Journal of Neuroscience Methods 233 (2014) 63–72

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Computational Neuroscience

A wavelet based algorithm for the identification of oscillatory event-related potential components

Arun Kumar Aniyan[a,*], Ninan Sajeeth Philip[a], Vincent J. Samar[b], James A. Desjardins[c], Sidney J. Segalowitz[c]

[a] St. Thomas College, Kozhencherry 689641, Kerala, India
[b] Rochester Institute of Technology, 52 Lomb Memorial Drive, Rochester, NY 14623, USA
[c] Brock University, 500 Glenridge Avenue, St. Catharines, ON L2S 3A1, Canada

HIGHLIGHTS

- We present a novel method for detecting specific event related potential (ERP) components from single trial EEG data.
- We provide evidence that wavelet asymmetry is unique for a specific ERP component and hence can be used for detecting it in single trial EEG data.
- Our results indicate high detection accuracy in offline mode and we discuss a few of the method's potential applications.

ARTICLE INFO

Article history:
Received 16 April 2014
Received in revised form 3 June 2014
Accepted 4 June 2014
Available online 12 June 2014

Keywords:
Single-trial EEG
Wavelet asymmetry
N170 ERP detection

ABSTRACT

Event related potentials (ERPs) are very feeble alterations in the ongoing electroencephalogram (EEG) and their detection is a challenging problem. Based on the unique time-based parameters derived from wavelet coefficients and the asymmetry property of wavelets a novel algorithm to separate ERP components in single-trial EEG data is described. Though illustrated as a specific application to N170 ERP detection, the algorithm is a generalized approach that can be easily adapted to isolate different kinds of ERP components. The algorithm detected the N170 ERP component with a high level of accuracy. We demonstrate that the asymmetry method is more accurate than the matching wavelet algorithm and t-CWT method by 48.67 and 8.03 percent, respectively. This paper provides an off-line demonstration of the algorithm and considers issues related to the extension of the algorithm to real-time applications.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The ability to detect single-trial event related potentials (ERPs) in real-time EEG signals has many clinical and research applications, particularly in the field of brain computer interfaces (Barrett, 2000; Birbaumer et al., 2008). ERPs appear as dynamic alterations in ongoing EEG frequency components that are very feeble signals compared to background EEG and have low signal-to-noise ratio when recorded from electrodes attached to the scalp. Detection of ERP components from real-time EEG is therefore a challenging problem.

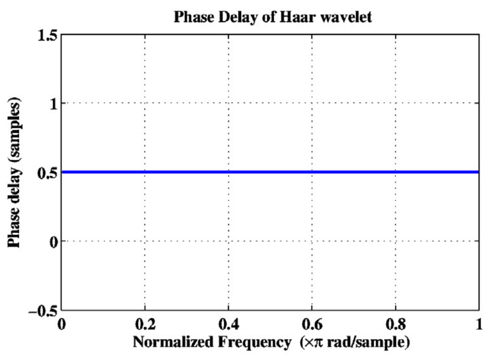
Studies based on unique ERP features (Wilkinson and Seales, 1978) and conventional anomaly detection algorithms like filtering (Cong et al., 2011) and matching pursuit have given limited success for the detection of ERPs (Rondik and Ciniburk, 2011). However, use of a band-pass filter specifically tuned for EEG/ERP frequencies improves signal to noise ratio. While Thesasiri et al. (2008) have shown that linear FIR filters may not perform optimally, filters tailor made for the particular ERP, such as Woody filters and matched filters provide better detection accuracy (Ford et al., 1994; Serby et al., 2005). Also Ciniburk and Mautner (2008) have shown that the Hilbert–Huang transform (Huang and Shen, 2005) could further improve the discrimination power of filter based approaches. But these filtering variations are limited in their success rate with real time signal detection.

The joint time-frequency analysis of signals is a solution to overcome the limitations of conventional filtering techniques. Wavelets can be used for the joint time-frequency analysis of EEG signals and they provide more robust measures for the detection and analysis of ERP components (Blanco et al., 1998).

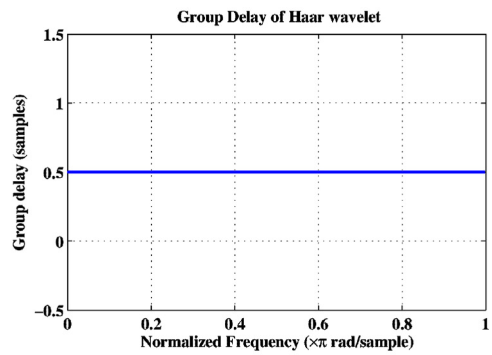
Samar et al. (1999) and Quian Quiroga et al. (2001) have presented evidence that wavelets may improve the extraction and

* Corresponding author. Tel.: +91 9446186842.
E-mail addresses: aka.bhagya@gmail.com (A.K. Aniyan), nspp@iucaa.ernet.in (N.S. Philip), vjsncr@rit.edu (V.J. Samar), jdesjardins@brocku.ca (J.A. Desjardins), ssegalowitz@brocku.ca (S.J. Segalowitz).

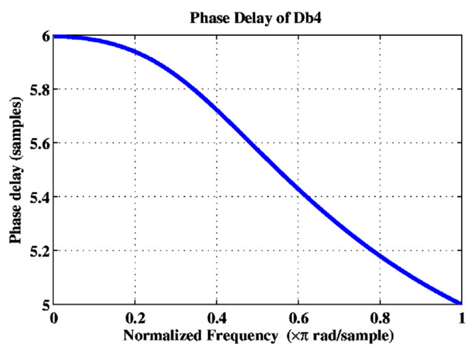
http://dx.doi.org/10.1016/j.jneumeth.2014.06.004
0165-0270/© 2014 Elsevier B.V. All rights reserved.



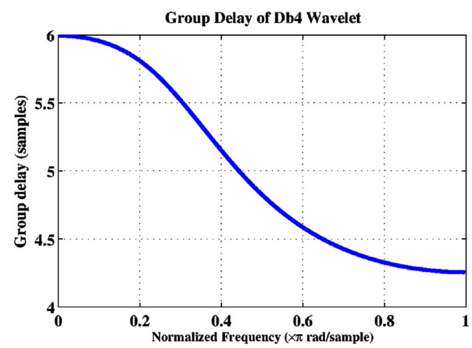
(a) Haar Phase Delay



(b) Haar Group Delay



(c) Db4 Phase Delay



(d) Db4 Group Delay

Fig. 1. (a) and (b) The flat response of the Haar wavelet which is a symmetric filter. Db4 is an asymmetric filter whose phase delay and group delay are shown by (c) and (d). Since the wavelet filter is not symmetric, the filter responds with time delays.

analysis of ERP waveforms. The applications of wavelets to ERPs are broad ranging, including joint time-frequency analysis of ERPs (Samar et al., 1992), artifact removal (Jiang et al., 2007) and event detection (Demiralp et al., 1999; Samar et al., 1995). Furthermore, features derived from wavelet coefficients (Merzagora et al., 2006; Trejo and Shensa, 1999) perform well in preprocessing (Kalayci et al., 1994) stages of classification problems using statistical learning algorithms (Abootalebi et al., 2006; Browne and Cutmore, 2002).

A variety of wavelet based methods have been used to study different aspects of EEG/ERP signals. Methods based on the discrete wavelet transform (DWT) (Burger et al., 2007; Herrera et al., 2000) and continuous wavelet transform (CWT) (Bostanov and Kotchoubey, 2004), in combination with other statistical measures (Lim et al., 1995), have been tried for the detection as well as the analysis of ERPs. Variable threshold schemes (Fatourechi et al., 2004) and wavelet packet analysis (Graimann et al., 2004) have shown reasonable results when there is no background noise. A more accurate method proposed by Chapa (1995) and Chapa and Rao (2000) for the detection and multiresolution analysis of ERPs is computationally expensive and at times gave unbounded errors.

We propose a generalized, yet simple and powerful scheme using wavelets to detect specific ERP components from EEG data. The algorithm makes use of a less-used asymmetry property of wavelets along with time base properties of the target ERP component. Asymmetry is associated with the observed phase shift of wavelet coefficients when the wavelet transform is performed on a signal. The amount of phase shift produced by a wavelet for a specific ERP is unique and can be used for its detection. A detailed description of wavelet asymmetry is given in Section 2.

Our method can be used to detect different ERP components by changing the wavelet basis function and time base parameters. It is also automated with self-correction and validation mechanisms using wavelet features and time-based properties of the ERP components as a guide. This paper outlines the general approach, provides an off-line demonstration of the detection performance of the algorithm using the N170 component of ERPs to 'face' versus 'non-face' stimuli, and considers issues related to the extension of the algorithm to real-time applications.

2. Asymmetry in wavelets

When the phase difference between the input and output signal is zero, the corresponding digital filter is said to be linear. Linear filters are symmetric. Wavelets behave exactly like filters and a wavelet function ψ when convolved with an input signal $f(t)$ will project the signal onto an orthogonal subspace ξ as $\hat{f}(\xi)$. In terms of symmetry, a wavelet filter with coefficients a_n is linear if the phase of the function $a(\xi)=\sum_n a_n e^{in\xi}$ is a linear function of ξ for some $l \in \mathbb{Z}$ (Daubechies, 1992). This essentially means that the filter delays each frequency in the input signal in equal amounts at the output. The phase delay and group delay of such filters will have a flat profile for all the input frequencies similar to the one shown in Fig. 1a and b.

When the filter response is non linear, which means different frequencies are shifted by different amounts at the output, the filter is said to be asymmetric. The phase delay response and group delay response of asymmetric filters will not have a flat profile. An example is shown in Fig. 1c and d where each frequency component of the signal is shifted by a specific number of samples.

2.1. Asymmetry as a measure

Filter phase response is quantified in terms of group delay $\tau(\omega)$ which is given as

$$\tau(\omega) = -\frac{d\theta(\omega)}{d\omega} \quad (1)$$

Download English Version:

https://daneshyari.com/en/article/6268478

Download Persian Version:

https://daneshyari.com/article/6268478

Daneshyari.com