Time-frequency analysis of visual evoked potentials using chirplet transform

J. Cui, W. Wong and S. Mann

Chirplet time-frequency representation has been applied to characterise visual evoked potentials (VEPs) successfully. The approach presented here can represent both transient VEPs and steady-state VEPs clearly. Comparison to the method of short-time Fourier transform (STFT) is reported.

Introduction: Detecting signals of visual evoked potentials (VEPs) elicited by repetitive stimuli is generally difficult, since the signal-to-noise ratio (SNR) of VEPs embedded in strong background noise and spontaneous EEG is rather low [1]. When the complete information of the signal to be detected is known, the optimal detector (in the Neyman-Pearson sense) is the likelihood ratio test which is usually implemented by a matched filter. Therefore, knowing the properties of the VEP signals related to a visual stimulus is important for designing detectors.

Previous studies show that a steady-state VEP (ssVEP) is established if the repetition rate of visual stimuli is higher than some value and the shape of the resulting response becomes sinusoidal [1]. A transient process, however, precedes the formation of steady-state, characterised by abrupt changes of VEP amplitude within a short time interval.

Under steady-state condition, the detection task can be reduced to finding a sinusoidal signal in noise by modelling the ssVEP signal as the summation of a fundamental frequency component and the higher harmonics, and ignoring the transient component. But because of the variability in the mental state of the subject (perhaps due to a lack of concentration, tiredness or accommodation), various factors can perturb the steady-state components. Moreover, from a physiological point of view, transient VEP appears to be more appropriate for rapid and reliable signal detection. Efforts have been made recently to characterise VEP signals over both its transient and steady-state portions [2].

Matching pursuit (MP) has been recently proposed as a nonlinear decomposition algorithm to decompose a signal into a very broad class of waveforms [3]. In MP, a sub-family of time-frequency atoms is chosen from the repertoire of the waveforms in such a way as to best match the local signal structure. In this Letter, we propose applying the method of MP algorithm using four-parameter chirplet atoms to do time-frequency analysis of VEPs. The purpose is to characterise both the transient and the steady-state of visual responses.

Computational method: We propose a method whereby the VEP signal is decomposed over Gaussian chirplet atoms using the MP algorithm. A Gaussian chirplet atom is a four-parameter wave packet with a Gaussian envelope [4]:

$$g_\beta(t) = \frac{1}{\sqrt{\sqrt{\pi}\Delta_t}} \exp\left\{ -\frac{1}{2}\left(\frac{t-t_c}{\Delta_t}\right)^2 + j\cdot 2\pi[c(t-t_c)+f_c](t-t_c) \right\} \tag{1}$$

where $j=\sqrt{(-1)}$, $t_c \in R$ is the centre of the energy concentration in time, $f_c \in R$ is the centre frequency, $\Delta_t > 0$ is the spread of the pulse, and chirprate c reflecting how quickly the chirp changes in time. The symbol $\beta = (t_c, f_c, \Delta_t, c)$ denotes the set of these four parameters. Our interest in using a Gaussian chirplet atom is mainly due to the fact that it is the function that has the highest joint time-frequency resolution and the only function whose Wigner distribution is non-negative. In practice, all four parameters should be discretised. The set of the parameter discretised atoms are called a dictionary.

The first step ($n=0$) of the MP procedure is to choose the chirplet atom g_{β_0} from the dictionary so that the amplitude of the inner product (chirplet coefficient) $|\langle f, g_{\beta_0}\rangle|$ between this atom and signal $f(t)$ is largest. Then the residual signal $R^1 f$, obtained after extracting the approximation of f in the direction of g_{β_0} from f, is decomposed in the similar way. Iterative procedures are applied to the subsequent residues:

$$\begin{cases} R^0 f = f; \\ R^{n+1} f = R^n f - \langle R^n f, g_{\beta_n}\rangle \end{cases} \quad n \in z \tag{2}$$

In this way the signal f is decomposed into a sum of chirplet atoms that best match its residues:

$$f = \sum_{n=0}^{m} \langle R^n f, g_{\beta_n}\rangle g_{\beta_n} + R^{n+1} f \tag{3}$$

The amplitude of residue $|R^n f|$ decreases exponentially with each iterative step [3]. However, low amplitude residues may mainly be due to noise, and can be measured by correlation ratios [3]:

$$\lambda(R^n f) = \frac{|\langle R^n f, g_{\beta_n}\rangle|}{\|R^n f\|} \tag{4}$$

That is, the larger the correlation ratios of the signal residues, the more coherent a residue and the less likely it is corrupted by noise.

As a first-order approximation, the VEP signal is represented by a chirplet coefficient that results in the highest correlation ratio. From (4), to approximate $R^0 f = f$ with the highest correlation ratio is equivalent to selecting Gaussian chirplet atom g_{β_0}. The energy density of the approximated VEP signal in the time-frequency plane can be visualised by the Wigner distribution of the selected chirplet atom, i.e. g_{β_0}. Because their Wigner distributions do not include interference terms, they thus provide a clear picture in the time-frequency space.

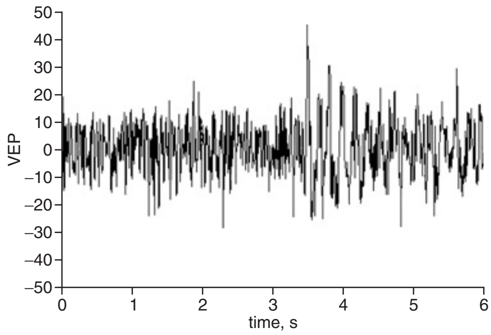

Fig. 1 *Averaged VEPs for 6 s*

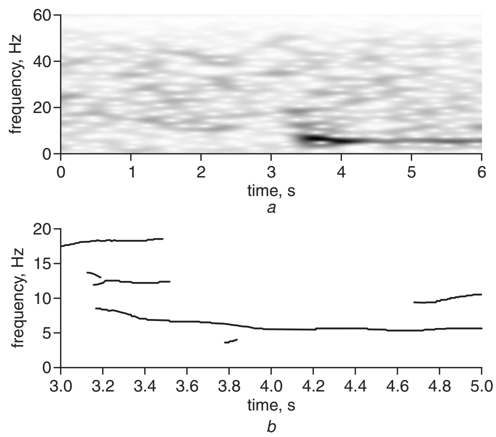

Fig. 2 *Spectrogram of averaged VEP and windowed Fourier ridges of VEP signal between the third and fifth second*

a Spectrogram
b Windowed Fourier ridges

Results and discussion: The visual stimulus was presented as a sinusoidally oscillating single vertical-bar movement. The signal trace began with a 3 s interval without bar movement followed by another 3 s interval for the target signal. It is in this latter interval that the single horizontal bar undergoes a 3 Hz oscillatory motion. The third second of this 6 s epoch was called the onset of the stimulus. After amplification and filtering (lowpass filter at 40 Hz) the VEP data were sampled at 250 Hz and passed through an A/D converter. Fig. 1 shows the averaged VEP signal over 50 single sweeps. In Fig. 2, the spectrogram (STFT) of the averaged VEP is computed. The windowed Fourier ridges of the STFT spectrum are also shown in Fig. 2. In the spectrum, it is sufficient to distinguish the characters of ssVEP around 6 Hz where the second harmonic (2×3 Hz) is expected because of sufficient frequency resolution. However, the transient process of the VEP is blurred owing to poor time resolution.

In practice, the epoch of 6 s was divided into 15 segments (400 ms each) to select 15 atoms (Fig. 3). The visualisation of time-frequency distribution (the Wigner distribution) of the selected chirplet atoms offers a relatively clearer picture of the transient components of VEP changes. Recall that the onset was at the third second. Fig. 3*a* shows a sharp spindle occurring about 300 ms after the onset of visual stimulus, followed by a slow down chirp (chirprate: 4 Hz in 400 ms). This can be observed by comparing the zoomed area of the time-frequency plane shown in Fig. 3*b*. From this Figure, three typical characteristics of VEP responses can be observed: (i) a transient component after the onset of each stimulus; (ii) a delayed steady-state component of the response around the second harmonic; and (iii) suppression of alpha activity (4–12 Hz) during stimulation.

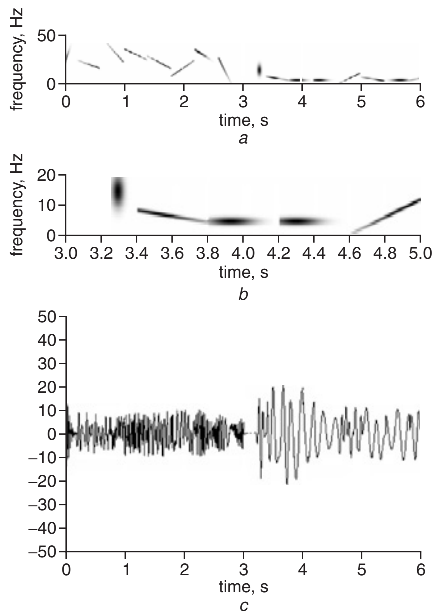

Fig. 3 *Visualisation of MP decomposition using chirplet atoms*

a Wigner distribution of selected chirplet atoms
b Zoomed in area of 3–5 s and 0–20 Hz
c Reconstructed (approximated) VEP signal from atoms in *a*

Since we note that the STFT uses a 'windowed sinusoidal wave' to approximate the frequency component within a specific time-interval, we can think of the Fourier approach as approximating the signal (over a short window) with a straight 'horizontal' line segment, parallel to the time-axis, in the time-frequency plane. Thus, if there are components of the VEP which are rapidly changing in frequency, the STFT is not an efficient method to analyse such signals. Alternatively, the chirplet transform uses chirp functions as its basis which in theory should be more suitable for approximating fast changes in frequency content even over short time periods. Therefore, we conclude that it is a promising new method for analysing the transient process of VEP signals.

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