.02356	-0.00546	1.0923	2.9786	19.5486
	Maximum Coefficient	35.234	104.765	238.765	120.644	642.932
	Minimum Coefficient	-32.023	-86.876	-236.543	-249.654	-352.768
Set E	Standard Deviation	66.698	277.336	274.57	869.37	1236.70
	Mean	-0.34931	0.33589	21.7432	-41.1128	198.2345
	Maximum Coefficient	257.86	937.234	1955.062	1711.487	2789.321
	Minimum Coefficient	-320.123	-1269.762	-2153.23	-2744.12	-2925.21

V.RESULTS AND DISCUSSION

In this paper, two types of observations operated for the before and after downsampling. 102 series data available in every data set, which contains 4098 data samples. The first observation of basic data contains 4098 samples of every series. It used for directly extracting the feature using curvelet transform. The second observation describes discrete data of 256 chosen with a rectangular window. After the observation sampling to 102 series data set and overall 1650 vectors obtained from every data set. Retrieved information used for characteristic extraction by PCA. Figure 2 displays the following outcome downsampled.

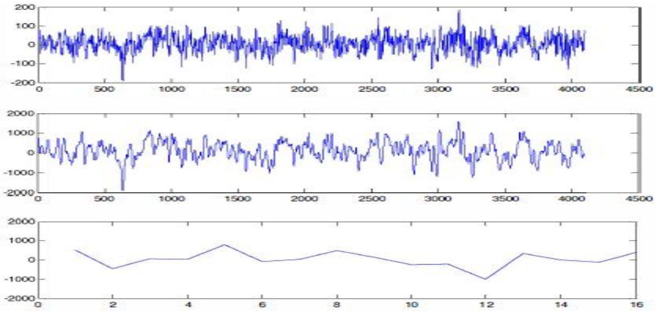

Figure 2. EEG curve form earlier and later downsampling

In table 1 given for every model of the outcome get after characteristic extraction. ANN classifier using for measurement of feed-forward neural network with multiple hidden layers with the final outcome layer. It trained with the backpropagation algorithm for computing weights. The asymmetric sigmoid function used for activation of entire units using MATLAB. The following table provides the comparison of DCT, PCA with a combination of ANN classifier.

Table 2. Comparison of DCT and PCA applied on ANN throughput

Parameters	DCT and ANN	PCA and ANN
MSE Training	0.1912	0.0923
MSE Testing	0.1	0.0952
Time in Sec.	70.57	143.23
Classification %	97.32	95.2

V. CONCLUSION

Electroencephalography identifies to be the majorly deliberate for calculate the recordings of brain activity. Our proposed method used to extract and analyze the characteristics of the EEG signal. They organize signal for BCI can be discriminate against and serve up human emotions. The projected method recognizes EEG information retrieving and computing feature extraction and classification. These signal dissimilar frequency stages for Data waves are theta, alpha and beta. The combination of curvelet transform and the principal component analysis compute the dimensionality shrink and optimal characteristic extraction. The classification of EEG signals, Artificial Neural Network impact on this process of classification. The artificial neural network is working optimally with the combination of curvelet transform and principal component analysis.

REFERENCES

1. G Shivangi R. Mishra, S.B. Somani, and Pranjali Deshmukh, "EEG signal processing and classification of sensorimotor rhythm-based BCI", international Journal of Engineering Research & Technology, vol. I, Issue 4, 2012.
2. Ting Wu, Banghua Yang and Hong Sun, "EEG classification based on artificial neural network in brain computer interface", Communications in Computer and information Science, vol.97, pp 154-162, 2010.
3. Pari Jahankhani, Vassilis Kodogiannis and Kenneth Revet!, "EEG signal classification using wavelet feature extraction and neural networks", IEEE John Vincent Atanasoff international Symposium on Modern Computing, oct.03-06, 2006.

4. Dipti Upadhyay, "Classification of EEG signals under different mental tasks using wavelet transform and neural network with one step secant algorithm", international Journal of Scientific Engineering and Technology, vol.2, Issue 4, pp: 256-259, 20 l3.
5. C. Bugli, P. Lambert, "Comparison between principal component analysis and independent component analysis in electroencephalograms modelling", Biometrical Journal, 48, 2006.
6. Lan-Lan, Chen, Jun-Zhong, Zou, Jian, Zhang, Chun-Mei Wang, Min Wang, "EEG feature extraction during mental fatigue and relaxation by principal component analysis", Advances in Cognitive Neurodynamica(J), pp 371-374, 2011.
7. Abdulhamit Subasia, M. Kemal Kiymika, Ahmet Alkana, Etem Koklukayab, "Neural network classification of EEG signals by using AR with MLE preprocessing for epileptic seizure detection ", Mathematical and Computational Applications, vol. 10, no. 1, pp. 57-71, 2005.
8. Subhani Shaik and Dr. U. Ravibabu "EEG Signals Analysis for motor imagery based on Curvelet Transform" Paper selected for IJARCS (UGC approved Journal) publishing, March- April 2017.
9. Subhani Shaik and Dr. U. Ravibabu "Classification of EMG Signal Analysis based on Curvelet Transform and Random Forest tree Method" Paper selected for Journal of Theoretical and Applied Information Technology (JATIT), Vol 95, December, 2017.
10. Subhani Shaik and Dr. U. Ravibabu, "Curvelet based Signal Detection for Spectrum Sensing using Principal Component of Analysis", in the 2nd IEEE International Conference on Engineering and Technology (ICETECH-2016) held at Rathinam Technical Campus, Coimbatore, India from 17th & 18th March 2016.

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