DETECTION OF EEG BASIC RHYTHM FEATURE BY USING BAND RELATIVE INTENSITY RATIO(BRIR)

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ABSTRACT

In the clinical analysis and processing for EEG, because of the difference of ages and pathology, it is possible to appear abnormal waves related with pathology. Also, the restrain of normal rhythms could be abnormal. But at present doctors estimate if certain rhythm is restrained only by using the method of eyeballing or by some simply analysis methods in clinical EEG detection, which will inevitably lead to some errors and not observable. By "the virtual EEG record and analysis instrument" introduced in this paper, all kinds of characteristic waveforms (e.g. epileptic wave and spikes wave etc.) can be detected and analyzed in time-frequency domain. From the view of clinical application, the concept of band relative intensity ratio (BRIR) is introduced with time-frequency domain analysis, by the use of which, we can obtain the relative intensity of all basic rhythms in a certain time period, and this is believed to provide a good assistant analysis method.

Keywords: EEG, basic rhythms, BRIR, time-frequency analysis methods

1. INTRODUCTION

Studies on different types of rhythms of the brain and their relation with different pathologies and functions have attraction the attention of researchers since the beginning of electroencephalography (EEG). Based on different states, functions and pathologies of different brain activities, brain oscillations have been divided into the following frequency bands[1]:

δ rhythms（0.5Hz~3.5Hz）: Having the feature of deep sleep stage. Furthermore, in this frequency band the δ activity with some certain specific morphologies, location and rhythmicity has relation to different pathologies;

θ rhythms（3.5Hz~7.5Hz）: They are enhanced during sleep and play an important role in the brain electrical activity of infants and children. For the awake adults, high θ activity is considered abnormal and it is related with different brain disorders;

α rhythms（7.5Hz~12.5Hz）: They appear spontaneously in normal adults during wakefulness under relaxation and mental inactivity conditions. They are best seen with eyes closed and most pronounced in occipital locations;

β rhythms（12.5Hz~30.5Hz）: They are best seen in central and frontal locations and have less amplitude than α waves. They are enhanced upon expectancy states or tension. Usually, they are subdivided into β_1（12.5Hz~18Hz）and β_2（18Hz~30Hz）oscillations.

The patients with different ages or in different conditions have different brain oscillations. Traditionally, there is a dominant frequency, that is to say, there exits a background rhythm which is the most prominence and distinctness in EEG record. Such that the background rhythms during wakefulness: infants are 4~5Hz（δ waves and θ waves）; children are 5~8Hz（θ waves）and adults are 8~10Hz（α wave）. But in sleep, background rhythm is 5~6Hz（θ waves）during slight sleep and 2~3Hz（δ waves） during deep sleep. The background rhythm can be considered as a macro-index of excitability of central neuro-system, whose frequency increase with age increscent （to manhood）and slow down during sleep, especially deep. β waves can appear in 14Hz spindles during slight sleep. It can be considered abnormal that normal rhythms are restrained during EEG record and detection.

However, the physicians can only judge if certain background rhythm is restrained by the method of eyeballing or by some simply analysis methods in clinical EEG detection, which will inevitably lead to some errors and not observable. So, during the study of "virtual EEG record and analysis instrument", From the view of clinical application, the concept of band relative intensity ratio (BRIR) is introduced with time-frequency domain analysis, by the use of which, we can obtain the relative intensity of all basic rhythms in a certain time period, and this is believed to provide a good assistant analysis tool for doctors.

2. TIME-FREQUENCY ANALYSIS THEORY

Brain electrical signals are time-varying and non-stationary signals, which have different frequency elements at different time. The pure analytical methods in time domain and frequency domain keep relation by Fourier Transform, whose complete detachment is based upon the precondition that the frequency of signals is of time invariability or stationary. But because of the "uncertainty principle" of the resolution in time domain and frequency domain, it is impossible to get high resolution in time domain and frequency domain at the same time. Furthermore, many pathological changes in EEG appear by the type of instantaneous, for getting better analysis results, it is necessary to join time with frequency. The time-frequency representation of signal provides a better application foreground for brain electrical signals. At present, Gabor transform, wavelet transform and wavelet-packet transform have been used diffusely in the analysis and transaction of brain electrical signals.

2.1. Gabor transform

The Gabor transform of a signal $x(t)$ is defined as follows:

$$g_D(f,t)=\int_{-\infty}^{+\infty}x(t')g_D^*(t'-t)e^{-i2\pi ft'}dt' \qquad (1)$$

where $*$ denotes complex conjugation. The Gabor transform can be considered as an inner product between the signal $x(t)$ and the complex sinusoidal function $e^{-i2\pi ft'}$ modulated by the window function g_D, i.e.

$$g_D(f,t)=\left\langle x(t'),g_D(t'-t)e^{-i2\pi ft'}\right\rangle \qquad (2)$$

The window function g_D is introduced in order to localize the Fourier transform of the signal at time *t*. So, the window function must be peaked around *t* and falling off rapidly. There are several window functions such as Hanning window function, Hamming window function and Gaussian window function etc., which can be used to achieve this goal. Among these, Gabor proposed to use a Gaussian window function :

$$g_\alpha(t)=\left(\frac{\alpha}{\pi}\right)^{1/4}e^{-\frac{\alpha}{2}t^2} \qquad (3)$$

Since the Fourier transform of a Gaussian function is still a Gaussian function, which allows a simultaneous localization in time domain and frequency domain. It should be noted that the Gaussian function is defined as the function of a positive constant α, while the window function in equation (1) was defined as the function of the window width D. This is because Gaussian function do not have compact support. However, they approach asymptotically to zero with a rate determined by the parameter α. The result is that if a reasonable decay α is used, the Gaussian function can be assumed as the window function which can be truncated to have a window length D and in the borders their values would be nearly 0. Then, in the case of Gaussian window function, the Gabor transform can be explicitly defined as a function of the parameter α:

$$g_D(f,t)\to g_D^\alpha(f,t) \qquad (4)$$

Consider the general case of any arbitrary window function and the inverse transformation, we can get the equation as follows:

$$x(t)=\frac{1}{\|g_D\|}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}g_D(f,t')g_D(t-t')e^{i2\pi ft}dfdt' \qquad (5)$$

where $\|g_D\|=\int_{-\infty}^{+\infty}|g_D(t')|^2dt'$. The equation（5）is the inverse Gabor transform, which implies that the original signal $x(t)$ can be completely reconstructed from the coefficients $g_D(f,t)$.

Because the Gabor transform gives a time-frequency map of every time dot of the original signal, it is highly redundant. For decreasing the redundancy, a sampled Gabor transform can be defined by taking the discrete values of time and frequency, i.e.

$$g_D(f,t)\to g_D(mF,nT) \qquad (6)$$

where F and T represent the sampling steps of the frequency and time. Small F steps can be obtained by taking large window length, and small T steps can be obtained by using high overlapping between successive windows. Base on the resolution required, the redundancy will be decreased by the proper choice of F and T, which can save computational time, but the price to pay is that the reconstruction of a signal will be no longer straightforward as the same as the equation (5).

2.2. Wavelet transform

Because wavelet transform is of the property that multiresolution (multiscale), the character factor, i.e. the relative band width (the ratio of central frequency and band width), is invariable, and the wavelet will be of the ability to represent the localization of a signal in time domain and frequency domain by proper choice of wavelet basis. When small scale is used, the observational range is small in time, while the high frequency resolution is obtained in frequency, which equal to do refined observation by high frequency wavelet; by contrast, when large scale is used, the large observational range can be obtained in time domain and just do general observation in frequency domain by low frequency wavelet.

The wavelet transform of a signal $x(t)$ is defined as follows:

$$\begin{aligned}WT_x(\tau,a)&=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}x(t)\overline{h\left(\frac{t-\tau}{a}\right)}dt\\&=\sqrt{a}\int_{-\infty}^{+\infty}x(at)\overline{h\left(t-\frac{\tau}{a}\right)}dt\end{aligned} \qquad (7)$$

In wavelet transform (WT), the analysis for a signal is finished by the mother-wavelet function $h(t)$. The function is transformed in time domain to select the parts of a signal to be analyzed, then the selected parts dilate by a scale parameter *a*. It is the same as for frequency. For small scale *a*, the wavelet is a narrow function of the original signal which correspond to the high frequency parts of the signal; and for large scale *a*, the wavelet is extended and correspond to the low frequency. In WT, the time resolution used in the analysis for the high

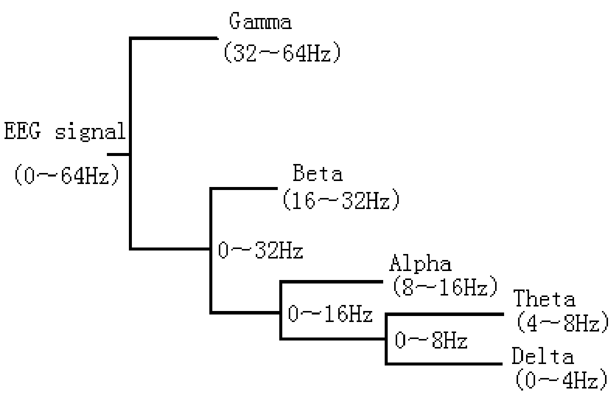

Fig.1 Decomposition of EEG signals by wavelet

frequency is acuter than for the low frequency. This is the property we hope to get, which is of more efficiency especially for complex non-stationary signal such as brain electrical signal.

Figure 1 is a tree-liked chart of the decomposition of brain electrical signal by wavelet transform. From Figure 1, it can be seen that the wavelet transform only decomposes the low frequency of the signal.

2.3. Wavelet packet transform

The divisions of frequency band are more flexible by the method of wavelet packet transform than by wavelet transform. Because the wavelet decomposition algorithm only decomposes the low frequency of the signal (the approximated signals), but does not decompose the high frequency, while wavelet packet decomposition algorithm decomposes gradually not only the low frequency of the signal, but also the high frequency. Furthermore, wavelet packet decomposition can choose corresponding frequency band in accordance with the feature of the analyzed signal, and make a good match with the spectrum of the signal, which can improve the time-frequency resolution.

Figure 2 is the wavelet packet decomposition of the brain electrical signals. More detailed information of brain electrical signal can be obtained by wavelet packet transform.

3. EEG RECORD AND ANALYSIS INSTRUMENT SYSTEM

Figure 3 is the "Virtual EEG record and analysis instrument system". During the development of the instrument system, the authors consider the need of clinical diagnosis, introduce the concept of band relative intensity ratio (BRIR), and realize function of computing qualitatively the relative intensity of different frequency bands in the instrument by the time-frequency analysis method of Gabor transform.

By using the instrument, all kinds of characteristic waveforms (e.g. epileptic wave and spikes wave etc.) can be detected and analyzed in the time-frequency domain. The information of the feature of brain electrical signals can be extracted effectively by these qualitative analyses methods, which can provide more diagnostic information for doctors.

The instrument system realizes the extracted function of basic rhythms of brain electrical signals by frequency band

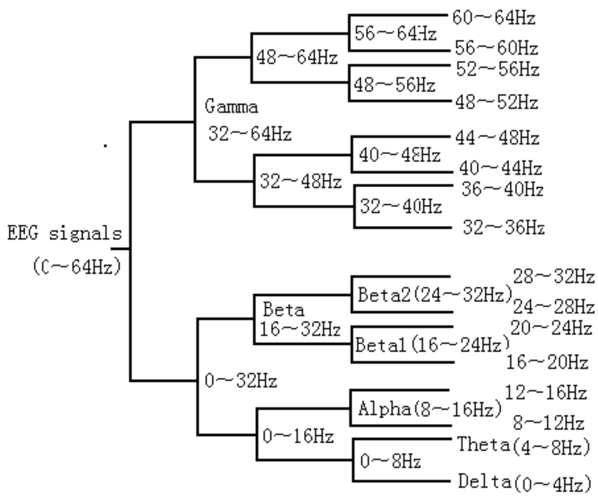

Fig. 2 Decomposition of EEG signal by wavelet packet

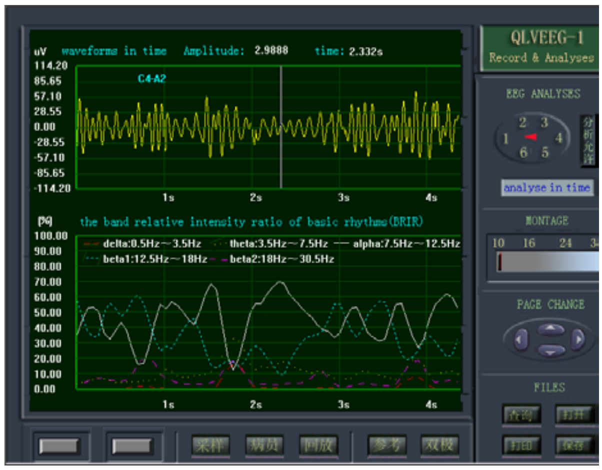

Fig. 3 EEG record and analyses instrument

relative intensity ratio (BRIR) defined by Gabor transform.

By the continuous Gabor transform defined in equation (1), the spectrum can be defined as follows:

$$I(f,t)=\left|g_D(f,t)\right|^2=g_D^*(f,t)g_D(f,t) \quad (8)$$

and a time-frequency representation of the signal can be obtained by using a recursive algorithm that slides the time window and plots the energy (I) as a function of frequency and time.

In order to qualify the information, define the band power spectral intensity for each one of the EEG basic rhythms ($i=\delta,\theta,\alpha,\beta\cdots$) as

$$I^{(i)}(t)=\int_{f^{(i)}_{\min}}^{f^{(i)}_{\max}} I(f,t)df \qquad i=\delta,\theta,\alpha,\cdots \quad (9)$$

where $\left(f^{(i)}_{\min}, f^{(i)}_{\max}\right)$ denotes the frequency limits for the band i. Accordingly, the different frequency bands division of EEG are not arbitrary which correspond to different origins and functions of brain activity.

Obviously the total power spectral intensity will be:

$$I_T(t) = \sum_i I^{(i)}(t) \qquad i = \delta, \theta, \alpha \cdots \tag{10}$$

so the band relative intensity ration(BRIR) for each frequency band i can be defined as:

$$BRIR^{(i)}(t) = \frac{I^{(i)}(t)}{I_T(t)} \times 100 \tag{11}$$

In the instrument system, the realization of the function is placed in the analysis of brain electrical signals feature in time domain, as shown in Figure 3. This is because the doctors often observe the brain electrical signals in time domain when they do general EEG detection and analyses.

4. ANALYSIS RESULTS AND DISCUSSION

4.1. Analysis results

"Virtual EEG record and analysis instrument" makes use of Gabor transform to do BRIR analyses. In the system, the window length is 128 sampling dots and the window shifts 16 dots every time. By analyzing the sleep EEG which has been filtered (11Hz~18Hz) by the bandpass filter function of the instrument, its waveforms in time domain and the band relative intensity ratio of basic rhythms are obtained, as shown in Figure 4. From the figure, it is easy to see the relative intensity of different bands at certain time, and can find that the α waves and β_1 waves are the main frequency bands of the signal. In the figure, other three bands also exist because of the side bands effect of the filter.

Figure 5 shows the waveforms in time domain and the BRIR at every time of the EEG data of a patient for alcoholism. From its analyses of BRIR, it is distinct to see that the δ rhythm is the dominance frequency.

4.2. Discussion

When Gabor transform is used to analyze BRIR, the analysis results do not become better along with the length of selected window becoming shorter. This is because the obtained spectrum becomes no meaning after the window is shortened to a certain degree. So we can only make a compromise between the localizations of time and frequency. To what extent the compromise is determined by the window, signal, time and frequency, and which is emphasized between the time resolution and the frequency resolution. In clinical diagnoses, the doctors' concern is that if the "background rhythm" is restrained and the relative intensity of different rhythms, so from the view of enhancing the EEG frequency resolution, the authors adopt relative large window length during the study of the instrument system.

The relative intensity of different rhythms can be given qualitatively by BRIR, which is difficult to obtain from the waveforms in time domain or the spectrum of the EEG, just as the waveforms in time domain as shown in Figure 4 and 6. The change of different frequency bands can be followed accurately by BRIR.

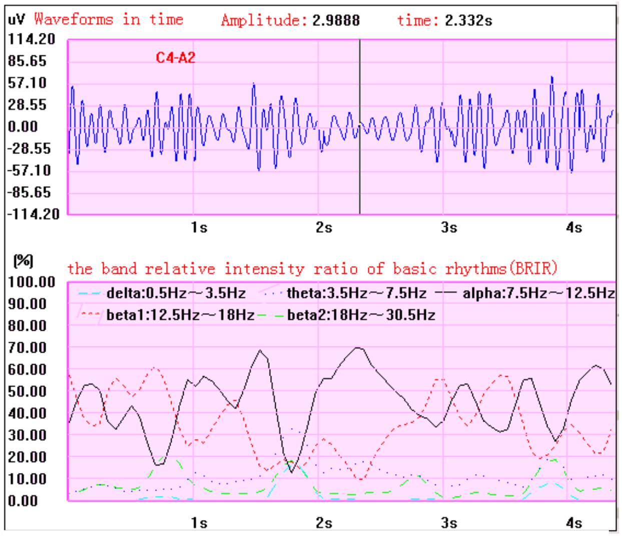

Fig.4 Waveforms in time domain and its BRIR of the EEG data in the C4-A2 channel

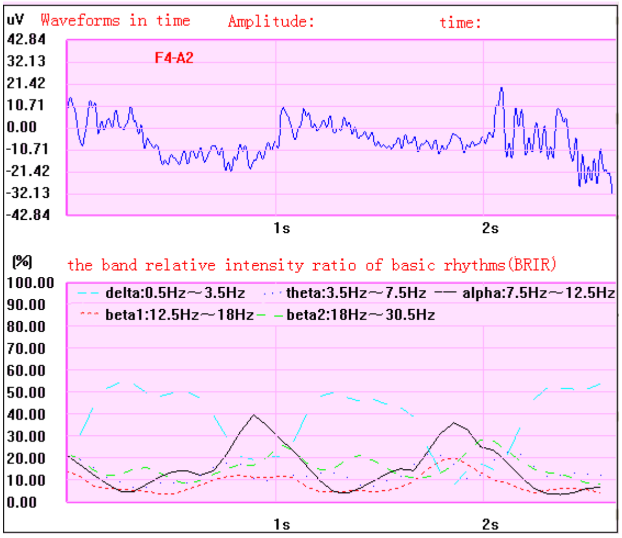

Fig. 5 Waveforms in time domain and the BRIR of EEG data in F4-A2 channel

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