The Classification of Transient Time-Varying EEG Signals Via Wavelet Packets Decomposition

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Abstract  The classification of transient time-varying electroencephalography (EEG) is quite important for further understanding the brain function. In order to classify different kinds of non-stationary EEG rhythms, wavelet packet analysis is used for designing sub-band filters with specified band-passed characteristics. Four kinds of wavelet packet decomposition using Daubechies wavelet are employed to investigate the nonstationarity of clinical EEG signals. Several real EEG signals with different brain function states are analyzed and compared via the dynamic rhythms. It is indicated from the experimental results that the non-stationary characteristics of clinical brain electrical activities can be classified by using wavelet packet decomposition. The method in this paper also proposes an effective way to form the Dynamic Topographic Brain Mapping (DTBM) to present the dynamic EEG topography.

Keywords:  EEG signal processing, brain function, rhythms classification, wavelet packet decomposition.

Topic Category:  5.12

1 Introduction

EEG signals are the electrical activities in the cortex or on the surface of scalp causing by the physiological activities of the brain. In general, EEG signals are the typical multi-dimensional non-stationary random processes. Classification of the changes of these special waves is critical for understanding of brain functions.

Many modern techniques such as CT, MRI etc. are continuously coming into use for investigating the brain, but EEG signal, as a nondestructive testing method, is still play a key role in the diagnosis of brain and the functional determination of brain. Over the years, various digital signal processing techniques have been widely applied to the analysis of clinical EEG signals since EEG was discovered by Hans Berger in 1929. Fourier transformation, as a conventional method, has been widely used for the standard quantitative analysis of the spectral decomposition and the clinical applications of EEG signals [1][2]. As we known, the validity of the power spectral estimation depends on the hypothesis that the signals satisfy the second-order stationarity for the given interval. However, in clinical practice, the simplifying assumption of EEG stationarity is not satisfied because various causes of the spontaneous brain activity under different states of the brain function, such as sleep stages, epilepto-genic transients and the changes of the physiological state of the patients. Furthermore, the evoke potentials (EP) reflects the event related non-stationary phenomena as both temporal variations of its mean value and temporal variations of the energies of the underlying rhythms, i.e. event related spectral perturbations. As a traditional analysis technique, the FFT-based spectral estimation involves a long time averages of the EEG data. The methods based on the standard spectral analysis are of limited applicability to the transient time-varying EEG signals.

The rapid developments of modern signal processing techniques enable us to investigate the transient characteristics of non-stationary EEG recordings. They include the short time Fourier transform (STFT), the Wigner-Ville representation and the time-varying parametric model. The STFT assumes the stationarity of the signal within a temporal window to match the time-frequency resolution chosen for the spectral analysis. The main problem of STFT for providing the time-varying spectrum of signal is the fixed time-frequency resolution trade-off that results from windowing of the signal. Wigner-Ville distribution (WVD) is another useful method for demonstrating the time-frequency characteristics of the signal, but the most significant drawback of WVD is the existence of the cross-terms in the WVD which leads to the low resolution level of the time-frequency spectral
estimation of the signal. Some methods for cancellation of the cross-terms of the WVD are proposed by using various optimal kernels to smooth the WVD. For the parametric model approach, the AR model with time-varying coefficients is another common method for the parametric spectral estimate for nonstationary EEG signals. The significant limitation of time-varying parametric models is the difficulties to establish the model properly for different EEG signals [2, 5, 6].

There have been some attempts to the auto-recognition of transients in EEG signals, particularly some types of artifacts and epileptogenic transients in various clinical EEG applications. However, automatic methods generally do not stand comparison with traditional visual EEG analysis by trained EEG experts. For this purpose, a novel method for effective classifying the transient rhythms of the EEG signals by using wavelet packet transformation is proposed in this paper to study the different brain function changing with time. The time-varying characteristics of the spontaneous brain rhythms in several brain function is mainly investigated. In addition, the multi-channels time-varying rhythms are employed to construct the Dynamic Topographic Brain Mapping (DTBM), which will enable the physician to detect the changes of the multi-channel brain activities in specific rhythm for the analysis of the transient of EEG signals.

2 Wavelet Packet Decomposition

Wavelet transform is one of useful method for analyzing the non-stationary process, as we know, wavelet transformation is a two dimensional time-scale processing method for nonstationary signals [3-5]. The main advantage of the scalegram is to provide simultaneous information on frequency and time location of the signal characteristics in terms of the representation of the signal at multiple resolutions corresponding to different time scales. Though wavelet has been widely used in various areas in non-stationary signal processing, many important problems still need further research in wavelet theory and its applications. Recently, wavelet packets have been proved as a powerful tool to match the time-varying characteristics for the non-stationary signal analysis in many disciplines [9-11].

If scaling function \( \phi(t) \) can be defined as

\[
\phi(t) = \sum_{k} h(k) \phi(2t - k)
\]

and defining the wavelet function \( \psi(t) \) as

\[
\psi(t) = \sum_{k} g(k) \phi(2t - k)
\]

where \( \{h(k)\} \) and \( \{g(k)\} \) are the coefficients. The following admissibility condition must be satisfied

\[
\int_{-\infty}^{\infty} \psi(t) dt = 0
\]

Let the time series be \( x(n) \) \( (n = 0, \pm 1, \pm 2, \ldots \ldots) \), a binary tree structure can be expressed as [11-12]:
This two-channels quadrature mirror filter bank is shown in Fig.1. Two kinds of analysis filters divide frequency range into two halves. The filters are orthogonal and the output signal can be reconstructed to obtain an input.

\[
x_0(n) = \sum_k p(2n - k)x(n)
\]

\[
x_1(n) = \sum_k q(2n - k)x(n)
\]

In fact, this method is also known as the tree structured perfect reconstruction filter banks. The procedure above can be repeated in a binary tree structure. The frequency resolution of the sub-band filters can be adjusted by choosing a desired tree structure. If the time series \(x_1(n)\) and \(x_0(n)\) are further decomposed by using the equation (7), the components of the time series \(x(n)\) decomposed at different levels are obtained by choosing the specified tree structure corresponding to the different frequency band of the rhythms of the EEG signals. The binary tree structure for wavelet packet analysis is shown in Fig. 1. Obviously, the bandwidth of the filter will cover a large frequency span if the filters are near the root of the tree structure. Different frequency resolution is chosen in order to meet the characteristics of the signals under investigation. Fig. 2 shows the tiling representations of two tree-based expansions. Fig.2 (a) represents the tree structure of wavelet transformation, and Fig. 2 (b) shows the tree structure of wavelet packet decomposition. As a comparison, tiling representations of three tree-based expansions are demonstrated in Fig. 3. The tree-based expansions for STFT is shown in Fig. 3 (a). Fig. 3 (b) describes the discrete WT decomposition, and an example of wavelet packet decomposition is shown in Fig. 3 (c).

Fig. 1 Two channel quadrature mirror filter bank

Fig. 2 Binary tree structure for wavelet packet

Fig. 3. Tiling representations of three tree-based expansions: (a) STFT, (b) WT decomposition, and (c) an example of wavelet packet decomposition.
3 Results and Discussion

Real EEG signals were digitally collected and stored as data files for further analysis through a PC computer. 14 channels analogy electroencephalograph signals were converted to digital format through an A/D converter at a sampling rate of 100Hz. Each signal was amplified and filtered through a 1-50 Hz band-pass filter. The EEG signals were recorded at the location of the scalp according to the international 10-20 system known as [14]: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T5, T6. The reference electrode was placed on the tip of the nose and grounding through linked earlobes. Artifact rejection was performed off-line by an experienced EEG expert visual inspection of the recordings. The EEG signals for test include the signals under different brain function. The experiments were performed in an acoustically and electrically shielded room where the subjects were seated comfortably in a reclining chair. Calculation of the wavelet packet decomposition of the EEG signals was performed with Matlab.

For the specified rhythms of the EEG, the best combination of components in terms of the multi-resolution decomposition of a signal can be decided by using wavelet packets transformation. A particular choice of tree-structure containing various components referred to as “wavelet packet decomposition” is applied to the time-varying filter in 4 different filter banks corresponding to 4 kinds of time-varying brain rhythms. A six-levels decomposition of Daubechies wavelet was applied to the EEG signals [13, and four kinds of rhythms of EEG can be obtained: beta rhythm (13.28-30.47Hz), alpha rhythm (7.81-13.28Hz), theta rhythm (3.91-7.81Hz) and delta rhythm (0.78-3.91Hz). The experimental results of EEG wavelet packet decomposition are tested to provide the satisfied filtering characteristics for classification of 4 kinds of EEG rhythms. Fig. 4 demonstrates the results of 4 kinds of time-varying brain rhythms in terms of the wavelet packet multi-resolution decomposition of a typical EEG record with subjects at rest with eyes closed.

Moreover, a method is proposed to construct the Dynamic Topographic Brain Mapping (DTBM) to describe the dynamic EEG topography so that we can demonstrate the transient time-varying characteristics of different rhythms of multi-channel EEG signals in the scalp, which will enable the physician to detect the transient of brain activities in specific rhythm with color image. For example, the alpha rhythm transient reflects the main changes of brain electrical activity of the normal person. The time-varying energies of event related to brain rhythms may be tracked by observing the DTBM in terms of the temporal variations of the squares of the coefficients of the wavelet packet. The time location and duration of each topographic brain mapping can be adjusted easily depending on the transient characteristics of the EEG signals observed. Fig. 5 demonstrates the DTBM of a typical record of normal EEG signal with a subject rest at eyes closed.

Fig. 4 (a) A segment of 14 channel EEG recordings with subjects at rest with eyes closed. (b) The corresponding four kinds of time-varying brain rhythms of the EEG record in channel C3.
4 Conclusion

In this paper, a novel method for effective classifying the transient rhythms of EEG signals was proposed to study the EEG in different brain function changing with time. The time-varying characteristics of the spontaneous EEG rhythms in several brain functions is mainly investigated. We employed the multi-channels time-varying rhythms to construct the Dynamic Topographic Brain Mapping (DTBM), which will enable the physician to detect the changes of the multi-channel brain activities for the specific rhythm for the analysis of the transient of EEG signals. The experimental results illustrate how wavelet packet can be applied to the EEG rhythms decomposition with high time-frequency location resolution and to forming the dynamic EEG topography. Wavelet packet-based filter banks yield superior performance to the commonly Daubechis wavelet filter banks in EEG applications. The method proposed in this paper is more flexible and accurate due to the better matching in time-frequency characteristics of EEG signal for extracting 4 kinds of EEG rhythms. The results of DTBM have verified its superior performances of the new algorithm by using wavelet packet analysis.

Although the new applications of wavelet packet in clinical EEG signal processing is addressed, open problems still remain. One is the optimal segmentation length resolution, which is obviously related to the time-varying characteristics of the EEG signals observed. It will be an interesting and challenging research project to built an optimal segmentation-based adaptive algorithm.

References