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Extracting Single Trial Visual Evoked Potentials using Selective Eigen-Rate Principal Components

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***Abstract*—**In single trial analysis, when using Principal Component Analysis (PCA) to extract Visual Evoked Potential (VEP) signals, the selection of principal components (PCs) is an important issue. We propose a new method here that selects only the appropriate PCs. We denote the method as selective eigen-rate (SER). In the method, the VEP is reconstructed based on the rate of the eigen-values of the PCs. When this technique is applied on emulated VEP signals added with background electroencephalogram (EEG), with a focus on extracting the evoked P3 parameter, it is found to be feasible. The improvement in signal to noise ratio (SNR) is superior to two other existing methods of PC selection: Kaiser (KSR) and Residual Power (RP). Though another PC selection method, Spectral Power Ratio (SPR) gives a comparable SNR with high noise factors (i.e. EEGs), SER give more impressive results in such cases. Next, we applied SER method to real VEP signals to analyse the P3 responses for matched and non-matched stimuli. The P3 parameters extracted through our proposed SER method showed higher P3 response for matched stimulus, which confirms to the existing neuroscience knowledge. Single trial PCA using KSR and RP methods failed to indicate any difference for the stimuli.

***Keywords*—**Electroencephalogram, P3, Single trial VEP.

I. Introduction

SINGLE trial analysis of Visual Evoked Potential (VEP) signals is an important step in the analysis of VEP signals. Multi-trial averaging is the de facto standard to reduce the effects of background electroencephalogram (EEG) from VEP, enabling single trial analysis [1]. However, it is disadvantageous as information will be lost from multi-trials, which are not strictly time-locked. Therefore, it has become a common practice to use Principal Component Analysis (PCA) for this purpose [2]-[4].

The existing methods to select principal components (PCs) for standard PCA are like Kaiser (KSR) and Residual Power (RP) [5]. However, our results show that these methods are unable to retain their performance when the signal to noise ratio (SNR) of VEP to background EEG is high.

To solve this problem, in a previous paper [3], we proposed the Spectral Power Ratio (SPR) method that gave significant improvement by selecting specific PCs. In this paper, we propose another elite procedure that is more efficient than SPR.

Therefore, the purpose of this paper is to investigate the efficiency of the proposed Selective Eigen Rate (SER) method in selecting PCs for the effective reconstruction of the VEP, which is especially suitable when the amount of noise is very high.

SER's potential in selecting the appropriate PCs for the effective reconstruction of the source signal (i.e. VEP) even with high EEG contamination will aid in proper neuropsychological analysis in clinical applications.

First, we will set out to prove the effectiveness of our proposed method through a simulation study using emulated VEP signals buried in real EEG. SNR calculation will be used to show the advantage of our proposed method as compared to KSR, RP and SPR methods in selecting the PCs. Next, we will use the SER method to analyse single trial P3 responses for matched and non-matched stimuli.

II. Methods

A. Emulated VEP Simulation

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

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

where σ is the standard deviation, μ is the mean, and A is the amplitude. These emulated VEPs, X were limited to 8 Hz to simulate P3 responses, which are limited to 8 Hz [6].

These were mixed with the real EEG signals, which were obtained from a subject at rest. These EEG signals, Y were whitened to remove their correlation, before adding to the emulated VEP signals to produce a matrix, W.

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

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The contaminated signals, W of dimension 64 x 256 was then normalised to zero mean and unit variance.

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

B. Principal Component Analysis

PCA to extract VEP from the EEG contaminated signal 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 eigen-values, $D= diag\ (d_1....d_n)$. 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 VEP representing PCs from the overall PCs were carried out by four different methods, namely KSR, RP, SPR, and SER.

These selected VEP were then used in reconstruction (the remaining PCs were omitted), 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 eigen-vectors and PCs.

C. PC Selection

i) Percentage of total residual power retained (RP)

In the RP method [5], the first few PCs were selected from the sorted array of eigen-values where the percentage of selected eigen-values covers 95% of the total eigen-values.

ii) Kaiser' rule (KSR)

In the KSR method [5], the selection of PCs was carried out such that the eigen-values of selected PCs were more than 1.0.

iii) Spectral Power Ratio (SPR)

In the SPR method [3], only the PCs that contained significant amount of 0-8 Hz spectral power were selected. This frequency limit could be varied according to the purpose. In this case, we considered the P3 responses; so the limit was 8 Hz. After some experimental simulations, a value of 0.5-0.6 was sufficient as threshold i.e. for the PC under consideration, if the ratio of spectral power below 8 Hz over total spectral power exceeded this threshold, then that PC would be selected [3].

iv) Selective Eigen Rate (SER)

In SER, the PC selection starts from the highest eigen-value and continues up to the condition that the difference between the normalised consecutive eigen-value should not exceed the chosen threshold value. After various experimental simulations, we fixed this value to 0.005.

We found that the best method for normalising the obtained eigen -values is by simple normalisation:

$$Normalised\ eigen\text{-}value = obtained\ eigen\text{-}value/sum\ of\ all\ eigen\text{-}values. \quad (7)$$

D. SNR Computation

In order to compute the efficiency of the four different PC selection methods, SNR computations were carried out for the reconstructed VEP signals as well as the original VEP signals. The SNR for the original signal was computed by

$$SNR=10log_{10}(variance(X)/variance(W–X)). \quad (8)$$

Similarly, the SNR values for all the 64 reconstructed VEP signals were calculated for each method.

E. Different Noise Factors

The entire experiment was repeated for all the four methods with the signal, W but adding different amounts of EEG noise, i.e. EEG signals with amplitude in multiple factors of 2, 5 and 10:

$$W(n)_{VEP+noise} = X(n)_{VEP}+NY(n)_{noise}, \quad (9)$$

where $N\ factor$ = 2, 5, or 10.

Again, the performances of all the four methods were investigated using their resultant SNR values.

F. Single Trial P3 Responses using Real VEP

Using all the above four PC selection methods, another experiment using real VEP signals was also 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 (SV) picture set [7]. Figure 1 shows samples of these pictures, and Figure 2 shows an example of the stimuli presentation. Figure 3 shows the position of the 64 electrodes.

The sample stimulus (S1) shown to the subjects was a randomly chosen picture from the SV set. The second stimulus shown was chosen as either matching (S2M) or non-matching (S2N) relative to the initial stimulus S1. To reduce the possibility of 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 eagle is shown for S1, then S2N will not be a picture from the bird category. One-second measurements after each stimulus presentation were recorded. We randomly selected a few trials from four different subjects for the purpose of this purpose.

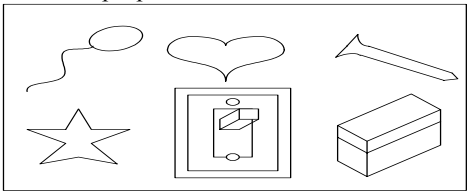

Fig. 1 Sample pictures from Snodgrass and Vanderwart picture set

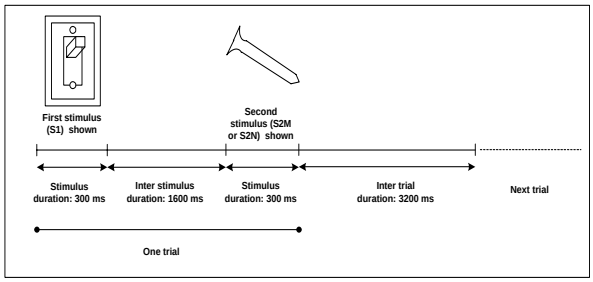

Fig. 2 Example of stimulus presentation for the case of S2N

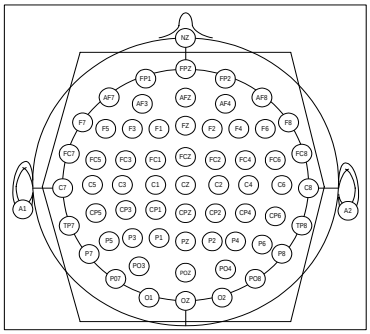

Fig. 3 Electrode positions

The eye-blink contaminated VEP signals were removed from the records, and were detected based on amplitude discrimination; by using the threshold value of 100 μV as blinking typically produces potential of 100-200 μV lasting for 250 ms [8].

Next, to set the pre-stimulus baseline to zero, the data were made zero mean [6]. Following the approach by Begleiter *et al* [9], where P3 responses were band-limited to 8 Hz, the extracted VEP signals from S2M and S2N stimuli were low pass filtered using a combination of a 9th order forward and 9th order reverse Butterworth digital filter with a cutoff frequency at 8 Hz. A minimum attenuation of 30 dB was achieved in the stop band, with the transition band being between 8 and 12 Hz. The reason for both forward and reverse filtering was to ensure that there would be no phase distortion.

Single trials of VEPs from the Pz channel were analysed, because the P3 response is highest in midline parietal area [6]. 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.

III. Results and Discussion

The results of the emulated VEP analysis are given in Tables 1-5 and Figures 3-6. Only 4 figures are shown (with EEG factor of 5) due to unavailability of space but the total and average for 64 emulated VEP signals are given in the tables. The evidence on the effectiveness of our proposed SER method could be seen from the increased SNR as compared to the original signal and when comparing results using KSR, RP and SPR methods.

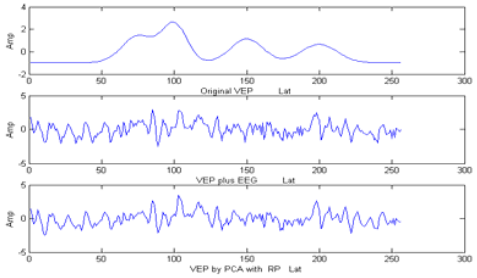

Fig. 4 Artificial VEP signals with PCs selected using RP (EEG factor of 5)

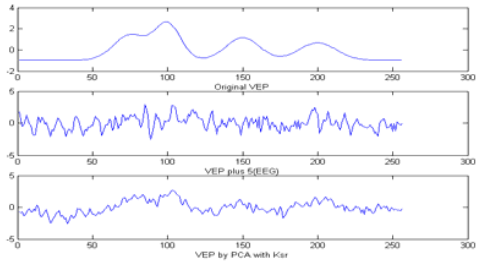

Fig. 5 Artificial VEP signals with PCs selected using KSR (EEG factor of 5)

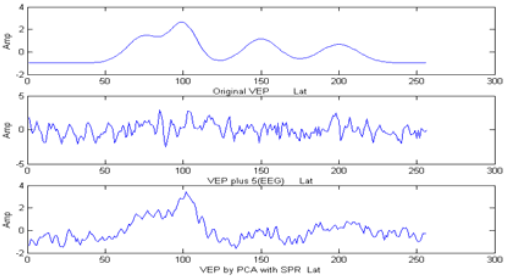

Fig. 6 Artificial VEP signals with PCs selected using SPR (EEG factor of 5)

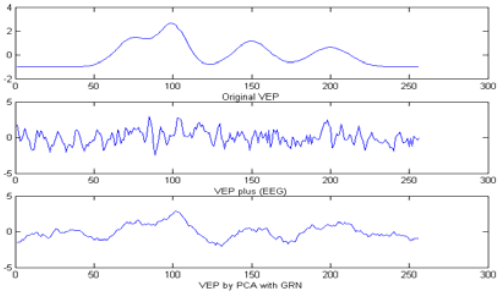

Fig. 7 Artificial VEP signals with PCs selected using SER (EEG factor of 5)

It is also clear that the proposed SER method gives even better performance in comparison of KSR, RP and SPR, when the noise (EEG) factors were higher.

Table 5 gives the result of the t-test analysis of P3 latencies and amplitudes. The hypothesis tested for latency was that S2N>S2M, while for amplitude, the hypothesis tested was S2M>S2N. The results indicate that only P3 parameters extracted using PCs with SPR and SER methods showed significant differences, while with KSR and RP methods, no significant differences were obtained. The results using SPR and SER methods shows that P3 amplitudes were higher for S2M as compared to S2N (with $p<0.05$). In addition, it also showed that P3 latencies were smaller (i.e. P3 responses were 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 [10].

TABLE I
COMPARISON OF SNRS WITH EEG NOISE FACTOR=1

Signals (randomly selected)	SNR				
	Original	RP	KSR	SPR	SER
1	0	7.67	12.69	12.69	12.69
2	0	2.92	9.16	9.16	9.16
3	0	2.93	12.57	12.57	12.57
4	0	1.98	10.60	10.60	10.60
Total (64 signals)	0	185.00	698.71	698.71	698.71
Average (64 signals)	0	2.89	10.91	10.91	10.91

TABLE II
COMPARISON OF SNRS WITH EEG NOISE FACTOR =2

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

TABLE III
COMPARISON OF SNRS WITH EEG NOISE FACTOR =5

Signals (randomly selected)	SNR				
	Original	RP	KSR	SPR	SER
1	-13.97	-1.24	3.98	4.01	4.43
2	-13.97	-1.54	3.79	4.16	4.36
3	-13.97	-1.66	3.14	4.47	4.95
4	-13.97	-1.58	2.53	3.16	3.69
Total (64 signals)	-894.68	-120.67	61.64	107.17	149.81
Average (64 signals)	-13.97	-1.88	-0.9	1.67	2.34

TABLE IV
COMPARISON OF SNRS WITH EEG NOISE FACTOR =10

Signals (randomly selected)	SNR				
	Original	RP	KSR	SPR	SER
1	-20	-1.79	2.28	2.37	2.52
2	-20	-2.13	1.64	2.49	2.51
3	-20	-2.28	-0.23	1.08	2.00
4	-20	-2.50	-2.40	-0.85	0.08
Total (64 signals)	-1280	-146.69	-51.91	-27.20	45.33
Average (64 signals)	-20	-2.29	-0.81	-0.42	0.70

Therefore, in conclusion, our proposed SER method is efficient and suitable for extraction of single trials of VEP signals as long as the frequency range of the parameter that is to be extracted is known.

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REFERENCES

[1] Aunon, J.I., McGillem, C.D. and Childers, D.G., "Signal Processing in Event Potential Research: Averaging and Modelling," *CRC Critical Review Bioengineering*, vol. 5, pp. 323-367, 1981.

[2] Lange, D.H., and Inbar, G.F., "Variable Single-Trial Evoked Potential Estimation via Principal Component Identification," *Proc. of IEEE EMBS International Conference*, pp. 954-955, 1996.

[3] Andrews, S, Palaniappan, R., and Asirvadam, V.S., "Single Trial Source Separation of VEP Signals Using Selective Principal Components," *Proc. 2nd International Conference on Advances in Medical Signal and Information Processing*, pp. 51-57, 5-8 September 2004.

[4] Celka, P., Mesbah, M., Keir, M., Boashash, B., and Colditz, P., "Time-varying Dimension Analysis of EEG Using Principal Component Analysis and Model Selection", *Proceedings of IEEE EMBS International Conference*, pp. 1404-1407, 2000.

[5] Jolliffe, I.T., *Principal Component Analysis*, Springer-Verlag, 1986.

[6] Polich, J., "P300 in Clinical Applications: leaning, Method and Measurement," *American Journal of EEG Technology,* vol. 31, pp. 201-231, 1991.

[7] Snodgrass, J.G. and Vanderwart, M., "A Standardized Set of 260 Pictures: Norms for Name Agreement, Image Agreement, Familiarity, and Visual Complexity," *Journal of Experimental Psychology: Human Learning and Memory*, vol. 6, no. 2, pp. 174-215, 1980.

[8] Misulis, K.E., *Spehlmann's Evoked Potential Primer: Visual, Auditory and Somatosensory Evoked Potentials in Clinical Diagnosis*, Butterworth-Heinemann, 1994.

[9] Begleiter, H., Projesz, B., Reich, T., Edenberg, H.J., Goate, A., Blangero, J., Almasy, L., Foroud, T., Eerdewegh, P.V., Polich, J., Rohrbaugh, J., Kuperman, S., Bauer, L.O., O'Connor, S.J., Chorlian, D.B., Li, T.K., Conneally, P.M., Hesselbrock, V., Rice, J.P, Schuckit, M.A., Cloninger, R., Nurnberger Jr., J., Crowe, R. and Bloom, F.E., "Quantitative Trait Loci Analysis of Human Event-related Brain Potentials," *Electroencephalography and Clinical Neurophysiology,* vol. 108, pp. 244-250, 1998.

[10] Bentin, S. and McCarthy, G., "The Effects of Immediate Stimulus Repetition on Reaction Time and Event-Related Potentials in Tasks of Different Complexity," *Journal of Experimental Psychology: Learning, Memory and Cognition*, vol. 20, no. 1, pp. 130-149, 1994.

TABLE V
T-TEST RESULTS OF P3 LATENCIES AND AMPLITUDES FOR STIMULI S2M AND S2N

Subjects	RP		KSR		SPR		SER	
	Latency	Amplitude	Latency	Amplitude	Latency	Amplitude	Latency	Amplitude
1	0.3397	0.8219	0.5111	0.7844	0.9978	0.0034	0.9978	0.0019
2	0.8798	0.3063	0.5980	0.4561	0.9994	1.89e-015	1.0000	0
3	0.1425	0.1814	0.0546	0.8401	1.0000	8.11e-004	1.0000	0.0149
4	0.4590	0.4142	0.7279	0.5998	0.9683	1.26e-010	0.9961	0.0043