TIME-VARYING BISPECTRAL ANALYSIS OF AUDITORY EVOKED MULTI-CHANNEL SCALP EEG

Vinod Chandran
School of Electrical Engineering and Computer Science, Queensland University of Technology, Brisbane, Queensland, Australia

ABSTRACT

Time-varying bispectra, computed using a classical sliding window short-time Fourier approach, are analyzed for scalp EEG potentials evoked by an auditory stimulus and new observations are presented. A single, short duration tone is presented from the left or the right, direction unknown to the test subject. The subject responds by moving the eyes to the direction of the sound. EEG epochs sampled at 200 Hz for repeated trials are processed between -70 ms and +1200 ms with reference to the stimulus. It is observed that for an ensemble of correctly recognized cases, the best matching time-varying bispectra at (8 Hz, 8Hz) are for PZ-FZ channels and this is also largely the case for grand averages but not for power spectra at 8 Hz. Out of 11 subjects, the only exception for time-varying bispectral match was a subject with family history of Alzheimer’s disease and the difference was in bicoherence, not biphase.

1. INTRODUCTION

Higher order spectral analysis [1, 2] has been used to investigate nonlinearity and phase coupling between Fourier components of the EEG signal [3] and extract features that can classify EEG segments targeted towards applications such as early detection of the onset of epilepsy [4-6], early detection of the onset of seizures in infants [7], classification of brain states [8], etc. Phase relationships are introduced as a result of synchronous discharges in populations of neurons and although the evidence of it is weakened as a result of superposition of signals from many regions in the data acquired from scalp EEG electrodes, it can still be statistically significantly observed using higher order spectral analysis with sufficiently large ensembles of epochs for averaging to obtain estimates.

Unlike physical systems where models and equations might predict such behavior in the modes of possible oscillations of the system, the human brain is a large and complex collection of billions of neurons that does not lend itself to simple modeling even for simple stimulus-response behavior. When a number of stimulus-locked epochs, captured synchronously with respect to the stimulus on each trial, are available, ‘grand average’ waveforms [9] of the evoked EEG have been found to be very useful in describing auditory [10], visual [11] and somatosensory [12] responses. Negative and positive peak potentials have been identified at given latencies with respect to the stimulus in each case [9]. The ‘grand average’ is a time-varying mean computed by averaging over a number of epochs and is a first order statistic. A spectrogram [13-16], depicting time-varying power spectral density would be a second order statistical description. Similarly, the time-varying bispectrum [17, 18] and time-varying bicoherence [19] and biphase can describe the response using third order statistics.

It has been established that particular cortical regions are associated with particular types of processing [20] and evoked potentials from these regions have been used to check for abnormality arising from lesions, trauma and disease [21-23]. The primary auditory cortex is located in the temporal lobe over both hemispheres. Additional regions such as the secondary auditory cortices, the insular gyrus, planum temporal, anterior and posterior parts of the T1 gyrus [24] are also known to be involved in auditory processing. Functional connectivity between different regions for auditory processing of amplitude modulated white noise was investigated in [24] using the signal analysis tool of directed Coherence (reference in [24]), a second order statistical approach. Results of EEG analysis using first, second and third order statistics can be compared in the context of this knowledge.

The binaural human auditory system is good at determining the left/right direction of the source of a sound using inter-aural time and level differences [25, 26]. It has been reported that the brain stem auditory pathways responsible for detecting inter-aural time differences are present even at birth [25]. A logical next step from asking which regions are significantly active in response to an auditory stimulus is to ask which regions are similarly active in response. This work attempts to answer that question using scalp EEG. Scalp EEG is relatively inexpensive and non-intrusive and multiple epochs can be obtained from repeated trials from many subjects relatively easily. It can be acquired with good time resolution and from many channels. It is particularly interesting to investigate whether the same channels show similarity in first, second and third order statistics of the
evoked EEG response, and whether this is dependent on factors other than the stimulus/response paradigm.

2. PREVIOUS WORK

There are many publications in the areas of higher order spectral analysis of EEG [4, 27-29] and other biomedical signals [30]. A few have used time-varying analysis [31]. There is even a proprietary clinical tool for monitoring depth of anesthesia [32].

Time-varying bispectral analysis has been approached using the classical short time Fourier transform approach as used in this work [17, 19], using wavelet spectra [33-36], and using higher order extensions of the Wigner-Ville distribution [37-39]. Because of the non-stationary characteristic of the signal it is imperative to use a finite window of samples in the estimation via any of these approaches. Wavelet analysis can select an appropriate length window but it must be noted that modulation of the time signal by any variable weight will affect the bispectrum. Real-valued mother wavelets are often defined to be symmetric and these wavelet coefficients do not carry phase information. Complex-valued Morlet wavelets and Gabor filters retain phase information, but it is more difficult to identify triads that satisfy the resonance condition \( f_1, f_2, f_1 + f_2 \) in non-uniformly spaced scale space than in linear Fourier frequency space. There are also problems with lack of ensemble averaging resulting in spurious coherence with the Wavelet approach [36]. Wigner-Ville based approaches can provide higher resolution in the time-frequency plane but face challenges with multi-component signals. Phase is meaningless in this approach unless cross-Wigner Ville distributions are used. Phase synchronization is of greater interest in EEG signal processing than tracking variations in the frequency of one component, in the context of this work and the rectangular windowed short-time Fourier approach is adopted.

Statistically reliable estimates of bispectra are best obtained without sacrificing time-resolution using ensemble averaging from multiple trials. For a non-stationary signal, this is only valid if the ensembles are registered to a reference time. This is possible with repeated trials of stimulus-response evoked potentials. Previous work in such EEG analysis has largely used grand averages [41] and second order spectral coherence [42-44]. Time-varying bicoherence was used with EEG in inconclusively [19] and the study did not use evoked potentials. There is no other existing work that compares scalp EEG auditory evoked potentials with bicoherence and biphase, to the best of my knowledge.

3. THEORETICAL FRAMEWORK

Let \( x(t) \), \( -t_a \leq t \leq t_p \), represent the EEG signal from any channel as a function of time with the reference being the onset of the stimulus in each epoch or realization of this random signal. The grand average of this signal over a number of epochs is

\[
M(t_w) = E[x(t_w)]
\]  

(1)

where \( t_1 \leq t_w \leq t_2 \) is the duration of estimation. For the grand average, the window is one sample long and the resolution is the same as each epoch in the ensemble. For second and third order statistics, finite length windows are necessary. The time-varying power spectrum, estimated using a short time Fourier transform, is

\[
P(f(t_w)) = E[X(f(t_w)) X^*(f(t_w))]
\]  

(2)

where \( X(f(t_w)) \) is the Fourier transform of \( x(t) w(t-t_w) \) and

\[
w(t) = \begin{cases} 
1 & -\frac{\tau}{2} \leq t < \frac{\tau}{2} \\
0 & \text{otherwise}
\end{cases}
\]

(3)

is a rectangular window that is made to slide across for a time-varying representation. The time-varying bispectrum, a spectral representation of the third order cumulant of this signal is similarly estimated by

\[
B(f_1, f_2; t_w) = E[X(f_1; t_w) X(f_2; t_w) X^*(f_1 + f_2; t_w)]
\]  

(4)

It is a complex valued function of two frequencies, referred to as the bifrequency \( (f_1, f_2) \). Its phase is referred to as the biphase, \( \phi(f_1, f_2) \). A normalized form of its magnitude

\[
b^2(f_1, f_2; t_w) = \frac{|B(f_1, f_2; t_w)|^2}{E[X(f_1; t_w) X(f_2; t_w)]^2 E[X^*(f_1 + f_2; t_w)]^2}
\]

(5)

is called the bicoherence. The bicoherence lies between 0 and 1 and indicates the degree of phase coupling between Fourier components at frequencies \( f_1, f_2, f_1 + f_2 \). For a random phase triad of components, the bicoherence is expected to be zero and if the phase relationship is constant over all epochs it is expected to be 1. The bicoherence is a measure of the fraction of the total product of powers at these frequencies that is phase-coupled. For white Gaussian random noise, the bispectrum is zero. In practice, the expectation operation is an average over a number, \( N \), of epochs and bicoherence is chi-squared distributed with 95% of the values expected to be below 3/N.

Each of these statistical measures can be computed for each EEG channel. For estimation from sampled signals, the discrete Fourier transform computed using a fast Fourier transform (FFT) algorithm is used. In this work, only the auto-spectra (not cross-spectra) are investigated. The dissimilarity between statistical measures for two different channels is measured using an L1-distance, or mean absolute difference over the relevant duration of the response.

\[
S_q(A, B) = \frac{1}{(t_2 - t_1)} \int_{t_1}^{t_2} |q_A(t_w) - q_B(t_w)| dt_w
\]

(6)
where $q_A(t_w)$ is one of the statistical measures for channel A and $q_B(t_w)$ is the corresponding measure for channel B, after normalization to keep the absolute difference less than 1. The normalization factor is constant for all channels. The closer the value of S is to zero the more similar are the channels A and B. Integrability in equation 6 is not guaranteed for generalized functions as arise with power spectral densities of harmonic functions. However, with a short-time windowed record it will be. For discrete-time signals the integral is replaced by summation.

4. EXPERIMENTAL FRAMEWORK

EEG data were collected using a 24 channel Contec KT88-2400 system with a sampling frequency of 200 Hz. Electrodes were arranged using the standard 10-20 system. Left hemisphere electrodes were referenced to the left ear mastoid, right hemisphere electrodes to the right mastoid and median electrodes to Ground. 19 EEG channels were used. EEG channels comprised of Fp1, Fp2, F3, F4, F7, F8, C3, C2, C4, T3, T4, T5, T6, O1, O2, P3, PZ and P4. An electronic circuit was constructed to provide a step transition synchronous with the application of a single tone sound stimulus and this signal was synchronously digitized using one of the auxiliary channels. Auxiliary electrodes were also placed to the left and right of the eyes and above and below one eye to record horizontal and vertical eye movements. Skin impedances were adjusted to be appropriately low using LED indicators on the system. Data were continuously recorded and 512 sample epochs were segmented out around each stimulus onset reference, ranging from -0.56 seconds to 2 seconds. Segmentation was performed by software and epochs affected by eye blinking were also eliminated using software. Epochs were then manually checked to further eliminate any epochs with segmentation errors and epochs that exhibited noise owing to electrode movement. 50 Hz power frequency rejection is built into the system.

Initial data acquired from a couple of subjects was used to establish the details of the data collection paradigm and all data from one subject was rejected owing to excessive eye blinking. Complete usable epochs were obtained from 11 healthy subjects. They ranged in age from 19 yrs to 52 yrs. There were 8 males and 3 females. Subject 8 reported to be exposed to about 3.5 hrs a day to loud sounds and having ringing in the ears (tinnitus). Subject 11 reported having a family history of Alzheimer’s disease, and pointed to lack of attention and external sound disturbance being possible causes.

In this work, the ensembles of epochs consisting of correct responses to sound from the left and sound from the right are processed, separately, for each subject. The number of epochs used for each subject is as given in table 1 along with the age and gender of each subject.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age/Gender</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left</td>
<td>42</td>
<td>19</td>
<td>20</td>
<td>40</td>
<td>47</td>
<td>51</td>
<td>32</td>
</tr>
<tr>
<td>Right</td>
<td>48</td>
<td>27</td>
<td>20</td>
<td>30</td>
<td>47</td>
<td>52</td>
<td>32</td>
</tr>
</tbody>
</table>

For computing time-varying power spectra and bispectra, rectangular windowed blocks of 128 points are used, thus $r = 128, \quad t_1 = -0.07$ and $t_2 = 1.20$ seconds for the range for the centre of this window, $t_w$. Grand averages, power spectral density at 8 Hz and bicoherence and bisphase at (8 Hz, 8 Hz) were computed using equations 1 to 5 and all the available epochs in each ensemble for averaging. The frequency resolution is 1.5625 Hz owing to the 128 point blocks and sampling frequency of 200 Hz. Therefore, 8 Hz actually refers to the frequency bin at 7.8125 Hz but for the sake of clarity the nearest integer frequency is used in this manuscript. No interpolation was performed. For each time-varying statistical measure, a dissimilarity measure was computed for every unique pair of EEG channels using equation 6. This was used to identify the best matching pair of electrodes in each case.

5. RESULTS

First, second and third order time-varying statistical measures of the evoked EEG are computed for each channel and the pair of best matched channels is selected using the minimum of the measure in equation 6. Typical waveforms for subject 2 (ID E06) are given next followed
by atypical waveforms for subject 11 (ID E15). Time is in seconds for all figures. Amplitudes are scaled by a constant owing to amplification and A/D conversion. Bicoherence lies between 0 and 1, biphase between ±π.

5.1 Typical time-varying statistics

5.1.1 Grand Average

Figure 1. Grand average waveforms for the best matched channels, PZ (blue) and FZ (red) for sound from the left.

Figure 2. Grand average waveforms for the best matched channels, PZ (blue) and FZ (red) for sound from the right.

5.1.2 Power spectrum

Figure 3. The best matching time-varying power spectra for this subject are for T4 (blue) and P4 (red) for sound from the left.

Figure 4. The best matching time-varying power spectra for this subject are for T3 (blue) and F7 (red) for sound from the right.

5.1.3 Bicoherence

Figure 5. The best matching time-varying bicoherence for this subject are for PZ (blue) and FZ (red), shown here for sound from the left.

A prominent negative peak (N1) can be observed in the grand averages for PZ, FZ as expected. The amplitude and latency of this peak are known not to vary much with age [1]. The quality of some of the data is degraded probably owing to changes in skin contact impedance and peaks at higher latencies are harder to identify. There are also differences between subjects. It is known that the grand average response at CZ is the strongest and shows an inversion (negative peaks to positive peaks and vice versa) with stimulus change from left ear to right ear. This was roughly exhibited for data from all subjects with noise related smaller peaks degrading some of the data. It may be noted that the methodology described here does not need to identify peaks and latencies and is quite robust to such degradations.

Second order statistics (power spectra) do not match as well as first and third order statistics in the best matched cases.

Figure 6. The best matching time-varying bicoherence for this subject are for PZ (blue) and FZ (red), shown here for sound from the right.

5.1.4 Biphase

Figure 7. The best matching time-varying biphase for this subject are for PZ (blue) and FZ (red), shown here for sound from the left.
Figure 8. The best matching time-varying biphase for this subject are for PZ (blue) and FZ (red), shown here for sound from the right.

First and second order statistics match well in electrodes above the frontal and parietal lobes. Second order statistics match across from temporal to either frontal or parietal lobes for this subject. Cognition presumably happens largely in the first few hundred milliseconds. Later data may be dependent on the eye movement response in a subject dependent manner.

5.2. Atypical Case

Subject 11 (ID E15) has a family history of Alzheimer’s disease. First order statistics and third order statistics are different for subject 11 with sound from the right.

5.2.1 Grand Average

Figure 9. The best matching grand averages for subject 11 are for T6 (blue) and CZ (red), for sound from the right. For all others they were PZ and FZ.

5.2.2 Bicoherence

Figure 10. The best matching bicoherence for subject 11 are for C4 (blue) and C3 (red), for sound from the right. For all others they are PZ and FZ.

5.2.3 Biphase

Figure 11. The best matching biphase for subject 11 are for PZ (blue) and CZ (red), for sound from the right, the same as for all others.

It may be noted that the response of subject 8, who reported ringing in the ears was not atypical compared to the group. If it can be detected through second or third order spectral analysis, the frequency of interest is not 8 Hz (in the alpha EEG frequency band).

5.3. Performance across the data set

The best matching channels for each subject and each case (average, power spectrum and bicoherence/biphase) are shown in the tables that follow. It is of interest to check whether these are consistent across the subjects. Only the 8 Hz frequency component and the (8 Hz, 8 Hz) bifrequency are investigated here. This is in the alpha EEG band and a typical alpha rhythm for adults.

5.3.1 Grand Average

Table 2 Best matching channels using grand averages of evoked EEG with sound from the left

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>P3</td>
<td>PZ</td>
<td>F7</td>
<td>PZ</td>
<td>T4</td>
<td>PZ</td>
</tr>
<tr>
<td>Subject</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Best match channels</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>T6</td>
<td>T4</td>
</tr>
</tbody>
</table>

Table 3 Best matching channels using grand averages of evoked EEG with sound from the right

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>F7</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
</tr>
<tr>
<td>Subject</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Best match channels</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>T6</td>
<td>C3</td>
</tr>
</tbody>
</table>

5.3.2 Power spectrum

Table 4 Best matching channels using power at 8 Hz of evoked EEG with sound from the left

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>T4</td>
<td>T4</td>
<td>T4</td>
<td>T4</td>
<td>T3</td>
<td>T3</td>
</tr>
<tr>
<td>Subject</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Best match channels</td>
<td>F7</td>
<td>T4</td>
<td>T3</td>
<td>T3</td>
<td>F7</td>
<td>C3</td>
</tr>
</tbody>
</table>
Clearly, there is activity from first order and third order statistics. From the second order statistics and of frontal and parietal is evidence of temporal lobe and motor cortex activity saturating, inhibiting or boosting other regions etc. There many neurons in particular regions firing synchronously, channel specific information arising presumably from channels. If the data did not carry channel specific information it would be negligible. There are 19 EEG channels and thus 171 unique pairs of

### Table 5

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>F8</td>
<td>T3</td>
<td>P4</td>
<td>T4</td>
<td>T3</td>
<td>P4</td>
</tr>
<tr>
<td>F7</td>
<td>F7</td>
<td>C4</td>
<td>T3</td>
<td>F7</td>
<td>F8</td>
<td></td>
</tr>
</tbody>
</table>

### Table 5

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>T3</td>
<td>F4</td>
<td>F7</td>
<td>T3</td>
<td>T3</td>
<td>C3</td>
</tr>
<tr>
<td>F7</td>
<td>F7</td>
<td>C3</td>
<td>F7</td>
<td>C3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 5.3.3 Bicoherence and Biphase

#### Table 6

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
</tr>
<tr>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td></td>
</tr>
</tbody>
</table>

#### Table 6

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
</tr>
<tr>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td></td>
</tr>
</tbody>
</table>

#### Table 7

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best match channels</td>
<td>PZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>C4</td>
<td></td>
</tr>
<tr>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>FZ</td>
<td>C3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 6. INTERPRETATION OF RESULTS

There are 19 EEG channels and thus 171 unique pairs of channels. If the data did not carry channel specific evoked brain function information it would be uncorrelated random and there would be equal probability of any channel pair to be the best matching. In that case the probability of 10 occurrences of PZ-FZ as the best match would be one in $2.138 \times 10^{-22}$! Clearly, there is channel specific information arising presumably from many neurons in particular regions firing synchronously, saturating, inhibiting or boosting other regions etc. There is evidence of temporal lobe and motor cortex activity from the second order statistics and of frontal and parietal activity from first order and third order statistics.

From table 7 it can be inferred that subject 11 is abnormal compared to the test population with the probability 10 out of 11. The horizontal lines in figures 5, 6 and 10 indicate the 95% significance level of bicoherence for the number of epochs used. Figure 10 shows that for subject 11, there are low bicoherence values at C4 and C3 that are correlated and result in a low dissimilarity measure. PZ and FZ are not as well matched. The biphase values in figure 11 show some mismatch as well but they still place the subject in the normal category. Although the grand averages in table 3 also detect an abnormality in subject 11, best matching grand averages are not consistently PZ-FZ in table 2 unlike bicoherence values in table 6. Time-varying bispacial analysis can thus be sensitive in detecting abnormal brain function even when the responses are correct to simple sensory stimuli. It cannot be concluded that the abnormality is necessarily related to age or genetic link to Alzheimer's. However, subject 2 is close to subject 11 in age but has responses typical to the normal group.

The reason why abnormality shows up for the right direction response and not for the left could be either corruption from differences in the skin impedance of the mastoid references or a difference in proximity of cortical regions or pathways to the scalp in each case. Any corruption arising from the references would be more likely to produce deviation rather than constancy and also affects all channels equally. It is also interesting to note that brainstem auditory evoked potential asymmetry is recognized in neurophysiological research literature [45].

### 6.1 Comparisons with related work

Abnormality (age related changes) detection in auditory evoked EEG using FZ, PZ and CZ and grand averages is reported in [41]. The clinical utility of auditory evoked potentials in the diagnosis of dementia is reported in references cited in [41] and clinical usefulness in other ways is reported in [21, 23, 46].

Independent component analysis [47-49] (ICA) has been used to separate noise and artifacts from EEG data and locate sources. These methods also utilize higher-order moment and non-Gaussian distribution information but do so indirectly. They do not provide a higher order spectral decomposition and consequent selectivity as possible with the methodology described here. They are also better applicable to single trials because the separation is based on distribution of samples with time. They have the advantage of providing information bearing components with the same resolution as the original data. The method described here makes use of a large number of epochs in an ensemble and achieves noise immunity by averaging rather than separating noise out as a separate component with a Gaussian distribution. The proposed methodology uses a time domain window to obtain short-time spectra and achieves separation in higher order frequency space. Unlike ICA, the resulting time-varying waveforms in this methodology will not directly relate to the input time-domain EEG signal when
visualized in the time domain but they carry important information as can be seen in the figures in this work. Amplitudes and latencies of peaks in the brain stem auditory response have been extensively studies in works such as [25]. This work takes the analysis from such first order representations to second and third orders and compares them. It is shown that the third order approach based on time-varying bispectra can provide additional information.

7. CONCLUSIONS AND FUTURE WORK

Time-varying bispectral analysis of auditory evoked scalp EEG can provide useful information. It can detect changes in normal brain function with high sensitivity. Future work can explore other frequencies and include groups of subjects with specific known abnormalities in hypothesis testing frameworks. Better quality EEG data can be processed and other evoked potentials investigated. Early detection and assessment of changes can assist disease management.

ACKNOWLEDGEMENTS

The author is grateful to Miss Kassi Nofz for collecting all the data used in this work, to all the volunteers, to Mr. M. Gnanananthan for software that segments stimulus-time-referenced EEG data, to Mr. W. Maier for technical assistance and to QUT for providing computing facilities. This research was not funded by any external agency. QUT ethics clearance no. 1100000567 was obtained for the data collection.

REFERENCES


