EFFECTIVE NORMALISATION OF SELECTIVE EIGEN RATE METHOD TO SEPARATE PRINCIPAL COMPONENTS OF VEP AND EEG

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ABSTRACT

Here we give proof to the best suitable normalization method for the Selective Eigen Rate (SER) a novel technique, that is used in selecting only the higher rate of principal components (PCs) for using them in Principal Component Analysis (PCA) while separating Visual Evoked Potential (VEP) from electroencephalogram (EEG) signals, to enable single trial analysis. SER technique is designed and implemented to overcome heavy electroencephalogram (EEG) contamination in VEP signals. Normalisation of the eigen values which are obtained as a result of PCA is an important part for PC selection process in SER technique. In order to derive the maximum signal to noise ratio (SNR) from artificial VEP signals contaminated by EEG, three distinct normalisation methods were constructed and tested here. The best methods of normalisation suitable for the SER method is found and tested with added factors of noise in multiples of 2, 5 and 10 times. Assessment on the performance of this effective normalisation technique shows that application of SER with the proposed normalisation technique on contaminated signals outperformed the other normalisation techniques and existing PCA methods like Kaiser (KSR) and Residual Power (RP) and Spectral Power Ratio (SPR) in selecting the PCs. The SER adopting our proposed normalisation technique yields in an average positive SNR of 97.83 dB for higher noise levels while RP KSR and SPR gave less values of SNR in the same noise levels.

KEYWORDS

Principal components, P3, Signal to noise ratio, Single trial, Spectral Power ratio, Selective Eigen Rate, Visual Evoked Potential

INTRODUCTION

In order to overcome the disadvantages in the conventional averaging technique, that is used to solve the source separation of Visual Evoked Potential signals from EEG, the faster approaches as single trial analysis with PCA is followed. It is vital to extract the signal more accurately without damaging any valid information hidden in the contaminated signal, and hence efficient extraction techniques in PCA like SPR [1] and SER are followed.

The ultimate objective of this paper is to explore an efficient normalizing method of eigen values for the effective reconstruction of the VEP using SER method that results in a highest SNR value.

METHODS

Artificial VEP simulation & Principal Component Analysis

Collections of sixty-four artificial VEP signals were created using different combinations of Gaussian waveforms. The creation is carried out such that each signal having different mean, variance and amplitude. These signals were limited to 8 Hz [8] to simulate P3 responses, These basic waveforms for our experiment were created using the equation

$$G(n)=(A/sqrt(2\pi\sigma^2))exp(-((n-\mu)^2)/2\sigma^2) \quad (1)$$

These artificial VEP signals (X) were mixed with the real EEG signals, which were obtained when the subjects were at rest. These EEG (Y) signals were whitened to remove their correlation, before adding to the artificial VEP signals,

$$W(n)_{VEP+EEG} = X(n)_{VEP} + Y(n)_{EEG} \qquad (2)$$

The contaminated signal, W was then normalized to zero mean and unit variance.

$$W = (W - mean(W)) / Std(W) \qquad (3)$$

We applied PCA to extract VEP signals from EEGs. PCA is a linear mapping technique intended to map a set of high dimensional input data into a lower dimensional space. The data given to PCA should be a normalized one to reduce dimensionality. First, the covariance of the signal *W* was computed using

$$R = E(WW^T) \qquad (4)$$

Considering *F* be the orthogonal matrix of eigen vectors of *R* and *D* is the diagonal matrix of its eigen values $D = diag(d_1 .... d_n)$. Then the PCs for the given contaminated signal could be computed using,

$$Y = F^T W^T \qquad (5)$$

In the resultant PCs, some PCs will represent the VEP and some will represent the EEG. The selections of PCs for VEP from the total PCs were carried out by several PCA [2,3,4,5]methods. The methods like Residual power retained (RP), Kaiser' rule (KSR), Spectral Power Ratio (SPR) and Selective Eigen Rate (SER).

These selected PCs were then used in reconstruction, where the reconstructed signal now contains only VEP. The reconstruction was done using

$$X = FF^T YY^T \qquad (6)$$

Where the *FF* and *YY* corresponds to the selected eigenvectors and PCs [].

PC Selection Methods

i) Percentage of total Residual Power retained (RP)

In the RP method[6], the first few PCs were selected as the percentage of the higher eigen values covers up to ninety five percent over the total eigen values. The remaining PCs will be ignored and only the selected PCs were used for the reconstruction of the VEP signals.

ii) Kaiser' rule (KSR)

In KSR method [6], the PC selection was by selecting the PCs with eigen values more than 1.0. Any Pc whose eigen values less than that were omitted and only the selected PCs were used for the reconstruction of the VEP signals.

iii) Spectral Power Ratio (SPR)

By the SPR method, the picking up of PCs that contained only significant amount of 0-8 Hz spectral powers were selected. This frequency limit is chosen due to our estimate for P3 VEP signals. After some experimental simulations, we found that the values 0.5- 0.6 were sufficient as thresholds. I.e. for the PC under consideration, if the ratio of spectral power below 8 Hz over the total spectral power exceeded this threshold, then that PC would be selected.

iv) Selecting the PCs by Selective Eigen Rate (SER)

The EEG contamination on EEG is usually high and is always in multiples over the VEP signal strength. The SER technique is found to be an effective method of VEP extraction than any other methods among RP, KSR, and SPR [1]. In SER the PC selection starts from the highest value and continued up to the condition that the difference between the normalized consecutive eigen values should not exceed the given thresh hold value.

Different Normalisation methods

The normalization process is required for all the principal components and is carried out in order to avoid the omission of any principal component during the selection process by SER method. Since the PCs are found in a range of huge difference between each other.

The three methods available for normalizing the principal components are as follows. The eigen values of all the principal components are sorted in descending order before we do the normalisation.

In Method 1, the first eigen value that is having the greatest value is taken and is used to divide all the eigen values available.

Normalized eigen value (E) = obtained eigen value / greatest eigen value

$$E = ex / e_1 \quad (7)$$

In Method 2, all the eigen values that we have are summed and the sum is used to divide all the eigen values to get the values normalized.

Normalized eigen value (E) = obtained eigen value / Sum of all eigen values

$$E = e_x / e_N \quad (8)$$

Where EN is the sum of all eigen values

In Method 3, we find the difference between the consecutive eigen values and that value is divided by the corresponding eigen value.

Normalized eigen value (E) = the difference between consecutive obtained eigen values / obtained eigen value

$$E = e_x - e_{x+1} / e_x \quad (9)$$

SNR Calculation

In order to compute the efficiency of the SER based PC selection, SNR computations were carried out for the reconstructed VEP signals and compared with the SNR gained by other methods. The SNR is calculated by

$$SNR=10\log_{10}(Variance(X)/Variance(W–X)) \quad (10)$$

The total SNR for all the 64 reconstructed VEP signals were also calculated for each method.

Influence of different noise factors

The entire experiment was repeated with the signal *W* but adding EEG signal with different noise levels, i.e. EEG signals with amplitude multiples of 2, 5, and 10

$$W(n)_{VEP+noise}=X(n)_{VEP}+NY(n)_{noise} \quad (11)$$

Where N = 2, 5, and 10.

Again, the performances of SER over the other methods were investigated.

RESULTS AND DISCUSSION

The results of the artificial VEP extraction from noises, based on different methods are given in Tables 1-3 and in Figure 1. All the sixty-four VEP signals are involved and the result is restricted to the total and average for 64 artificial VEP signals due to unavailability of space. The evidence of the effectiveness of our proposed normalization method to SER method could be seen from the increased SNR average as compared to the original, KSR, SPR and RP methods as well as the other two variants of normalizations in SER when the noise factors are high. Since the EEG contamination is very high on VEP signals, the higher noise factors are considered for this decision.

CONCLUSION

SER technique is designed and implemented to overcome heavy electroencephalogram (EEG) contamination in VEP signals in order to design an effective Brain Computer InterfaceBCI.[7] The advantage of our proposed normalization method to be used in SER method of PCs separation to elicit P300 amplitude for clinical purposes [10]can be found from the observations of the given tables. It is made further simple understanding to know the benefit of this method by the tables 2 and 3 when the noise level of contamination is very high on an original signal, which is obvious in the VEP-EEG combinations.

Fig 1: Artificial VEP signals with PCs selected using RP, KSR, SPR and SER Methods (EEG factor of 5)

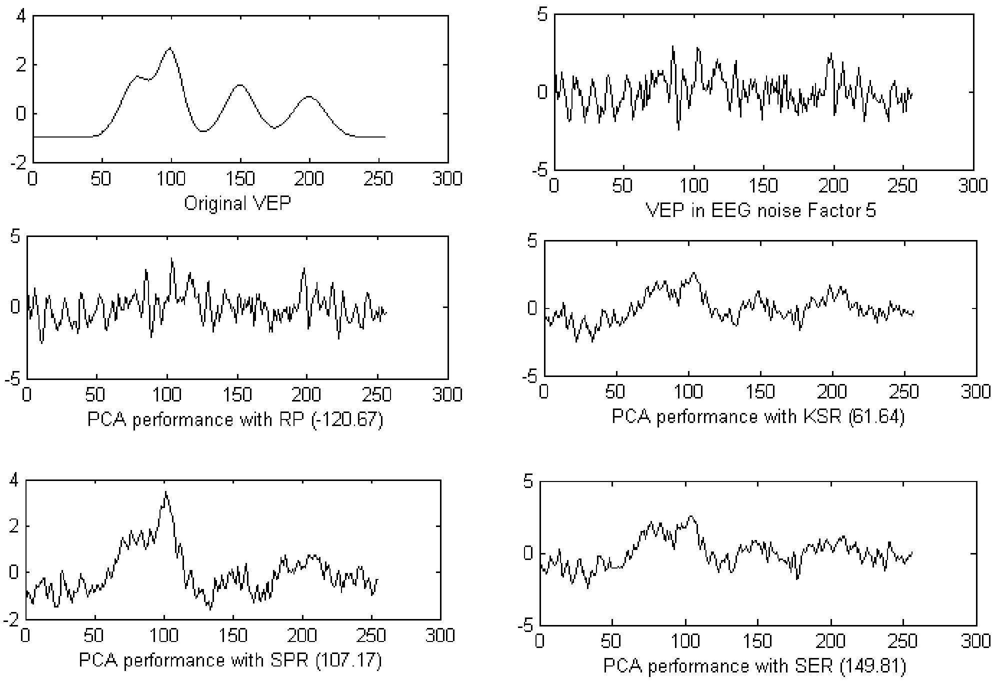

Table 1: Comparison of SNRs produced by RP, KSR, SPR and three variants of SER methods with different EEG noise factors *(For SER - these threshold values gave the best performance)*

Noise factor	Original	RP	KSR	SPR	SER-M1 (0.1)	SER_M2 (0.005)	SER_M3 (0.01)
1	0	185	698	698	554	698	348
2	-385	-13	390	428	428	428	302
5	-894	-120	61	107	149.80	149.80	151
10	-1280	-146	-51.9	-27.2	52.90	45.33	45.33
Average	-639.75	-23.5	274.27	301.45	295.97	330.08	211.58

Table 2: Comparison of SNRs produced by different SER methods with varying threshold values for different EEG Noise factors

Factor	Threshold	Method1	Method2	Method3
1	0.1	554	348	348
	0.05	708	554	348
	0.01	698.71	708	348
	0.005	698.71	698	348
	0.001	698.71	698	348
	ave	671.20	601.20	348
2	0.1	428	-	302
	0.05	428	302	302
	0.01	390	428	302
	0.005	390	428	302
	0.001	374.11	428	302
	ave	402.02	396.50	302
5	0.1	149	-	151
	0.05	149	-	151
	0.01	113.14	151	151
	0.005	113.14	149.80	151
	0.001	107.43	149.80	107
	ave	126.34	150.20	142.20
10	0.1	52.91	-	-
	0.05	45	-	45.33
	0.01	16.75	-	45.33
	0.005	16.75	45.33	16.75
	0.001	14.63	45.62	14.63
	ave	29.20	45.47	30.51
Total Average		307.20	298.35	205.67

Table3: Comparison of the average SNRs of different SER methods for higher and moderate EEG Noise factors (Lower noise 1 and 2, and higher noise 5 and 10)

Method	AVG -Lower noise	AVG -Higher noise	AVG -Total noise
M1	536.60	77.77	307.2
M2	498.85	97.83	298.35
M3	325.00	86.35	205.67

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