

Signal Refinement: Principal Component Analysis and Wavelet Transform of Visual Evoked Response

Ahmed Almurshedi and Abd Khamim Ismail

Department of Physics, Faculty of Science, Universiti Teknologi Malaysia, 81310 Johor, Malaysia

Abstract: This study presents an analysis on Visual Evoked Potentials (VEPs) recorded mainly from the occipital area of the brain. Accumulation of segmented windows (time locked averaging), Coiflet wavelet decomposition with dyadic filter bank and Principle Component Analysis (PCA) of three stages were utilized in order to decompose the recorded VEPs signal, to improve the Signal to Noise Ratio (SNR) and to reveal statistical information. The results shown that the wavelet transformation offer a significant SNR improvement at around four times compared to PCA as long as the shape of the original signal is retained. These techniques show significant advantages of decomposing the EEG signals into its details frequency bands.

Keywords: Electroencephalogram, principle component analysis, signal to noise ratio, visual evoked potentials, wavelet transforms

INTRODUCTION

Evoked Potentials (EPs) are the alterations derivative of the spontaneous ongoing electroencephalogram (EEG) produced by external stimulation (e.g., auditory, visual, etc.). They are Time Locked (TL) to the presentation of stimulus and contained a characteristic pattern of response which is more or less reproducible under similar experimental conditions (Başar, 1980; Galloway, 1990). In order to investigate the brain's response different tasks and events, sequences of stimuli are used, which allows the study of different cognitive or sensitive functions, states, diseases, etc. Thus, the EPs is an important tool in neuroscience.

VEPs are hardly seen in EEG signals due to their modest amplitudes as compared with the base EEG signal. Therefore, several trials are averaged in time locked with the stimulus in order to enhance the response. The contribution of trails are added together and accumulation of responses, while the ongoing EEG cancel each other's (Quiroga *et al.*, 2000). The number of trials is a very important parameter to care about in the experiment. Large number of trials can optimize VEP ratio but still there is concern of too large number of trials which may result into some disorder due to the tiredness. The success of averaged EPs presupposes less number of trials and would ultimately allow single trial EPs extraction from the background EEG (Quiroga, 2000). Researchers have proposed several methods for filtering averaged EPs. Starting from the last century, most of the approaches involved filter design such as invariant Wiener filtering and then

variant Wiener filtering to optimize the result of transient responses (evoked responses) related to specific time and frequency locations. The filter is based on Fourier transform (sine and cosine signals decomposition) so there was always doubt for imperfect reconstruction.

The above mentioned limitations can be resolved by using a Wavelet Transform (WT). The WT is a time-frequency representation proposed first by Grossmann and Morlet (1984), which has an optimal resolution in both frequency and time domains and has been successfully applied to study EEG-EP signal (Bertrand *et al.*, 1994; Demiralp *et al.*, 1999; Schiff *et al.*, 1994). Wavelet analysis allows a selection of window with appropriate length but it must be noted that the modulation of time by any variable weight can affect the spectrum. Real-valued mother wavelets are often defined to be symmetric and these wavelet coefficients do not carry phase information. Complex-valued Morlet (Gurley *et al.*, 2003) wavelets and Gabor filters retain phase information. On the other hand, Principle Component Analysis (PCA) is also used for EEG analysis which capable to enhance Neural Network for detection of Seizure and Epilepsy (Ghosh-Dastidar *et al.*, 2008). PCA with the help of density estimation has successfully employed for denoising of multi-channel EEG signals (Dong and Luo, 2012) and in multifocal mfVEPs (Zhang and Hood, 2004). PCA has also been applied for VEPs especially for noise reduction and separation from EEG background (Palaniappan *et al.*, 2002; Sharmilakanna and Palaniappan, 2005).

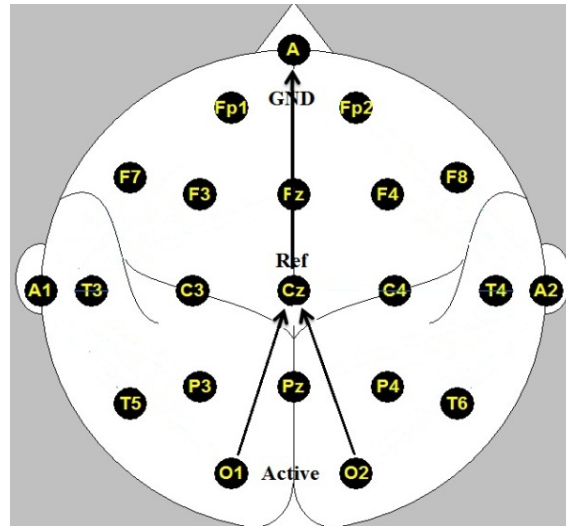


Fig. 1: Scalp electrode map of 10-20 stem electrode montage

TL averaging technique shows milestones of evoked signal but with high frequency, it may lead to probable errors due to unclear peak positions and values (Turker *et al.*, 2008; Mizota *et al.*, 2007). This study presents and applies a straightforward WT and PCA denoise on real recorded transient VEPs with checkerboard stimulation to overcome this drawback. However, to decompose the signal to its frequency bands, a comparative analysis of transient VEPs using both WT and PCA techniques has been performed. Here, the wavelet dyadic filter bank is used to cancel unwanted signal (noise) and decompose the signal to its detailed frequency bands. The key point in the denoising of VEPs with WT is the selection of the mother wavelet domain. PCA of multi stages is also used to eliminate and denoise VEP signal after TL average, since choosing a proper component of the signal for which to extract is an important step in PCA.

Both comparative analysis of WT and PCA shows improvement in the VEPs signal. However WT shows better SNR improvement compared to PCA. Other statistical analysis also revealed that the WT is much better than PCA.

METHODS AND EXPERIMENT

VEPs recordings are obtained using pattern reversal checkerboard stimulation to the brain from normal subjects. The subjects are instructed to focus on the red point at the center of LCD screen, 100 cm away with temporal frequency of 1 Hz and checkerboard resolution of 12×16. Scalp recordings are obtained from the visual primary sensory area (Occipital O1 and O2) electrodes which are linked to central area (Cz) as a reference (Fig. 1). Sampling rate is 1000 Hz and the data is pre-processed with band pass filter in the range of 0.1-100 Hz and Notch filter of 50 Hz for power line

noise rejection. EAD-AGC8S Shielded Differential Electrode Sintered Ag/AgCl electrodes are used to record signals. BioTower-4ERG with 4-channel Bio-amplifier is used to amplify the signals with 10,000 time amplification. The data is acquired using OMB-DAQ-3000 Series 1-MHz, 16-Bit USB Data Acquisition Modules. The recording session is consisted of 60 stimuli presentations of a total of 120 reversals.

Transient VEPs response consists of a sequence of different peaks that occurs at constant latency after onset of stimulus. VEPs responses consist of first negative to appear at around 75 ms (N75), positive peak at 100 ms (P100) and another negative at 135 ms (N135).

WAVELET TRANSFORMS

The advantage of the Wavelet Transform (WT) over Fourier based methods is that the functions matched with the signal is not necessarily sinusoidal. In fact, there are many different functions as wavelets, each one carries different characteristics that are more or less appropriate and depends on the application. Irrespective of the mathematical properties of the wavelet to choose, a basic requirement is that, it looks similar to the patterns to be localized in the signal. This allows a good localization of the structures of interest in the wavelet domain and moreover, it minimizes spurious effects in the reconstruction of the signal via the inverse wavelet transform (Quian Quiroga *et al.*, 2001). WT can be expressed as time integrated product of a signal using a set of basic functions which are dilated (or contracted) and shifted versions of some prototype of ‘mother wavelet’. The mother wavelet can have different forms subject to certain mathematical constraints.

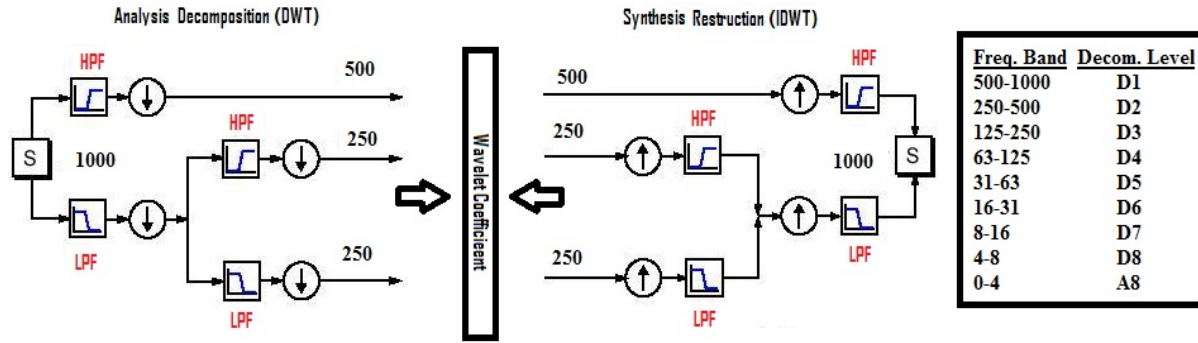


Fig. 2: Dyadic wavelet filter bank

The original space of orthogonal wavelet is split into a sequence of subspaces and each subspace carries a spectrum half the size of the previous (octave-band decomposition). Such decomposition is appropriate for smooth sequences with isolated discontinuities.

The j -level orthogonal discrete wavelet transformation (DWT) of a sequence is a function of $l \in \{1, 2, \dots, j\}$ which is given as:

$$\alpha_k^{(j)} = \langle x_n, g_{n-2^j k}^{(j)} \rangle_n = \sum_{n \in \mathbb{Z}} x_n g_{n-2^j k}^{(j)} \quad (1)$$

$$\beta_k^{(l)} = \langle x_n, h_{n-2^l k}^{(l)} \rangle_n = \sum_{n \in \mathbb{Z}} x_n h_{n-2^l k}^{(l)} \quad (2)$$

where, $l \in \{1, 2, \dots, j\}$

The inverse DWT is given as:

$$x_n = \sum_{k \in \mathbb{Z}} \alpha_k^{(j)} g_{n-2^j k}^{(j)} + \sum_{l=1}^j \sum_{k \in \mathbb{Z}} \beta_k^{(l)} h_{n-2^l k}^{(l)} \quad (3)$$

where,

- $\alpha_k^{(j)}$ = The scaling coefficient
- $\beta_k^{(l)}$ = The wavelet coefficient

The equivalent filter $g^{(j)}$ is often called the scaling sequence and $h^{(l)}$ wavelets (wavelet sequences), $l = 1, 2, \dots, j$.

The orthogonal DWT is implemented using a J -level octave-band orthogonal filter bank as shown in Fig. 2. This particular version of the DWT is called the dyadic DWT as each subsequent channel carries half of the coefficients of the previous one.

The wavelet used for the decomposition is Coiflet of order 5, which is deemed to be closest in resemblance to the signal waveforms under consideration. This family of wavelets is built by Daubechies at the request of Coifman of order 1-5. The wavelet function has $2N$ moments equal to 0 and the scaling function has $2N-1$ moments equal to 0, which is compactly supported (filter width $6N-1$ and filter length $6N$) (Hassoney *et al.*, 2012).

The conventional method of denoising implies a thresholding criterion in the wavelet domain. The signal

is reconstructed from noisy data by setting wavelet coefficients below a certain threshold (hard denoising) equal to zero or with the use of a smoother transformation (soft denoising) (Donoho, 1995). However, this procedure is not optimal for recovering the EPs because these wavelet coefficients are of the order or even smaller than the background EEG. Therefore, instead of using a thresholding criterion, a denoising based on the specific time and frequency localizations of the evoked responses are implemented.

For this study, orthogonal coiflet wavelet is chosen as mother functions due to their similarity with the evoked responses. Following properties that make them optimal in signal analysis (Chui, 1993; Cohen *et al.*, 1992; Unser *et al.*, 1992) see for details) such as nearly symmetric, smooth, nearly optimal time-frequency resolution and compact support.

PRINCIPLE COMPONENT ANALYSIS

PCA is a powerful data analyzing technique used to identify patterns of data by highlighting their similarities and differences. It is also used to reduce the number of dimensions by compressing high dimensions without much loss of data information. Subtracting the mean from each of the data dimensions is an important step in order for PCA to work properly. The mean subtracted is the average across each dimension, so this produces a data set whose mean is zero.

The eigenvectors and eigenvalues of the matrix are calculated since they are carries useful information about the patterns of the data. The eigenvectors are perpendicular to each other, in such away one of the eigenvectors goes through the middle of the particular points. That eigenvector provides information of how these two data sets are related along that line. The second eigenvector gives pattern in the data, that all the points follow the main line, but are off to the side of the main line to some extent. So, the eigenvectors of the covariance matrix help to extract lines to characterize the data.

The eigenvalues are quite different values. In fact, it turns out that the eigenvector with the highest

eigenvalue is the principle component of the data set. Some of the information may lost, but if the eigenvalues are small, the information lose is less. By leaving out some components, the final data set has fewer dimensions than the original.

By considering matrix X to represent the mixture signals including VEP, the covariance of matrix x can be computed by using following relation (Sharmilakanna and Palaniappan, 2005).

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

where, E is the orthogonal matrix of eigenvector of R .

$$Y = E^T X^T \quad (5)$$

VEP signal can be reconstructed from the selected eigenvalue by using:

$$\vec{X} = \vec{E}\vec{Y} \quad (6)$$

where, \vec{E} and \vec{Y} are eigenvectors and principle component, respectively.

RESULTS

Time Lock (TL) averaging, wavelet analysis and PCA of the evoked EEG are computed for occipital channels. Typical waveforms averaged from O1 are given, followed by typical waveforms from O2 for one subject. Time is recorded in milliseconds and amplitudes in microvolts.

Accumulation of VEP segments can remove some of the noise, since the TL averaging technique remove the noise of opposite phase but this process doesn't filter all unwanted frequencies from the signal.

Figure 3 shows dyadic wavelet using coiflet analysis to decompose VEP signal into its EEG frequency bands Delta (0-4), Theta (4-8), Alpha (8-16), Beta (16-31) and Gamma (31-63) Hz (Mohd Tumari *et al.*, 2012). The wavelet dyadic filter bank is used to cancel unwanted signal (noise) and decompose the signal to its detailed frequency bands.

The VEP response with coiflet wavelet decomposition is correlated mostly with the coefficients in the details d6-d7 (Fig. 4). In essence, to avoid the fluctuations related to the spontaneous EEG and to get the peaks of interest only, the wavelet coefficients that not correlated with the VEP is set to zero as shown in Fig. 4.

PCA of 3 stages is also used to analyze VEP data. It is used as a technique to eliminate and denoise VEP signal after TL average. It is based on a fact of choosing the principle component (highest eigenvalue) and neglecting other components. In PCA, the selected component in the first stage is further analyzed in two different steps. In each step, the data is analyzed to extract two PCA and then the one with higher eigenvalue is selected (Sharmilakanna and Palaniappan, 2005). Figure 5 shows the principle components of the signals in the third stage and the variance and eigenvalues of PCA are summarized in Table 1.

By using PCA, it is possible to separate EEG noise from VEP signal using the fact that the EEG subspace

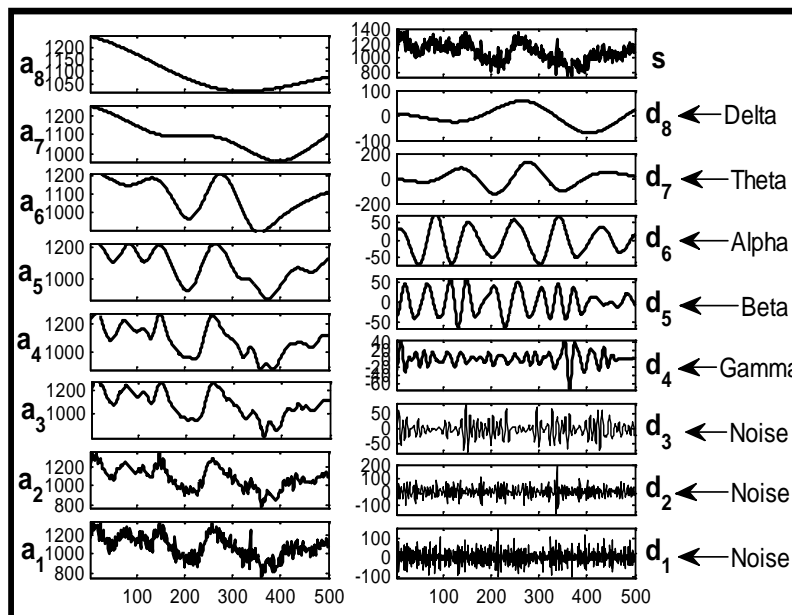


Fig. 3: Dyadic wavelet analysis of VEP signal using coiflet 5 for 8 levels

Table 1: PCA of VEP signal show the eigenvalue, the variance and cumulative

PCA	Eigenvalue	Percentage of variance (%)	Cumulative (%)
O1	PC 1	1.99507	99.75
	PC 2	0.00493	0.25
O2	PC 1	1.99852	99.93
	PC 2	0.00148	0.07

constitutes of principal components with eigenvalues below a certain threshold and eigenvalues with principal components above this threshold which represents the signal subspace.

DISCUSSION

WT and PCA are used to analyze the transient visual evoked potentials signals recorded experimentally from occipital lobe of brains stimulated using checkerboard pattern as preferred by ISCEV standard (Odom *et al.*, 2010). Figure 6a represents the TL averaging signals from two electrodes cite (O1 and O2). TL of 120 trails is averaged from reversal checkerboard pattern. Figure 6b shows the result of PCA of three stages. The principle component of the first stage is further analyzed to select the principle

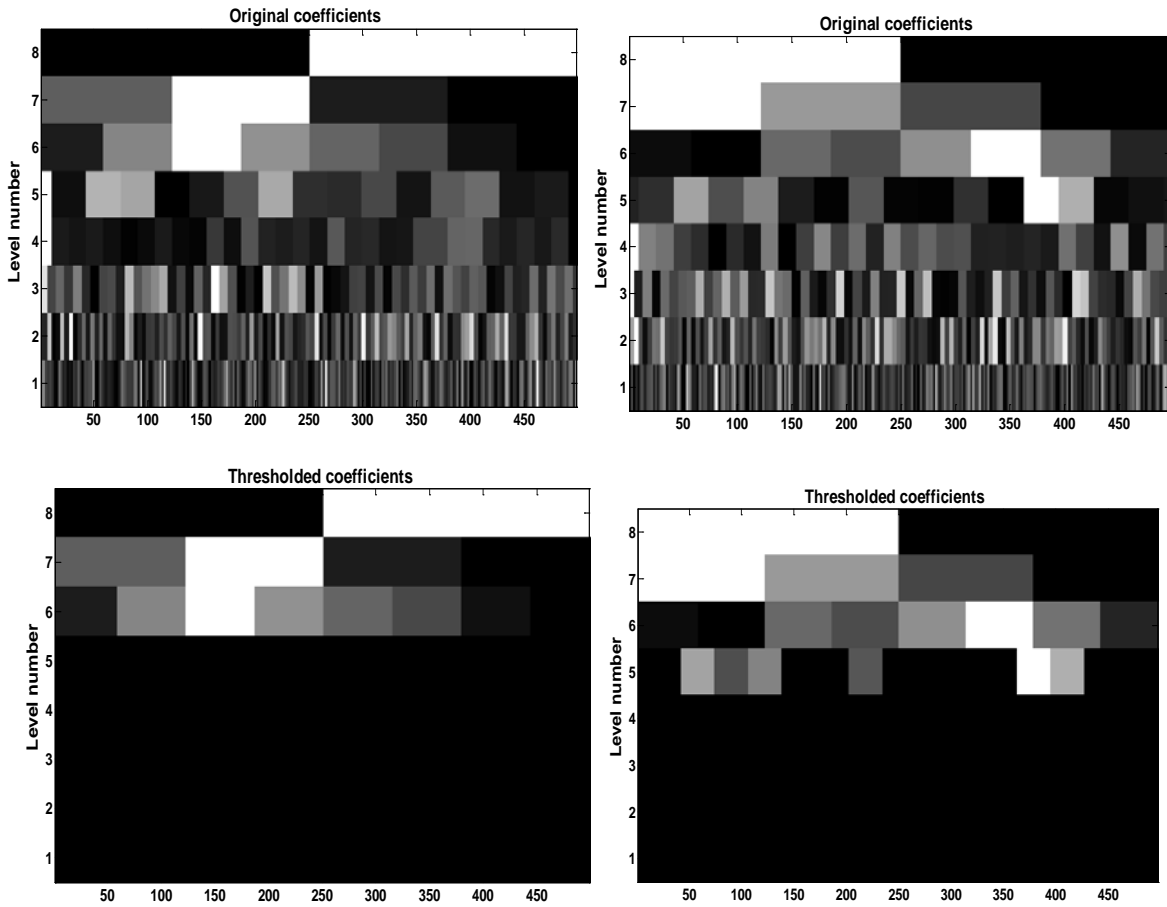


Fig. 4: Original and threshold wavelet denoising coefficient of VEP signals

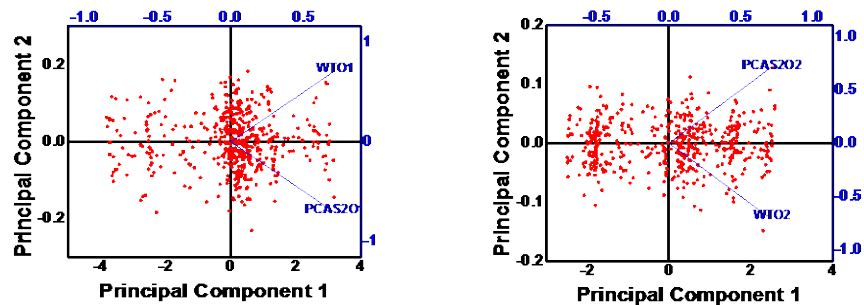


Fig. 5: Principle component analysis of VEP signals O1 and O2 computing eigenvectors and eigenvalue

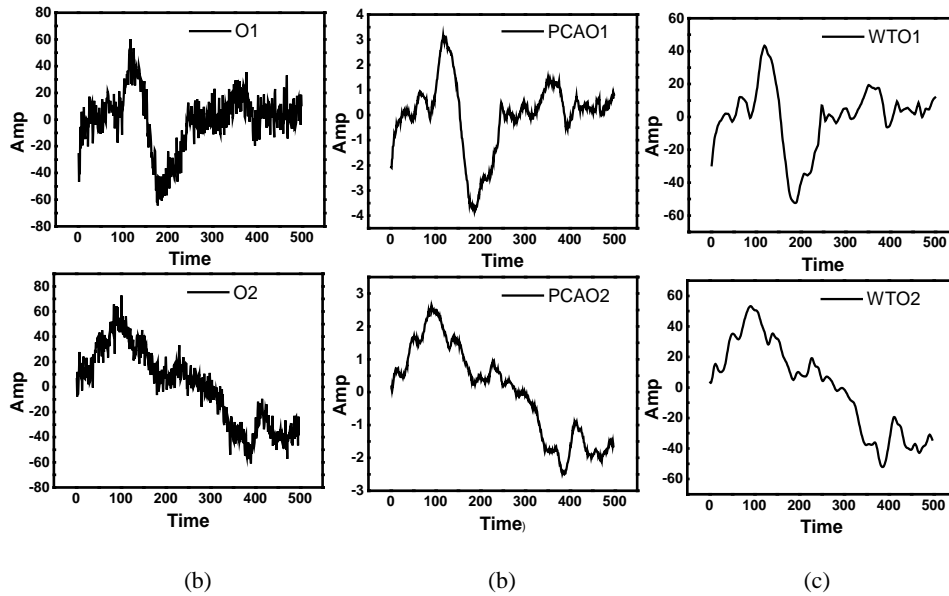


Fig. 6: VEP signals; (a): Time locked signal; (b): with PCA; (c): with WT. Note removing high frequency noise from the signals

Table 2: Summary of statistical analysis such as (mean, SD, SEM, p-value, variants and RMS), Signal to Noise Ratio (SNR) and root mean square analysis

VEP signals		Mean	S.D.	Standard Error of Mean (SEM)	t-Statistic	p-value	Variance	Root Mean Square (RMS)	Signal to Noise Ratio (SNR) (dB)
O1 Electrode	TL	0.5158	0.1722	0.0077	66.7546	9.09157E-10	0.0296	0.5439	9.487
	WT	0.5461	0.2059	0.0092	59.1053	5.55112E-17	0.0424	0.5834	31.256
	PCA	0.5454	0.2023	0.0090	60.1072	5.55112E-17	0.0409	0.5815	19.080
O2 Electrode	TL	0.4552	0.2277	0.0102	44.5615	1.04794E-9	0.0517	0.5093	9.798
	WT	0.4943	0.2818	0.0126	39.1103	4.93217E-13	0.0791	0.5694	49.475
	PCA	0.4893	0.2780	0.0124	39.2362	6.33771E-13	0.0771	0.5632	19.136

component and similarly for the third stage. Multi stages PCA is applied on emulated VEP signal (Sharmilakanna and Palaniappan, 2005). The result show strong agreement with the simulation result since PCA can effectively separate VEP response from EEG background noise. Figure 6c shows the result of WT analysis of denoising VEP signals with removal of unwanted EEG background noise. Wavelet result shows the flexibility and ability of wavelet to analyze VEP signals signal and decompose it into different frequency bands.

Statistical analysis: Is used to compare the data and to study the differences among analyzing techniques. T-test is used to study the mean, Standard Deviation (SD), Standard Error of Mean (SEM), the variance, Root Mean Square (RMS) and p-value. Signal to Noise Ratio (SNR) are also computed to see the improvement in the signal. Table 2 summarizes the statistical analysis applied to VEP signals. As shown in Table 2, SD, RMS, SEM, SNR and the variance are higher in WT than PCA. Both of the analysis WT and PCA show improvement in the signal. Since the SNR is much increased, WT show higher SNR than PCA. Other statistical analysis also supports WT than PCA.

CONCLUSION

This study describes the method and comparison of principle component analysis and wavelet transform techniques to extract and denoise real experimental recorded transient VEP signals. This research discusses the ability of PCA and WT to process the signal as:

- Decompose the signal to its detailed information and coefficients in such a way that it can break the signal to its frequency bands.
- Denoise the signal and remove unwanted signal without distorting VEP signal.
- Selecting of the principle component of VEP signals and separate it from EEG background. The statistical results show that wavelet analysis technique reduces RMS and improves SNR almost 4 times to its original value.

ACKNOWLEDGMENT

The authors would like to thank Department of Physics faculty of Science, Universiti Teknologi and Ministry of Higher Education for the financial supports. This research supported by Research University Grant, Vot Number: Q.J130000.2526.07H93.

REFERENCES

- Başar, E., 1980. EEG-brain Dynamics: Relation Between EEG and Brain Evoked Potentials. Biomedical Press, Elsevier-North-Holland.
- Bertrand, O., J. Bohorquez and J. Pernier, 1994. Time-frequency digital filtering based on an invertible wavelet transform: an application to evoked potentials. *IEEE T. Bio-Med. Eng.*, 41: 77-88.
- Chui, C.K., 1993. An Introduction to Wavelets. Vol. 1, Academic Press, Boston.
- Cohen, A., I. Daubechies and J.C. Feauveau, 1992. Biorthogonal bases of compactly supported wavelets. *Commun. Pure Appl. Math.*, 45: 485-560.
- Demiralp, T., A. Ademoglu, M. Schürmann, C. Basar-Eroglu and E. Basar, 1999. Detection of P300 waves in single trials by the Wavelet Transform (WT). *Brain Lang.*, 66: 108-128.
- Dong, K. and Z. Luo, 2012. A method of denoising multi-channel EEG signals fast based on PCA and DEBSS algorithm. *Proceeding of the International Conference on Computer Science and Electronics Engineering (ICCSEE, 2012)*, pp: 322-326.
- Donoho, D.L., 1995. De-noising by soft-thresholding. *IEEE T. Inform. Theory*, 41: 613-627.
- Galloway, N., 1990. Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine. *Brit. J. Ophthalmol.*, 74: 255.
- Ghosh-Dastidar, S., H. Adeli and N. Dadmehr, 2008. Principal component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection. *IEEE T. Bio-Med. Eng.*, 55: 512-518.
- Grossmann, A. and J. Morlet, 1984. Decomposition of hardy functions into square integrable wavelets of constant shape. *SIAM J. Math. Anal.*, 15: 723-736.
- Gurley, K., T. Kijewski and A. Kareem, 2003. First-and higher-order correlation detection using wavelet transforms. *J. Eng. Mech.*, 129: 188-201.
- Hassoney, A.F., A.K. Ismail and H. Hamza, 2012. Orthogonal and biorthogonal wavelet analysis of visual evoked potentials. *Int. J. Comput. Appl.*, 60: 50-52.
- Mizota, A., N. Asaumi, M. Takasoh and E. Adachi-Usami, 2007. Pattern visual evoked potentials in Japanese patients with multiple sclerosis without history of visual pathway involvement. *Doc. Ophthalmol.*, 115: 105-109.
- Mohd Tumari, S., R. Sudirman, A. Ahmad and A. Al-Haddad, 2012. Study of normal children electroencephalography signals using wavelet transformation. *Proceeding of the IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES, 2012)*, pp: 896-900.
- Odom, J.V., M. Bach, M. Brigell, G.E. Holder, D.L. McCulloch and A.P. Tormene, 2010. ISCEV standard for clinical visual evoked potentials (2009 update). *Doc. Ophthalmol.*, 120: 111-119.
- Palaniappan, R., S. Anandan and P. Raveendran, 2002. Two level PCA to reduce noise and EEG from evoked potential signals. *Proceeding of the 7th International Conference on Control, Automation, Robotics and Vision (ICARCV' 2002)*, 3: 1688-1693.
- Quian Quiroga, R., 2000. Obtaining single stimulus evoked potentials with wavelet denoising. *Physica D*, 145: 278-292.
- Quian Quiroga, R., O.W. Sakowitz, E. Basar and M. Schürmann, 2001. Wavelet transform in the analysis of the frequency composition of evoked potentials. *Brain Res. Protoc.*, 8: 16-24.
- Quiroga, R.Q., E. Basar, M. Schürmann and M.S. Urmann, 2000. Phase-locking of event-related alpha oscillations. *Proceeding of the Workshop on Chaos in Brain*, pp: 301-304.
- Schiff, S.J., A. Aldroubi, M. Unser and S. Sato, 1994. Fast wavelet transformation of EEG. *Electroen. Clin. Neuro.*, 91: 442-455.
- Sharmilakanna, P. and R. Palaniappan, 2005. EEG artifact reduction in VEP using 2-stage PCA and N4 analysis of alcoholics. *Proceeding of the 3rd International Conference on Intelligent Sensing and Information Processing (ICISIP' 2005)*, pp: 1-7.
- Turker, H., M. Terzi, O. Bayrak, N. Cengiz, M. Onar and O. Us, 2008. Visual evoked potentials in differential diagnosis of multiple sclerosis and neurobehcet's disease. *Tohoku J. Exp. Med.*, 216: 109-116.
- Unser, M., A. Aldroubi and M. Eden, 1992. On the asymptotic convergence of B-spline wavelets to Gabor functions. *IEEE T. Inform. Theory*, 38(2): 864-872.
- Zhang, X. and D.C. Hood, 2004. A principal component analysis of multifocal pattern reversal VEP. *J. Vision*, 4(1): 32-43.