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Detection of Dynamic Rhythms of Electroencephalogrphy by Using Wavelet Packets Decomposition

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Abstract

Wavelet packet decomposition is used to investigate the time-varying characteristics of clinical EEG signals. On the basis of the nonstationáry nature of clinical EEG rhythms, wavelet packet analysis is employed for designing filters with different frequency characteristics to detect 4 kinds of EEG rhythms. The coefficients of wavelet transformation corresponding to the rhythms are used to form the dynamic brain electrical activity mapping (DBEAM). In order to understand the dynamic rhythms of the EEG, some clinical EEG are analyzed and compared. It is indicated from the experimental results that the dynamic characteristics of clinical brain electrical activities can be provided in terms of wavelet packet decomposition.

I. Introduction

The brain is considered as the most complex biological existent structure. Electroencephalography (EEG) is the variations of electrical fields in the cortex or on the surface of scalp caused by the physiological activities of the brain. EEG is currently the most widely adopted method for assessing brain activities. Detecting the changes of these waves is critical for an understanding of brain functions. Over the years, there have been many modern methods such as CT, MRI etc. coming into use, but EEG signal, as a nondestructive testing method, is still play a very important role in the diagnosis of brain function [1,2]. Since EEG was discovered by Hans Berger in 1929, various digital signal processing techniques have been widely applied to the analysis of clinical EEG signals. As a common method, spectral analysis based on Fourier analysis has been widely employed for the standard quantitative analysis of the spectral decomposition of EEG signals [2,3]. As we known, the validity of the spectral analysis depends on the hypothesis that the signals are stationary random processes. In clinical practice, however, various physiological changes can affect the properties of the EEG processes, such as in the changes in the signal statistical structure or the rhythms [4,5]. Thus, the simplifying assumption of EEG stationary is not satisfied with the clinical EEG due to 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. EEG signals turns out to be an extremely nonstationary process.

In recent years, modern signal processing techniques allow us to pay more attention to the analysis of the transients in EEG recordings. There have been some attempts to automize the recognition of transients in EEG signals, particularly some types of artifacts and epileptogenic transients. However, automatic methods generally do not stand comparison with traditional visual EEG analysis by trained physicians. For this purpose, this paper presents a new method for effective analyzing the transient of the EEG rhythms by using wavelet packet transformation. The time-frequency characteristics of the spontaneous brain rhythms are investigated, and the new techniques for extracting time-varying rhythms of the processes are developed. Moreover, the time-varying EEG rhythms are employed to construct the Time-Varying Brain Electrical Activity Mapping (TMBEAM), which will enable physician to understand the changes of the multi-channel brain activities for the specific rhythm in order to study the transient of EEG signals. The procedures proposed in this paper also provide a new

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way for investigating other kinds of biomedical signals.

II. Methods

A. Wavelet Packet Decomposition

As a new method for investigating the time-frequency distribution of the processes, wavelet transform is a new two dimensional time-scale processing method for analyzing nonstationary signals [6,8-10]. Its main advantage 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 nonstationary signal processing, many important problems still need further research in wavelet theory and its applications. Recently, wavelet packets have appeared as a powerful tool to match the time-varying characteristics of some engineering signals.

The wavelet packet analysis is generalized orthogonal wavelet analysis. If scaling function $\phi(t)$ can be defined as

$$\phi(t) = \sum_k h(k)\phi(2t-k) \qquad 1$$

we can defined the wavelet function $\psi(t)$ as

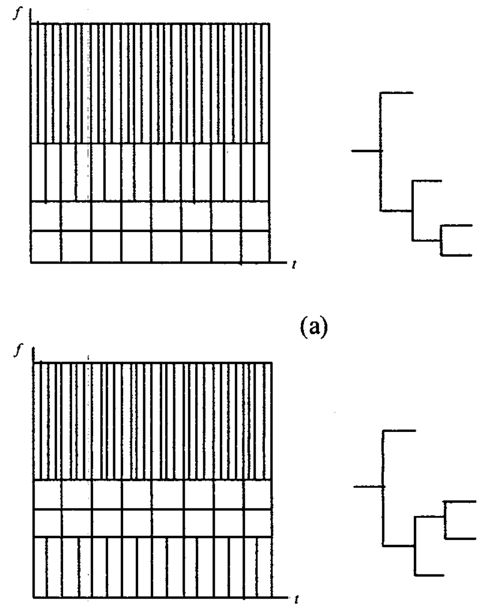
$$\psi(t) = \sum_k g(k)\phi(2t-k) \qquad 2$$

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

For the time series $s(n)$ a binary tree structure can be expressed as

$$\begin{aligned} s_0(n) &= \sum_k p(2n-k)s(n) \\ s_1(n) &= \sum_k q(2n-k)s(n) \end{aligned} \qquad 3$$

The relationship above represents the two channel quadrature mirror filter bank. Two analysis filters divide frequency range into two halves. The filters are orthogonal and the output signal is identical to the input. This method is also known as the tree structured perfect reconstruction filter banks. This procedure can be repeated in a binary tree structure. The frequency resolution of the analysis can be adjusted by choosing an arbitrary tree structure. If the time series $s_1(n)$ and $s_0(n)$ are further decomposed by using the equation (3), the components of the time series $s(n)$ decomposed at different levels are obtained by choosing an arbitrary tree structure. 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 can be chosen in order to match the characteristics of the EEG signals under investigation. Fig. 1 shows the tiling representations of two tree-based expansions. Fig.1 (a) represents the tree structure of wavelet transformation, and Fig.1 (b) describes the tree structure of one kind of wavelet packet decomposition.



(a)

(b)

Fig.1. Tiling representations of two tree-based expansions: (a) wavelet transformation (b) wavelet packet decomposition example.

B Detection of the Rhythms

In order to detect the different kinds of EEG rhythms, we can choose the best combination of components for the representation of the EEG rhythms in terms of the multi-resolution decomposition of the signal based on the wavelet packets transformation. According to the frequency band of 4 basic rhythms of EEG signal, a particular choice of tree-structure containing various components referred to as "wavelet packet decomposition is employed to the time-varying filter in 4 kinds of different filter banks corresponding to 4 kinds of time-varying brain rhythms, such as beta rhythm, alpha rhythm, theta rhythm and delta rhythm. A six-levels decomposition of Daubechies wavelet is applied to obtain 4 kinds of sub-band filters for the decomposition of the EEG signals. Obviously, the lowest frequency resolution of the decomposition can be obtained as $\Delta f = f_s 2^{-7} = 0.7812Hz$. Thus, 4 kinds basic rhythms can be approximately defined as: 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) [7]. In fact, the larger the level number for the wavelet packet decomposition, the higher the frequency resolution that can be performed for each basic rhythm.

III. Results and Discussion

Clinical EEG signals were digitally stored as data files for further analysis via a personal computer. 14 channels analogy EEG signals were converted to digital format through an A/D converter at a sampling rate of 125Hz from the international 10-20 system. All electroencephalograph signals with 14 channels were recorded at the location of the scalp known as: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T5, T6 [7]. The EEG data acquisition were performed in an acoustically and electrically shielded specialized room where the subjects were comfortably in the bed. Each EEG record was amplified and filtered by using a 1-50 Hz band-pass filter.

The experimental results of EEG wavelet packet decomposition are tested to indicate the satisfied filtering characteristics of 4 brain rhythms. Fig.2 demonstrates the results of 4 kinds of time-varying brain rhythms in terms of the wavelet packet multiresolution decomposition of a typical seizure EEG record when subjects with eyes closed. The transitions of 4 kinds of rhythms are clearly indicated. By comparing the original EEG record with 4 basic rhythms, it can be seen that the seizure periods is mainly in the alpha and the delta rhythms, while the beta rhythm keep unchanged. Moreover, to indicate the reasonable result of the decomposition, 4 kinds of rhythms were used to reconstruct the EEG record, which was compared with the original record, as shown in Fig. 3.

In order to demonstrate the time-varying characteristics of different rhythms of multi-channel EEG signals by using wavelet packet decomposition, we propose a method to form the Dynamic Brain Electrical Activity Mapping (DBEAM) to present the dynamic EEG topography, which will enable physician to understand the changes of all 14 channel brain activities in a specific rhythm. For example, the alpha rhythm transient often reflects the main changes of brain electrical activity of the normal person. The time-varying energies of event related to the brain rhythms may be tracked by observing the DBEAM 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.4 shows 14 typical channels EEG record with subjects' eyes closed and open alternately. From the record, it can be seen that the period with eyes open is from 9 to 27 seconds. Fig.5 demonstrates the DBEAM constructed from the 14 channels EEG signals. The EEG signal in each channel is divided into 12 periods with 3 seconds in each period. The DBEAM in Fig. 5 shows the changes of alpha rhythm in the scalp in every 3 seconds.

Conclusion

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 has 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.

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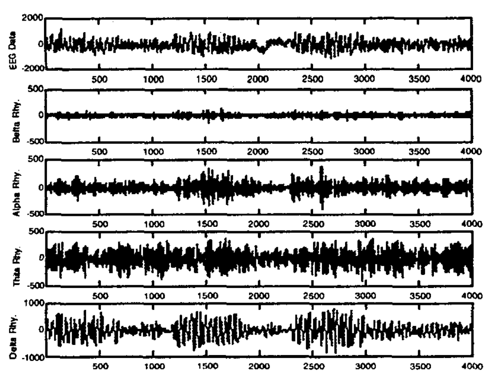

Fig. 2 Four kinds of time-varying brain rhythms of a typical EEG record with subjects at rest with eyes closed.

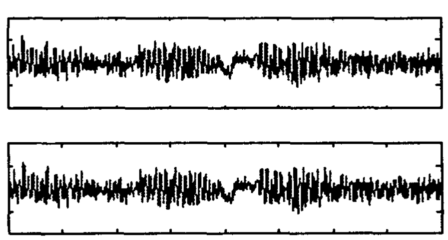

Fig .3 Comparing the original EEG record (top) with the signal (bottom) reconstructed through the 4 kinds of rhythms shown in

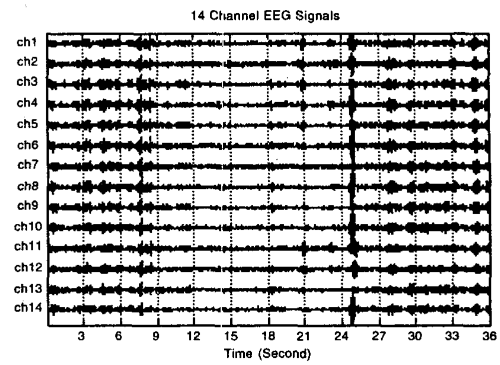

Fig. 4 shows a typical 14 channels EEG record with subjects' eyes closed and open alternately. The period with eyes open is from 9 to 27 seconds.

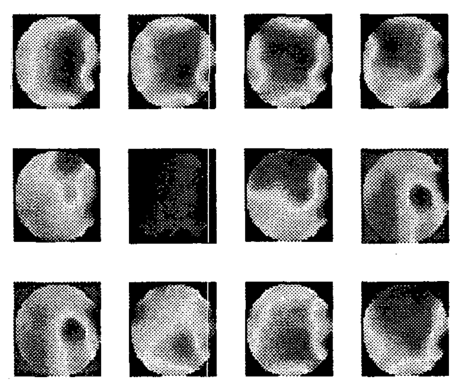

Fig. 5. The DBEAM constructed from the 14 channels EEG signals. The EEG signal in each channel is divided into 12 periods with 3 seconds in each period. The DBEAM shows the changes of alpha rhythm in the scalp in every 3 seconds.