SINGLE TRIAL SOURCE SEPARATION OF VEP SIGNALS USING SELECTIVE PRINCIPAL COMPONENTS

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ABSTRACT

Single trial source separation problem of VEP signals has been addressed Principal Component Analysis. Here, we propose a new method, spectral power ratio that selects specific principal components (PCs) in PCA to perform the source separation. We have applied the method to separate artificial VEP signals contaminated with background electroencephalogram (EEG) signals, where the focus was on extracting the P3 parameters. The proposed method resulted in increased signal to noise ratio as compared to other existing methods to select PCs like Kaiser (KSR) and Residual Power (RP). This was especially true when the noise (i.e. EEGs) were high. Next, we applied the method to real VEP signals to analyse the P3 amplitude and latency responses for matched and non-matched stimuli. The P3 parameters extracted through our proposed method showed faster and higher P3 response for matched stimuli, which confirms to the existing neuroscience knowledge. Single trial PCA using KSR and RP methods did not indicate any difference for the stimuli.

KEYWORDS

Principal components, P3, Signal to noise ratio, Single trial, Spectral power ratio.

INTRODUCTION

The common method of solving the electroencephalogram (EEG) contamination in Visual Evoked Potential (VEP) is through averaging [1]. However, averaging requires many trials and it might distort the single trial information.

Recently, methods using Principal Component Analysis (PCA) have been proposed for this purpose [2, 3, 4, and 5]. These methods are suitable since they result in single trials of VEP signals.

Here, we use PCA for performing single trial analysis of VEP signals. The existing popular procedures to select principal components (PCs) for PCA are Kaiser (KSR) and Residual Power (RP) [6]. However, our results show that these methods are unable to retain their performance when the content of background EEGs are high.

The purpose of this paper is to explore a more efficient method of selecting PCs for the effective reconstruction of the VEP even when the EEGs are high.

The proposed method (SPR) selects the appropriate PCs for the effective reconstruction of source signal (i.e. VEP) even when the presence of high EEG contamination. This will aid in extracting undistorted VEP by selective principal components, which will be of much useful in neuropsychological and clinical applications. The spectral methods are used by other researchers for BCI [7] but using it for selecting principal components is novel here.

First, we set to prove the effectiveness of our proposed method through a simulation study using artificial VEP signals buried in real EEG. Signal to noise ratio (SNR) calculation is used to show the advantage of our proposed method with KSR and RP methods in selecting PCs. Next, we use our SPR method to analyze single trial P3 amplitude and latency responses for matched and non-matched stimuli.

METHODS

Artificial VEP simulation

Sixty-four artificial VEP signals were created using different combinations of Gaussian waveforms, each with different mean, variance and amplitude. These basic waveforms were created using the equation

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

These VEPs were limited to 8 Hz to simulate P3 responses, which are limited to 8 Hz [8, 9].

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

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

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

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

Principal Component Analysis

PCA to extract VEP signals from EEGs was carried out. First, the covariance of the signal *W* was computed using

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

Let *F* be the orthogonal matrix of eigen vectors of *R* and *D* is the diagonal matrix of its eigenvalues $D = diag\ (d_1 \ldots d_n)$. Then the PCs could be computed using,

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

Some of the PCs will represent the VEP and some will represent the EEG. The selections of PCs from all PCs were carried out by 3 methods say KSR, RP and SPR.

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

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

where the *FF* and *YY* corresponds to the selected eigenvectors and PCs.[10]

Selecting the PCs

i) Percentage of total residual power retained (RP)

In the RP method [6], the first few PCs were selected where the percentage of eigenvalues covers 95% over the total eigenvalues. The remaining PCs were omitted and only the selected PCs were used for the reconstruction of the VEP signals.

ii) Kaiser' rule (KSR)

In KSR method [6], the selection of PCs was carried out such that the eigenvalues of selected PCs were more than 1.0. The remaining PCs were omitted and only the selected PCs were used for the reconstruction of the VEP signals.

iii) Spectral Power Ratio (SPR)

In SPR method, only the PCs that contained significant amount of 0-8 Hz spectral powers were selected. This frequency limit could be varied according to the purpose. In this case, since we considered the P3 responses, the limit was set to 8Hz. 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.

The other PCs with SPR below this threshold were set to zero. Next, these selected PCs were used to reconstruct the VEP signals.

SNR calculation

In order to compute the efficiency of the 3 different PC selection methods, SNR computations were carried out for the reconstructed VEP signals. This is implemented by

$$SNR=10\ log_{10}(Variance(X)/Variance(W–X)) \quad (7)$$

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

Different noise factors

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

$$W(n)_{VEP+noise} = X(n)_{VEP}+NY(n)_{noise} \quad (8)$$

where N = 2, 5, and 10.

Again, the performances of all the three methods were investigated.

Single trial P3 responses using real VEP

Here, an experiment using all the 3 PC selection methods were carried out. The real VEP signals were recorded from different subjects while being exposed to two stimuli, which were pictures of objects chosen from Snodgrass and Vanderwart picture [11]. Figure 1 shows some of these pictures.

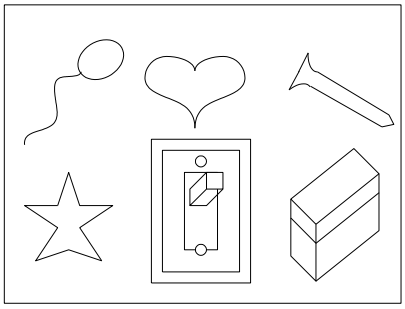

Figure 1: Some pictures from Snodgrass and Vanderwart picture set.

Figure 2 shows an example of the stimuli presentation with details.

The first visual stimulus (S1) shown to the subjects was a randomly chosen picture. The second stimulus shown was chosen according either to the matching (S2M) or non-matching (S2N) rule, related to the initial stimulus (S1). To reduce the possible ambiguity, S2N was chosen to be different from S1 not only in its visual appearance but also in terms of the semantics. For example, if a picture of an elephant is shown for S1, then S2N will not be a picture from the animal category. One-second measurements after each stimulus presentation were recorded. We randomly selected few trials from four different subjects.

The eye-blink artifact contaminated VEP signals were removed from the records, and were detected based on amplitude discrimination (the threshold value of 100 μV was used since blinking typically produces potential of 100-200 μV lasting for 250 ms [3].

Next, to set the pre-stimulus baseline to zero, the data were made zero mean [12]. Following the approach from by Begleiter *et al.* [9], where P3 responses were shown to be band-limited to 8 Hz, the extracted VEP signals from S2M and S2N stimuli were low pass filtered using a combination of a 9^{th} order forward and 9^{th} order reverse Butter worth digital filter with a cutoff frequency at 8 Hz. This way, a minimum attenuation of 30 dB was achieved in the stop band, with the transition band being between 8 and 12 Hz. Notice that the reason for both forward and reverse filtering was performed to ensure no phase distortion.

Single trials of VEPs from the Pz channel were analysed, because the P3 response reaches its maximum in the midline parietal area [12]. The amplitude and latency of P3 responses were detected via an automated procedure, whereby this component was identified as the largest positive peak in the period of 300-600 ms after the stimulus onset. The t-test was used to establish a statistical difference in P3 amplitudes and latencies between stimuli S2M and S2N.

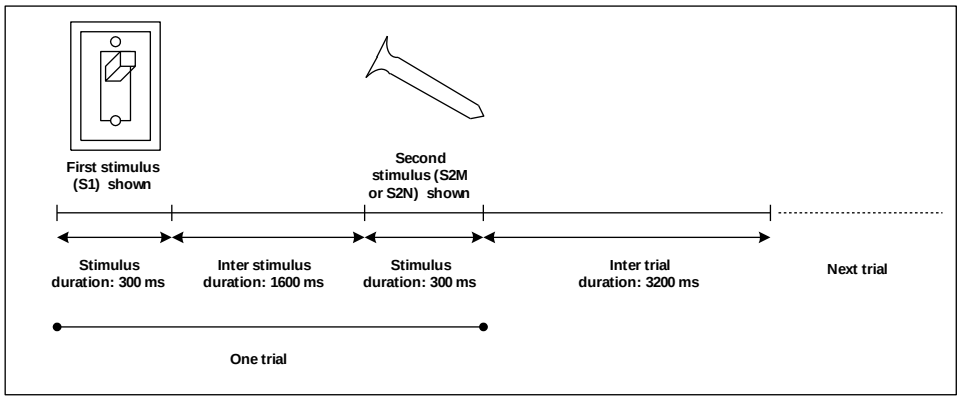

Figure 2: Example of stimulus presentation for the case of S2N

RESULTS AND DISCUSSION

The results of the artificial VEP analysis are given in Tables 1-4 and Figures 3-8. The number of VEP signals is restricted to 4 due to unavailability of space but the total and average for 64 artificial VEP signals are provided. The evidence of the effectiveness of our proposed SPR method could be seen from the increased SNR as compared to the original, KSR and RP methods.

It is also clear that the proposed SPR method gives improved performance in comparison of KSR and RP, when the EEGs were higher.

Table 5 gives the result for the t-test analysis of P3 latencies and amplitudes. The hypothesis tested for latency is that S2N>S2M, while for amplitude, the hypothesis tested is S2M>S2N. The results indicate that only P3 parameters extracted using PCA from SPR method shows difference, while KSR and RP methods do not indicate any differences. The results using SPR method shows that P3 amplitude were higher from S2M as compared to S2N (with $p<0.05$). In addition, it also shows that P3 latencies are smaller (i.e. P3 responses are faster) for S2M as compared to S2N (with $p>0.95$). These results confirm to the other studies conducted with matched and non-matched stimuli [13].

Therefore, in conclusion, our proposed is suitable for extracting single trials of VEP signals as long as we know the frequency range of the parameter that we wish to extract.

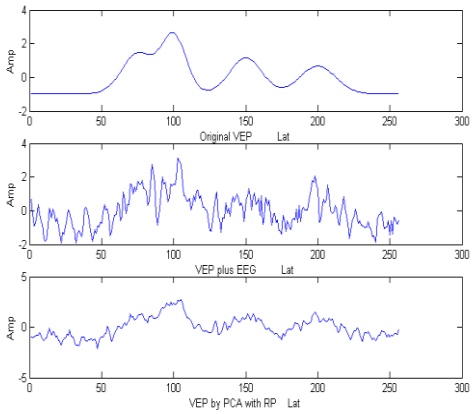

Figure 3: Artificial VEP signals with PCs selected using RP (EEG factor of 1)

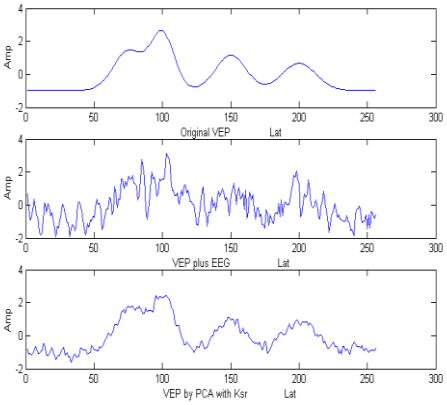

Figure 4: Artificial VEP signals with PCs selected using KSR (EEG factor of 1)

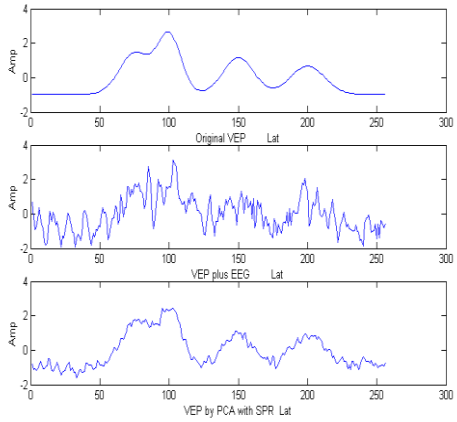

Figure 5: Artificial VEP signals with PCs selected using SPR (EEG factor of 1)

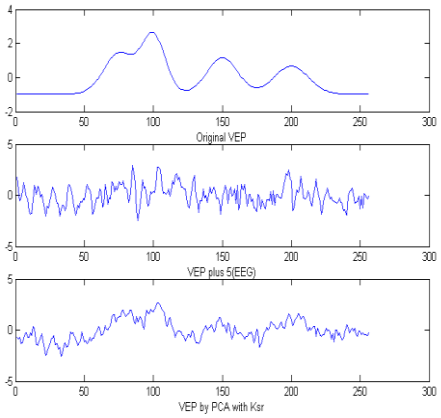

Figure 7: Artificial VEP signals with PCs selected using KSR (EEG factor of 5)

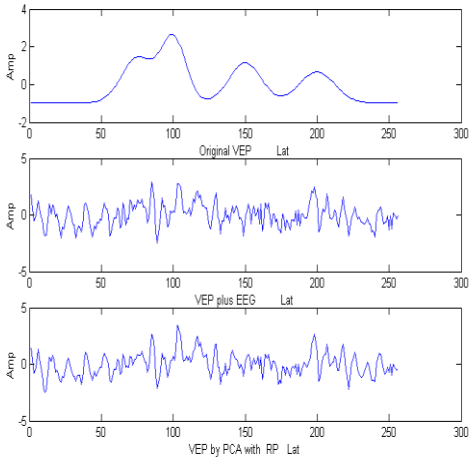

Figure 6: Artificial VEP signals with PCs selected using RP (EEG factor of 5)

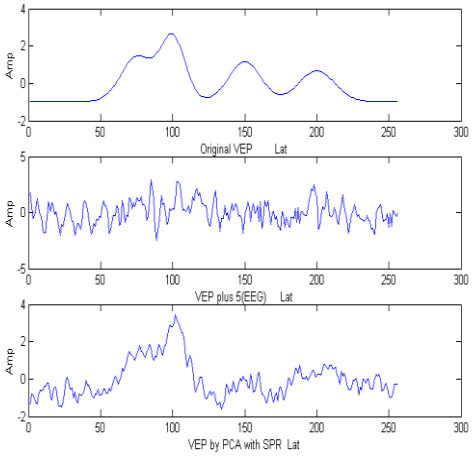

Figure 8: Artificial VEP signals with PCs selected using SPR (EEG factor of 5)

Table 1: Comparison of SNRs of RP, KSR and SPR methods with EEG factor=1

	SNR			
Randomly selected channels	**Original**	**RP**	**KSR**	**SPR**
1	0	7.67	12.69	12.69
2	0	2.92	9.16	9.16
3	0	2.93	12.57	12.57
4	0	1.98	10.60	10.60
Total (64 signals)	**0**	**185**	**698.71**	**698.71**
Average (64 signals)	**0**	**2.89**	**10.91**	**10.91**

Table 2: Comparison of SNRs of RP, KSR and SPR methods with EEG factor=2

	SNR			
Randomly selected channels	**Original**	**RP**	**KSR**	**SPR**
1	-6.02	2.59	8.32	8.76
2	-6.02	-0.07	6.35	6.48
3	-6.02	0.04	5.28	5.83
4	-6.02	0.32	4.83	5.21
Total (64 signals)	**-385.31**	**-13.43**	**390.45**	**428.32**
Average (64 signals)	**-6.02**	**-0.20**	**6.10**	**6.69**

Table 3: Comparison of SNRs of RP, KSR and SPR methods with EEG factor=5

	SNR			
Randomly selected channels	**Original**	**RP**	**KSR**	**SPR**
1	-13.97	-1.24	3.98	4.01
2	-13.97	-1.54	3.79	4.16
3	-13.97	-1.66	3.14	4.47
4	-13.97	-1.58	2.53	3.16
Total (64 signals)	**-894.68**	**-120.67**	**61.64**	**107.17**
Average (64 signals)	**-13.97**	**-1.88**	**-0.9**	**1.67**

Table 4: Comparison of SNRs of RP, KSR and SPR methods with EEG factor=10

	SNR			
Randomly selected channels	**Original**	**RP**	**KSR**	**SPR**
1	-20	-1.79	2.28	2.37
2	-20	-2.13	1.64	2.49
3	-20	-2.28	-0.23	1.08
4	-20	-2.50	-2.40	-0.85
Total (64 signals)	**-1280**	**-146.69**	**-51.91**	**-27.20**
Average (64 signals)	**-20**	**-2.29**	**-0.81**	**-0.42**

Table 5: T-test results of P3 latencies and amplitudes for stimuli S2M and S2N

Subjects	**RP**		**KSR**		**SPR**	
	Latency	**Amplitude**	**Latency**	**Amplitude**	**Latency**	**Amplitude**
1	0.3397	0.8219	0.5111	0.7844	0.9978	0.0034
2	0.8798	0.3063	0.5980	0.4561	0.9994	1.89e-015
3	0.1425	0.1814	0.0546	0.8401	1.0000	8.11e-004
4	0.4590	0.4142	0.7279	0.5998	0.9683	1.26e-010

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