International Journal of Engineering

Journal Homepage: www.ije.ir

A Unique Approach of Noise Elimination from Electroencephalography Signals between Normal and Meditation State

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PAPER INFO

Paper history:
Received 24September 2017
Received in revised form 04November 2017
Accepted 28December 2017

Keywords:
Singular Spectrum Analysis
Eigen Values
Electroencephalography

ABSTRACT

In this paper, unique approach is presented for the electroencephalography (EEG) signals analysis. This is based on Eigen values distribution of a matrix which is called as scaled Hankel matrix. This gives us a way to find out the number of Eigen values essential for noise reduction and extraction of signal in singular spectrum analysis. This paper gives us an approach to classify the EEG signals between normal condition (Controlled) and meditation condition, the extraction of various patterns, the EEG signal filtering and the noise removal from the signals. Different parameters are used as features for classification during subject's normal EEG segments and at the time of practicing Meditation. The results showed positive approach for noise removal in both EEG signals.

***doi**: 10.5829/ije.2018.31.04a.06*

1. INTRODUCTION[1]

Nowadays technological advancement in the science and technology field and advancement of lifestyle revolutionized human life at the extremely surprising level. But as every coin has two sides, these leads to great emotional and mental stress. Even the same situation seen in developed countries.

Poverty, racial discrimination, threats due to war and terrorism, drug addictions are the problems face by each and every country of the globe.

Is there a way to come out of all these threats for mental peace? Undoubtedly, the answer is yes. Vipassana Meditation is among such a method. This is a type of mindfulness meditation.

Electrical activity of the brain signals is called Electroencephalograph. Brain is the most complex computing system in the world. EEG signal is one of the important non-invasive methods for determining the behaviour of human brain.

It is useful for analysis of various neurological abnormalities. It is not only showing us brain function but also giving us the mental state of the human being and all body functions [1]. Moreover, the recorded EEG plays a vital role in the study of impact of meditation on human. Even with the help of EEG signal doctor be able to diagnose brain death [2].

These EEG signals are used as an important tool for study and research related with brain; but recorded signals always affected by different artifacts and noises, which is the main hurdle in the correct analysis of brain waves. Since, EEG signal's amplitude are very low (in the order of few microvolt's), it can be easily affected by noise. These noises can be generated due to electrical interference, or because of our body conditions [2]. Furthermore, muscle activities, blinking of the eyes are the different artifacts which are responsible for noise in EEG recording. It is always a complex task of detecting and reducing such noise from EEG recording. Even though Noise can affect EEG Signals, which has, unknown characteristics but they can be detected if the signal and noise subspaces are accurately separated. It is essential to remove noises and artifacts from the EEG signals for analysis and classification of EEG signals during Meditation and controlled states. There are various method implemented for reducing or removing noise from EEG signals such as independent component analysis (ICA) [3-5], principle component analysis (PCA) [6-8]and wavelet transforms (WT) [9].

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Please cite this article as: R. Ingle, R. Awale, A Unique Approach of Noise Elimination from Electroencephalography Signals between Normal and Meditation State, International Journal of Engineering (IJE), IJE TRANSACTIONS B: Applications Vol. 31, No. 5, (May 2018) 719-728

The complex dynamical systems are described by complex mathematical theory such as Chaos theory. In all Nonlinear Dynamical System, Chaotic behaviour can be observed [10]. Brain is also considered to be such nonlinear dynamical system of the body. An EEG signals is considered as a nonlinear time series, particularly when subjects are doing meditation, hence it can be considered as being chaotic in nature [10, 11]. Therefore, there are condemnatory chances to segregate unusual attractors in brain signals [12]. Furthermore, brain signal decomposition is also an important tool for identifying state of Meditation and control state from EEG signals. The extracted details from recorded EEG signals helpful for the identification of state of meditation. It is also a great challenge in analysing EEG signals when subject is in state of meditation, since recorded data is mostly non-stationary, especially when an unusual event is observed within the signals. Various methods have been employed for the analysis and discrimination of different categories of EEG signals. However, many of those available methods mainly depend on the limited known assumptions of the normality and linearity of the observed data. Thus, development of a new method, which is robust for analysing nonlinear, non-stationary time series data, is of prime importance in precise identification of state of Meditation. The singular spectrum analysis (SSA) technique can be useful for modelling and Analysis of physiological signals, since it is not based on these assumptions [13, 14].

Singular spectrum analysis is a comparatively new technique, which is used and developed specially for solving several problems related with biomedical field. One of the best example for this method is, it has been used for extracting weak ECG signals from Raw ECG signals contaminated by several noises [13]; discrimination of physiological signals such as electromyography (EMG) contaminated by electrocardiogram (ECG) [14]; various applications in image processing [15]; gene expressions from microarray of DNA [16]; detection of seizure from EEG signals of the infant [17]; and drowsiness and sleep detection from EEG data [18].

The primary focus of singular spectrum analysis is to analyse the main time series. Then, for further analysis, reconstructing this time series free from noise. It mainly relies upon two things for reconstruction; namely, the required number of Eigen values, represented by *r* and the window length represented by *L*. Thus, for accurate analysis and separability between time series components, proper selection of Eigen values (*r*) and window length (*L*) is essential. Here, it is necessary to select large value of window Length (*L*) but the condition is, it should be smaller than half of the time series[13]. As such there are no direct method for selection of optimal *L* and *r*; hence trial and error procedure can be adopted for obtaining optimal values of *L* and *r*.

In this paper, we have proposed an approach for the selection of the Eigen values (*r*) for filtering and reduction of noise from actual signal. This method mainly used to find out the required number of singular values/ Eigen values that correspond to the signal components. Those signal components mainly rely on Eigen value distribution using a matrix termed as scaled Hankel matrix. The statistical parameters such as kurtosis and skewness coefficients along with variation in the Eigen values distributions are used in this method. It is proved to be a new and efficient way, which can separate signal and noise components as it, divides the Eigen Values (*r*) into two groups. Several real time signals as well as simulated signals are used during this approach. The effectiveness of this method for Eigen values (*r*) selection is verified using these signals.

Here, in this paper, we developed a unique way for distinction of EEG signals during meditation and controlled states. It is also used for EEG signal filtering, reduction and elimination of noise from the signals.

This paper is organised as follows: Section 2 brief about the proposed method along with its algorithm. Section 3, presents the approach can decompose the synthetic data into two different subspaces. Section 4 describes how this method filters noise from EEG signals, extracting various patterns and features, and distinction between EEG signals during meditation and controlled states. Section 5 brief the conclusion and ideas for future.

2. THE PROPOSED METHOD

2. 1. Brief Description In this part, brief introduction of the method used in this work is explained. A Singular Spectrum Analysis is used for decomposing time series signal into a sum of its components either as noise or as actual signal. In the proposed method, our primary focus is to consider the complete signal to identify the proper Eigen Values (*r*) related to the signal component. Hence, selection of *L* is least important rational to the periodicity of the signal components [15]. Therefore, the method mostly focuses on the selection of Eigen Values (*r*) for identification the signal subspace.

Let us consider a one-dimensional series be represented as $Y_N = (y_1, y_2, ...y_N)$ having length *N*. As the above series shifted into a multi-dimensional series as $X_1, X_2, ..., X_K$,where $X_i = (y_1, y_2, ..., y_{i+L-1})^T \in R^L$ provides $X = (x_{i,j})_{i,j=1}^{L,K}$.This *L* is an integer whose value varies as $\left(2 \le L \le N/2\right)$ whereas the value of *K* is given as $K = N - L + 1$. This *X* is called a Hankel matrix. All diagonal elements of the Hankel matrix are $i + j =$ constant are same. Consider $B = XX^T$, and its Eigen values are denoted by λ_i where $(i = 1, 2, ..., L)$. The Eigen values of the matrix *B* is taken in decreasing order of its magnitude $(\lambda_1 \geq \lambda_2 \geq ....\lambda_L \geq 0)$ and the orthonormal system of Eigen Vectors of Matrix B corresponding to these Eigen Values are represented by $U_1, U_2, ..., U_L$.

The Single Value Decomposition (SVD) of Hankel Matrix X can be stated as:

$$X = X_1 + X_2 + ... + X_L \tag{1}$$

where, $X_i = \sqrt{\lambda_i} U_i V_i^T$. This combination of $(\sqrt{\lambda_i}, U_i, V_i^T)$ is called the Eigen triple of Single Value Decomposition. The Hankel Matrix X_i has rank *1*. The left and right Eigen Vectors of Hankel Matrix are denoted by U_i and V_i respectively. Here, we have to note that Frobenius Norm of Hankel Matrix is given by $\|X\|_F^2 = tr(XX^T) = \sum_{i=1}^{L} \lambda_i$ and $\|X_i\|_F^2 = \lambda_i$.

In Eigen Value behavior, series size is directly proportional to the Eigen values (λ_i). This indicates if series size increases then Eigen values also increases. This trouble can be overcome by dividing matrix *B* by its trace, $A = B / tr(B)$, which leads to several important properties. Consider, $\zeta_1, \zeta_2, ..., \zeta_L$ indicates Eigen values of Matrix *A* in decreasing order of magnitude $(1 \geq \zeta_1 \geq \zeta_2 \geq ... \geq \zeta_L \geq 0)$. Hence, the simulation technique is used to get distribution of ζ_i and to regulate the responses of each Eigen Value which will help us to find out the value of *r*. Here, main aim is to set up distribution and related form of ζ_i which is helpful for selecting correct value of *r* for removing noise from EEG signal.

The data reported in literature [14] shows that, the largest Eigen value has a positive skewed dispersal for a white noise process. Thus, for high skew(ζ_c) $(c \in \{1, 2, ..., L\})$, and identical pattern in skew(ζ_c) to skew(ζ_L), the same may be revealed for the white noise, then the initial (*r = c – 1*) Eigen values corresponds to the signal components and remaining to the noise. Same method can be use for the coefficients of kurtosis and variation of ζ_i. If $\rho_s(\zeta_{c-1}, \zeta_c)$ is the minimum, and the pattern for the set $\{\rho_s(\zeta_i, \zeta_{i+1})\}_{i=c}$ is identical to what was observed for the white noise, then we select the first *r = c−1* Eigen values for the signal and the remaining for the noise component.

In this paper, the concentration is mainly based on the distributed 3rd and 4th measures moments. Those are the Skewness (*Skew*) and kurtosis (*Kurt*). Skewness is actually a measure of the asymmetry of the probability distribution of a real- valued random variable about its mean and kurtosis is a measure of the "tailedness" of the probability distribution of areal-valued random variable. Kurtosis is a descriptor of the shape of a probability distribution. These are used for selecting the values of *r*, which can be calculated for m simulation as follows:

$$Skew(\zeta_i) = \frac{\frac{1}{m}\sum_{n=1}^{m}\left(\zeta_{i,n} - \overline{\zeta_i}\right)^3}{\left[\frac{1}{m-1}\sum_{n=1}^{m}\left(\zeta_{i,n} - \overline{\zeta_i}\right)^2\right]^{3/2}} \tag{2}$$

$$Kurt(\zeta_i) = \frac{\frac{1}{m}\sum_{n=1}^{m}\left(\zeta_{i,n} - \overline{\zeta_i}\right)^4}{\left[\frac{1}{m}\sum_{n=1}^{m}\left(\zeta_{i,n} - \overline{\zeta_i}\right)^2\right]^{2}} - 3 \tag{3}$$

The ratio of the standard deviation of Eigen Value $\sigma(\zeta_i)$ to the average of Eigen value ($\overline{\zeta_i}$) is termed as coefficient of variation (*CV*). Mathematically it is given by following formula:

$$CV(\zeta_i) = \frac{\sigma(\zeta_i)}{\overline{\zeta_i}} \tag{4}$$

The cut-off point of separability is given by the measures of difference between the Eigen values of Signal and Noise components. These give the number of Major *SVD* components that are separated from residual.

With the help of above criteria, the Eigen values can be divided into two groups; the first in Signal component and other in noise component. Moreover, for supporting the outcome obtained by above measures, the Spearman correlation ρ between ζ_i and ζ_j is also calculated. The absolute value of the correlation coefficient is considered *1* which shows that ζ_i and ζ_j has exact positive correlation, but when it is *0*, then it shows that there is no correlation between them. The matrix obtained from the Spearman correlation (ρ) of its absolute value is helpful in the complete analysis of the trajectory matrix. During the analysis, each Eigen value belongs to each elements of the SVD elementary matrix. It is observed that, if the absolute value of Spearman correlation ρ is close to zero, then the Signal and Noise component are almost orthogonal; however, if it is close to one, then these two components are not orthogonal, which can be tedious task to separate them. Thus, if Spearman correlation $\rho = 0$ between two components which is reconstructed from two main components, then these two reconstructed series are separable. The results of Spearman correlation (ρ)

between the Eigen values are fairly large for the white noise, which can easily segregate signal and noise.

As Eigen Values (r) is decided from the above method, then the matrices X_i can be split into signal and noise components. Equation (1) can be rewritten as:

$$X = S + E \quad (5)$$

where, the $S = \sum_{i=1}^{r} X_i$ is signal component in matrix form and $E = \sum_{i=r+1}^{L} X_i$ is the noise component in matrix. Matrix S is then transformed into new series of size N using average of diagonal elements of matrix S [13].

2. 2. Algorithm This algorithm is implemented in two main steps. In first step, coefficients of kurtosis, skewness, correlation and variation are taken into consideration for finding the optimal value of r. This value is then used to separate signal and noise component as the Eigen values splits into two groups as signal and noise component. In the second step, noise free series is reconstructed.

2. 2. 1. First step

1. *1-D* time domain signal $Y_N = (y_1, y_2, ..., y_N)$ is map into multidimensional series $X_1, X_2, ..., X_K$ having vector $X_i = (y_i, ..., y_{i+L-1})^T \in R^L$, where L denotes integer window length. The value of L varies from $2 \le L \le N/2$ and $K = N - L + 1$.We gets Hankel Matrix $X = [X_1, X_2, ..., X_K] = (x_{ij})_{i,j=1}^{L,K}$ using this step.
2. Then we need to calculate matrix $A = XX^T / tr(XX^T)$.
3. Decompose matrix A as $A = P\Gamma P^T$, where $\Gamma = diag(\zeta_1, \zeta_2, ..., \zeta_L)$ is the diagonal matrix of the Eigen values of A that has the order $(1 \ge \zeta_1 \ge \zeta_2, ..., \zeta_L \ge 0)$ and $P = (P_1, P_2, ..., P_L)$ is an orthogonal matrix whose columns are the corresponding Eigen vectors.
4. Eigen values are calculated by simulating original series m times. Then using uniform distribution with boundaries $y_i - a$ and $y_i + b$, we simulate y_i where $a = |y_{i-1} - y_i|$ and $b = |y_i - y_{i+1}|$.
5. Skewness Coefficient of every Eigen value is computed, skew(ζ_i). For maximum skew(ζ_c), we get identical pattern to white noise for skew(ζ_c) to skew(ζ_L), then we need to select $r = c - 1$.
6. Kurtosis coefficient is calculated for all Eigen values, *kurt* (ζ_i). For maximum value of *kurt* (ζ_c), select $r = c - 1$.
7. Calculate the *CV* (ζ_i). Eigen values gets divided into two parts using the result of coefficient of variation, one from ζ_1 to ζ_{c-1} correspond to the signal, and the other which have a *U* shape, leading to the noise.
8. In the last step, correlation matrix is calculated using Eigen values along with its absolute values. Then it needs to be indicated using a grey scale (of *20-grade*) from white to black. This is analogous to the values of the correlations from *0 to 1*. The derived matrix also divides Eigen values into two parts, from ζ_1 to ζ_r leading to the signal, and rest to the noise.

2. 2. 2 Second Step

1. The Approximated signal matrix $\tilde{S}$ is evaluated as $\tilde{S} = \sum_{i-1}^{r} X_i$. The r is obtained from the first step, and X_i is calculated as $X_i = \sqrt{\lambda_i} U_i V_i^T$. The U_i and V_i present in this equation represents left and right Eigen vectors of the matrix.
2. After taking mean of diagonals of matrix $\tilde{S}$, one-dimensional series is generated. This is the approximate signal $\tilde{S}$.

This was one of the criteria for distinction between controlled and meditated EEG signals. Later we used one more criterion for distinction, which is different from previous one with the help of highest Eigen value.

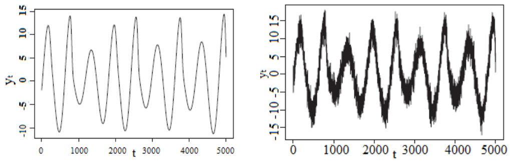
3. SYNTHETIC DATA ANALYSIS

3. 1. Example 1 Let us discuss this validity of proposed method using some examples. An EEG signal contains several components such as noise, other interfering signals and sum sinusoidal components responsible for chaotic behavior. Following two examples is useful for understanding the above two steps procedure.

To verify the relevance of the method, it is used to decay the synthetic series produced from the Rossler system known to us:

$$\begin{cases} \dfrac{dx}{dt} = -y - z \\ \dfrac{dy}{dt} = x + ay \\ \dfrac{dz}{dt} = b + z(x - c) \end{cases} \quad (6)$$

Figure 1a explains $S_N = \{s_t\}_{t=1}^{N}$ of length *N = 5000*. This Signal originated from the Rossler series. Figure1b illustrates $Y_N = \{y_t\}_{t=1}^{N} = S_N + E_N$,where $E_N = \{\in_t\}_{t=1}^{N}$ is called as white noise operation.

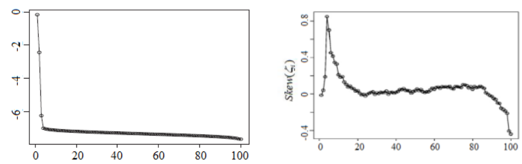


(a) (b)

Figure 1. (a) Rossler Signal. **(b)** Rossler Signal with noise component

In this section noise affected Rossler signal has been shown. Here S_N and E_N represent signal and noise respectively. *SNR* is an important phenomenon on which entire property of the system depends. In this case, the ratio of square of variance of the signal to square of variance of noise is called *SNR* (*SNR* $=\sigma_s^2/\sigma_\epsilon^2$) [18]. Here, *SNR* is = *14 dB*. Analysis using different SNR values are appraise in Section 3.3. In this way, performance of the method and its relevance in recognizing the value of *r* with respect to all noise components are evaluated. Here, proposed method can help us to determine number of Eigen values (*r*) required to eliminate the noise from EEG signal for appropriate analysis.

Addition of m-copies of noise in the Rossler signal, the proposed method is verified. In this case, time series Y_N^m (where *m = 1,...,105*) was analyzed which is not dependent on any other parameter; The window length is initially kept at *L = 100*. The independent signal or series in time domain was studied in depth using pattern of ζ_i (*i = 1 . . ., L*) and its concerned forms of matrix *A*. Figure 2a shows the mean of the Eigen values on logarithmic scale. It can be seen that the first three Eigen values have given excellent result and rest of the Eigen values are seems to be almost close to each others. This is happening because embedding dimension of Rossler system should be minimum three. Each and every singular value (Eigen value) contributes in the decomposition of trajectory matrix. One of the key feature of matrix *Hi* is the ratio $\overline{\zeta}_i \times 100$ to Equation (1). Hence, the $100\times\sum_{i=1}^{r}\overline{\zeta}_i$ is considered as the features of the best approximation of *H* by matrices of rank *r*.



(a) (b)

Figure 2. (a) Logarithm $\overline{\zeta}_i$ of noise added Rosseler Series **(b)** Results of $Skew(\zeta_i)$ versus Eigen values

Here, the analogous Eigen triples to the first three Eigen values can be considered as the key parameters for the original signal, as their ratio is *99*. Figure 2b explains the results of $Skew(\zeta_i)$ versus the Eigen Values.

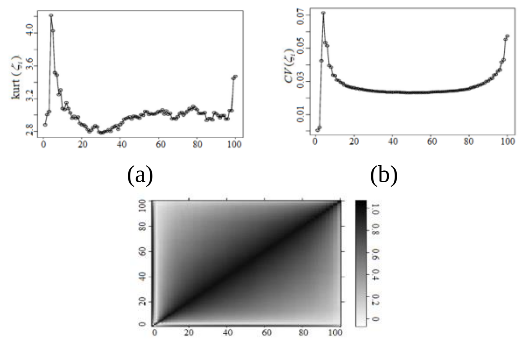
Figure 3a explains the results of $Kurt(\zeta_i)$, Figure 3b explains $CV(\zeta_i)$ and Figure 3c the matrix of the absolute value of ρ also called correlation matrix between the Eigen values.

The curve of skewness versus Eigen values divides the singular values into two parts. It is observed that at $\zeta_{c=4}$ have maximum value of skew. It is also noted that, from $Skew(\zeta_4)$ to $Skew(\zeta_L)$ has the pattern of noise component [19]. Hence, initial three Eigen values are related to the signal component and the remaining to the noise components. Similar results observed with the *Kurt* and *CV* parameters. It is also observed from the Figure 3b that second part of the results has a shape that is related to the noise part [19]. It is clear from Figure 3c that the correlation matrix of first three Eigen values related to Rossler signal and remaining large carbonated square reflecting white noise. Thus, the results of correlation matrix of Eigen Value can give us clear idea for separation of noise and signal component.

The above discussed results are also calculated using the *RMSE* (root mean square error) between the actual signal (Rossler) and the reconstructed signal using Eigen triples *1− i*, (*i = 1,....,100*) as shown in Figure 4a The result shows, that the least value of RMSE obtained for *r=3*, between the reconstructed and the actual signal by Eigen triples *1–3*. The blue line in Figure 4b indicates noise free signal by Eigen triples (*1-3*). The black line indicates original Rossler signal.

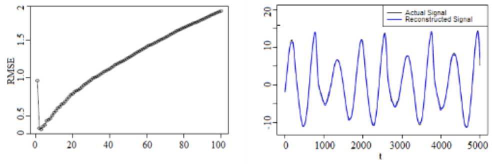
3.2. Example 2 In the second example, two signal components (one is Exponential signal and other is cosine signal) is mix with white noise:

$$y_t = s_t^{(1)} + s_t^{(2)} + \epsilon_t \quad (7)$$



(a) (b) (c)

Figure 3. (a) Results of $Kurt(\zeta_i)$ Versus Eigen values **(b)** Results of $CV(\zeta_i)$ versus Eigen values **(c)** Results of Correlation matrix.



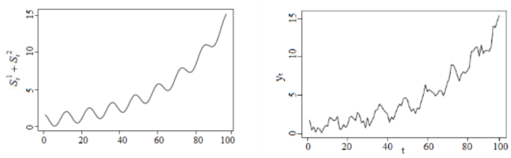
(a) (b)

Figure 4. (a) RMSE between the actual series (Rossler) and its reconstructed series using Eigen Triples **(b)** The reconstructed and original series.

where, $s_t^{(1)} = e^{(\alpha t)}$, $s_t^{(2)} = \cos(2\pi t / T)$, $\in_t \sim N(0,\sigma^2)$, $\alpha = 0.03$, $\sigma^2 = 5$, $T = 12$, and t = 1.....96. In this problem, the total signal consists of exponential component and harmonics. Figure 5a shows a signal component (exponential + cosine series) represented as $s_t^{(1)} + s_t^{(2)}$. Figure 5b shows total signal component y_t, for *SNR = 4.5dB*.

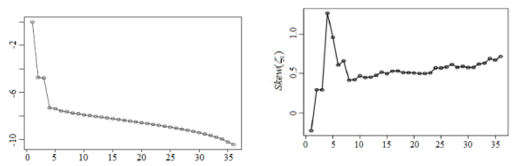
In Figure 6a the mean of Eigen values is described using logarithmic scale for *L=36*. It is clear from the Figure 6a that the value of $\overline{\zeta_1}$ is excellent, while that of $\overline{\zeta_2}$ and $\overline{\zeta_3}$ are near to each other. This is also presume that, the initial Eigen value belongs to Exponential signal and other two (second and third) belongs to harmonic component. In this case, the analogous Eigen triples to ζ_1, ζ_2 and ζ_3 can be appraise as the main components for the original signal as their ratio is approximately *99*. Figure 6.b shows the results of $Skew(\zeta_i)$ between Eigen values.

Figures 7a, 7b, and 7.c show the results of $Kurt(\zeta_i)$, $CV(\zeta_i)$ and matrix of ρ_s between the Eigen values, respectively.



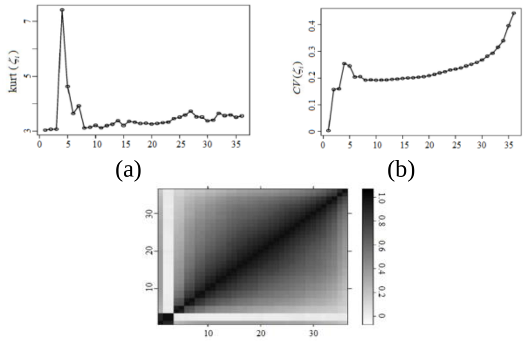
(a) (b)

Figure 5. (a) $s_t^{(1)} + s_t^{(2)}$ (exponential + cosine series) Signal **(b)** Total signal $y_t = s_t^{(1)} + s_t^{(2)} + \in_t$ with white noise



(a) (b)

Figure 6. (a) Logarithm of $\overline{\zeta_i}$ as described in second example **(b)** Results of $Skew(\zeta_i)$ between Eigen values



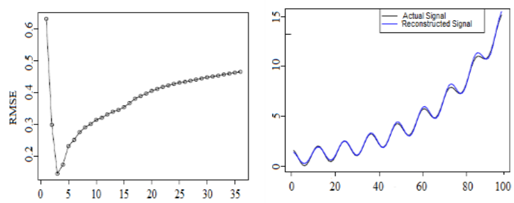
(a) (b)

(c)

Figure 7. (a) Results of $Kurt(\zeta_i)$ between Eigen Values **(b)** Results of $CV(\zeta_i)$ between Eigen values **(c)** Results of Correlation matrix between Eigen values

From the Figure 8a, results shown in this paper are also investigated using Root Mean Square Error between the original signal which is mathematically indicated by $(s_t^{(1)} + s_t^{(2)})$ and the reconstructed signal by Eigen triples *1–i*, (*i = 1... 36*). The result derived from RMSE curve proved that the value of *r* is *3*. Figure 8b illustrates the reconstructed noise free signal by Eigen triples *1-3* which is shown by blue line, and the original signal mathematically given by $(s_t^{(1)} + s_t^{(2)})$ by black line. As per the above discussion and result, optimal value of *r* is selected for the reconstruction and thus this method can be best suited for removing noise from EEG signals.

3. 3. The Impact of Noise Level In context to the foregoing results and for better interpretation of the impact of noise using proposed method, we also consider different *SNR's*. Here the *SNR* is the ratio of square of variance of the signal free from noise to square of variance of noise. Figures 9a to 9e show measure parameter Skew (ζ_i) versus Eigen values curve for different *SNR* values (*SNR's =1dB, 5dB, 10dB, 15dB & 20dB*) for Rossler signal. It is also confirmed from Figures 9.a. to 9e that for distinct values of *SNR*, the highest value of Skew is noticed for $\zeta_{c=4}$, which proved that value of *r* is *3*.



(a) (b)

Figure 8. (a) RMSE between the actual and reconstructed Components using Eigen Triples for second Example **(b)** The reconstructed signal (blue line) and the original signal series (black line) for second Example

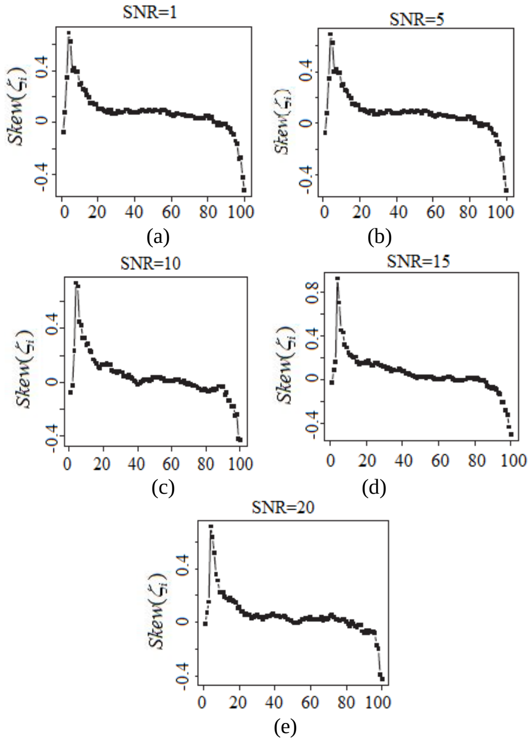


Figure 9. (a) Skewness coefficient Value of Eigen valuesfor Rossler signal when *SNR=1dB* **(b)** Skewnesscoefficient Value of Eigen values for Rossler signal when *SNR=5dB* **(c)** Skewness coefficient Value ofEigen values for Rossler signal when *SNR=10 dB* **(d)** Skewness coefficient Value of Eigen values for Rossler signal when *SNR=15 dB* **(e)** Skewness coefficient Value of Eigen values for Rossler signal when *SNR=20dB*

Identical results are observed by using other measures such as *Kurt*, *CV*, and ρ, thus they aren't described here. This result support that the new method works for any signal that is contaminated by all types of noise.

4. ANALYSIS OF REAL TIME EEG DATA

4. 1. EEG Data Acquisition Real time EEG data signal were used for this research study. The data required for this study were acquired from 8-channel Enobio data acquisition device manufactured by NE, Barcelona, Spain. The reference electrode is connected to ear lobe. The sampling frequency of this device is 500 Hz. This data is acquired from 20 healthy subjects. These subjects include age group from 20 to 60 years with an average age of 40 years of 10 healthy male and 10 healthy female.

The data is recorded for duration of *60* seconds for *20* trials each. The first data set is recorded from Expert meditator (which have more than three *10* days of mediation experience) were doing Vipasanna meditation with eyes closed using a standardized *10-20* electrode placement approach as shown in Figure 10. The second data set contains control signals from the same volunteers when seating at normal position.

Two specimens of the meditation and controlled signals are shown in Figure 11a and their distribution densities in Figure 11b. It is obvious that the distribution of the controlled EEG signals is symmetric, while it is skewed for the meditation EEG signal. It is worth mentioning that all 400 segments of the controlled set have a symmetrical distribution, whereas the meditation signal distribution can be skewed to the right or to the left.

4. 2. Noise Elimination from EEG signals The main aim of the method is to separate EEG signal and noise present in it. Once the optimal value of r is selected, we discriminated an Eigen triple which is responsible for noise in signal components. In this part, only two segments, from the controlled and meditation signals, were used. It is then simulated 104 times and then analyzed for eliminating noise from the EEG signal.

Figure 10. EEG recording during Meditation practice

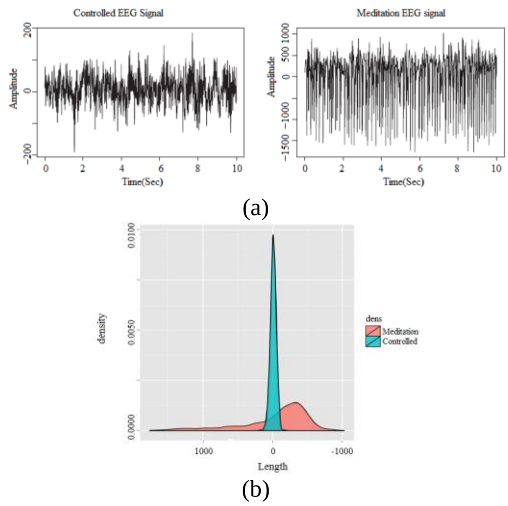


Figure 11. (a) Specimen of the controlled signal (left) andMeditation EEG signals (right) **(b)** Density of Meditation and Controlled Signal

The purpose in this section is to illustrate the application of proposed approach for each segment separation (Normal and meditation) though it will be applied to all segments as described in result section. To create simulated noisy signal with same form, appearance and distribution to the real signal segment we specifically obey the approach already explained in Section 2.2. Even though signal segments are moderately differing from one another, the results obtained in the form of number of Eigen values are same. Initially we examine a signal segment from each subject for learning each EEG signal. On account of this, each signal copy was simulated *104* times. Even the same method can be applicable for other segments too. Identical results were observed by taking each signal segment individually. In this work, the impact of the noise and artifacts are considered.

Figures 12a, 12.c and 12e show the results of the statistical parameters belongs to the normal condition and Figures 12b, 12d, and 12f belongs to Meditation condition. It is sure that the three parameters divide the Eigen values or Eigen triples into two distinct parts (signal and noise). It is clear from Figure 12a that the $Skew(\zeta_{c=52})$ is maximum for normal signal, while it is maximum for meditation signal for $Skew(\zeta_{c=48})$.

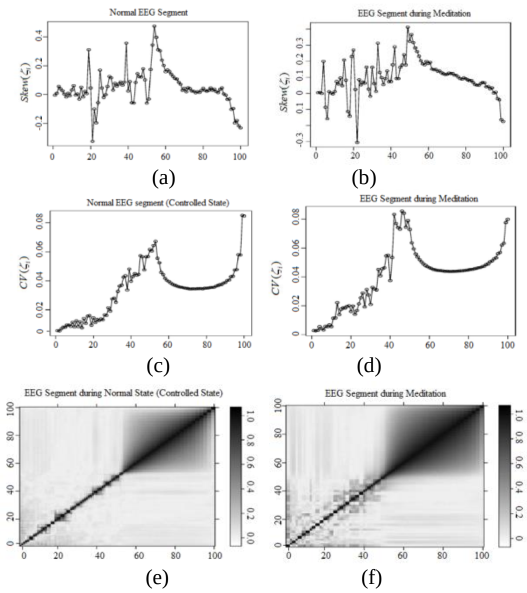


Figure 12. (a) Results of measure between Skew(ζ_i) and Eigen values for Normal EEG signal **(b)** Results of measure between Skew(ζ_i) and Eigen values for EEG signal during Meditation **(c)** Results of measure between $CV(\zeta_i)$ and Eigen values during normal EEG signal **(d)** Results of measure between $CV(\zeta_i)$ and Eigen values of EEG signal during Meditation **(e)** Results of correlation matrix of Eigen values of normal EEG signal **(f)** Results of correlation matrix of Eigen values of EEG signal during Meditation

Moreover, for both conditions, the figure of the skewness measure versus Eigen values belonging to the noise components has a slowly decreasing order. From the Figure 12c and 12d of *CV* measure versus Eigen value shows that the starting point of *U* shape is point of separation between the noise and signal spaces and *U* shape is a part of noise component. The graph of matrix of correlation between Eigen values shown in Figures 12e and 12f. guaranteed that the number of Eigen values belongs to Controlled state is *51* and that of Meditation state is *47*. Thus, signal is reconstructed by using Eigen triples belonging to these Eigen values after removing noise part. Figures13a, 13b, 13c and 13.d show the extracted signal and the noise series for normal and meditation signals.

4. 3. Discrimination of EEG signals In this section, the proposed method is validated for examining its capability of differentiating EEG signals into Normal and Meditation classes using *400* segments from each class. ζ_i was calculated by analyzing each channel of each class. Subsequently, matrix *A* was obtained from statistical analysis of each Eigen value. Then the similar measures used in previous sections were applied. These measures used as features for categorizing normal and meditated EEG signal. The results of those measures are quite identical as shown in Figures 12a to 12f.

It is clearly seen that value of *Skew* for the normal and meditation state are different, especially between the initial two values. Same results observed for both conditions using another statistical measure known as kurtosis. $Kurt(\zeta_i)$ was identical for first value during both conditions, whereas it is different for last *50* values (Figures 12.c and 12d). As shown in Figures 14a to 14c, it is clear that *CV* increases for the mediation signal for last *10* values, while it decreases for the normal signal.

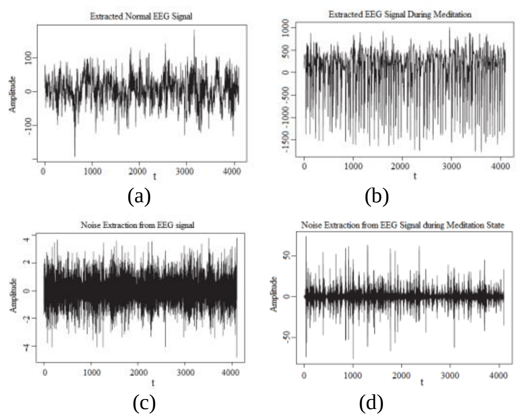


Figure 13. (a) Extracted normal EEG signal **(b)** Extracted EEG signal during Meditation **(c)** Extracted noise for normal EEG signal **(d)** Extracted noise for EEG signal during Meditation

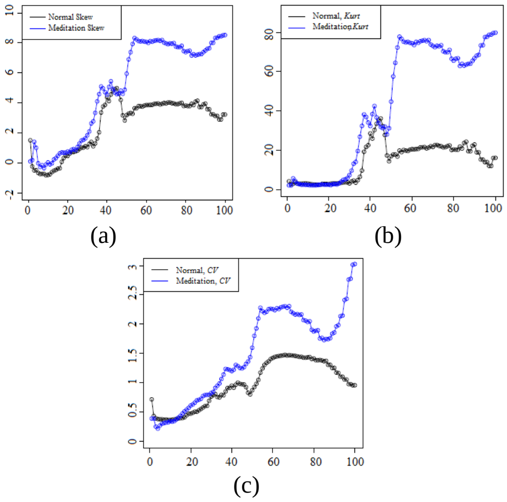


Figure 14. (a) Plot of Skewness for Normal and meditation Condition **(b)** Plot of Kurtosis for Normal and meditation condition **(c)** Plot of *CV* for Normal and meditation condition

5. CONCLUSION

Novelty has been included in the approach for decomposing EEG signal, which ultimately depends on the Eigen values distributions of a scaled Hankel matrix. The approach was specially utilized for noise elimination and bifurcating normal and Meditation EEG signal. At the beginning of this approach, only one specimen from each set were analyzed for finding the value of r which is then used for separating noise and EEG signals. After obtaining the value of r, signal component has been extracted.

In the later stage, all signals from each condition were used. Various plots and measures were applied to distinguish between Normal and meditation signals. The potentionality of the examined statistical measures depends on their values to differentiate between the two conditions. The results proved that there is obvious difference between the values of statistical measures used for the normal and meditating signals, which is an obvious solution for distinguishing normal and abnormal (Meditating) physiological condition using EEG signals.

In addition to above stages, several criteria have been introduced which is based on the highest Eigen value. These are then used as unique features to distinguish EEG signals and detect chaotic behavior. Several statistical parameters are used to show that the distribution of the highest Eigen value for the meditation signal is same for Rossler signal (chaotic). This is totally different from the normal EEG signal. Thus, the recommended features can be important for distinguishing EEG signals for any mental condition as well.

As a result of this, all our outcomes confirm the good performance of the proposed approach in distinguishing EEG signals during normal and meditating condition. This also performing better for separating noise and signal component from noisy time signal using r. The important point noted here is that, this approach does not base on any assumptions (such stationarity or linearity of the signal). This proved that, approach could be a useful for extraction of any physiological signal contaminated by noise or any other unwanted signal.

6. REFERENCES

1. Guerrero-Mosquera, C., Trigueros, A.M. and Navia-Vazquez, A., Eeg signal processing for epilepsy, in Epilepsy-histological, electroencephalographic and psychological aspects. 2012, InTech.
2. Khatwani, P. and Tiwari, A., "A survey on different noise removal techniques of eeg signals", ***International Journal of Advanced Research in Computer and Communication Engineering***, Vol. 2, No. 2, (2013), 1091-1095.
3. Walters-Williams, J. and Li, Y., "A new approach to denoising eeg signals-merger of translation invariant wavelet and ica", ***International Journal of Biometrics and Bioinformatics***, Vol. 5, No. 2, (2011), 130-148.
4. Vigário, R., Jousmäki, V., Hämäläinen, M., Hari, R. and Oja, E., "Independent component analysis for identification of artifacts in magnetoencephalographic recordings", in Advances in neural information processing systems., (1998), 229-235.
5. Inuso, G., La Foresta, F., Mammone, N. and Morabito, F.C., "Wavelet-ica methodology for efficient artifact removal from electroencephalographic recordings", in Neural Networks, 2007. IJCNN 2007. International Joint Conference on, IEEE., (2007), 1524-1529.
6. Kang, D. and Zhizeng, L., "A method of denoising multi-channel eeg signals fast based on pca and debss algorithm", in Computer Science and Electronics Engineering (ICCSEE), 2012 International Conference on, IEEE. Vol. 3, (2012), 322-326.
7. Babu, P.A. and Prasad, K., "Removal of ocular artifacts from eeg signals using adaptive threshold pca and wavelet transforms", in Communication Systems and Network Technologies (CSNT), 2011 International Conference on, IEEE., (2011), 572-575.
8. Karhunen, J. and Joutsensalo, J., "Generalizations of principal component analysis, optimization problems, and neural networks", ***Neural Networks***, Vol. 8, No. 4, (1995), 549-562.
9. Kumar, P.S., Arumuganathan, R., Sivakumar, K. and Vimal, C., "Removal of ocular artifacts in the eeg through wavelet transform without using an eog reference channel", ***International Journal Open Problems Computer and Mathematics***, Vol. 1, No. 3, (2008), 188-200.
10. Andrzejak, R.G., Lehnertz, K., Mormann, F., Rieke, C., David, P. and Elger, C.E., "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state", ***Physical Review E***, Vol. 64, No. 6, (2001), 061907.
11. Kantz, H. and Schreiber, T., "Nonlinear time series analysis, Cambridge university press, Vol. 7, (2004).
12. Lehnertz, K., Elger, C., Arnhold, J. and Grassberger, P., "Chaos in brain", in University of Bonn, Germany., (1999 of Conference).

13. Rukhin, A.L., *Analysis of time series structure ssa and related techniques*. 2002, Taylor & Francis.
14. Golyandina, N. and Zhigljavsky, A., "Singular spectrum analysis for time series, Springer Science & Business Media, (2013).
15. Rodriguez-Aragon, L.J. and Zhigljavsky, A., "Singular spectrum analysis for image processing", ***Statistics and Its Interface***, Vol. 3, No. 3, (2010), 419-426.
16. Liew, A.W.-C., Tang, V.T.-Y. and Yan, H., "Periodicity analysis of DNA microarray gene expression time series profiles in mouse segmentation clock data", ***Statistics and Its Interface***, Vol. 3, No. 3, (2010), 413-418.
17. Celka, P. and Colditz, P., "A computer-aided detection of eeg seizures in infants: A singular-spectrum approach and performance comparison", ***IEEE Transactions on Biomedical Engineering***, Vol. 49, No. 5, (2002), 455-462.
18. Welvaert, M. and Rosseel, Y., "On the definition of signal-to-noise ratio and contrast-to-noise ratio for fmri data", ***PloS One***, Vol. 8, No. 11, (2013), e77089.
19. Kannathal, N., Choo, M.L., Acharya, U.R. and Sadasivan, P., "Entropies for detectionof epilepsy in eeg", ***Computer Methods and Programs in Biomedicine***, Vol. 80, No. 3, (2005), 187-194.

A Unique Approach of Noise Elimination from Electroencephalography Signals between Normal and Meditation State

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PAPER INFO

Paper history:
Received 24September 2017
Received in revised form 04 November 2017
Accepted 28December 2017

Keywords:
Singular Spectrum Analysis
Eigen Values
Electroencephalography

چکیده

در این مقاله روش منحصر به فرد برای تحلیل سیگنال الکتروانسفالوگرافی (EEG) ارائه شده است. این براساس توزیع ارزش Eigen یک ماتریس است که به عنوان ماتریس مقیاس Hankel نامیده می شود. این ماتریس به ما امکان می دهد تا تعداد مقادیر Eigen مورد نیاز برای کاهش نویز و استخراج سیگنال در تجزیه و تحلیل طیف منحصر به فرد را پیدا کند. این مقاله روشی را برای طبقه بندی سیگنال های EEG بین وضعیت عادی (کنترل شده) و شرایط مراقبه، استخراج الگوهای مختلف، فیلتر کردن سیگنال EEG و حذف نویز از سیگنال ارائه می دهد. پارامترهای مختلف به عنوان ویژگی هایی برای طبقه بندی در بخش های طبیعی EEG طبیعی و در زمان تمرین مدیتیشن استفاده می شود. نتایج نشان داد که روش حذف صوتی در هر دو سیگنال EEG مثبت است.

doi: *10.5829/ije.2018.31.04a.06*