Processing and Analysis of Bio-signals from Human Stomach

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Abstract—In this article, the electrogastrography is utilized to detect slow wave of gastric digest motility after test meal. In order to extract useful information, this study used multi-resolution method with the Daubechies wavelet function to decompose EGG signal into 9 layers. We reconstructed the slow wave with decomposed signal after digital signal processing to achieve method of the slow wave detection of EGG. During strong contraction of stomach, there is a significant increase in frequency spectrum and power spectrum of the slow wave frequency region. And power spectrum of time windows of slow wave bandwidth increases clearly. The contribution of this paper was that the filter of CWT and Fourier transform was used to obtain the bandwidth of slow wave, and the proposed method was compared with Chebyshev filter. By calculation and analysis of experimental data, the EGG slow wave detection method of wavelet-based motility of gastric digestion was verified to be effective, and also provided a better clinical method to monitor the state of stomach activities. This method is also can be applied to human medical sensor network which includes electrogastrography, electrocardiogram, thermometer, sphygmomanometer.

I. INTRODUCTION

As is well known, human gastric motility is associated with action potential [1]. In normal stomach, the action potential presents circadian rhythm for digestion. Electrogastrogram (EGG) is the potential activity recorded with skin surface electrodes and corresponding location of the abdominal membrane inside the stomach [2]. Since 1950, scientists have begun to use expanded electronic devices with effective methods to record and analyze EGG [3-10]. EGG is attractive because of its non-invasive and does not disturb the behaviors of gastric movements. EGG is easy to measure, but is not easy to be exactly understood. The frequency domain of EGG is very low, and the amplitude of EGG is low at 0.066–0.15 Hz for bradygastria, 0.033–0.066 Hz for normal rhythm, and 0.066–0.15 Hz for tachygastria.

The signal of EGG is non-stationary. Its frequency, amplitude and phase characteristics of the slow wave are always different with time and people. Wavelet transform (WT) is a method that can be used to solve the problems of non-stationary signal. A series of basic translated and compressed wavelet function are used to describe the sampling signal [8]. It has a high resolution of frequency in low frequency, and a high resolution of time in part of high frequency. Wavelet transform can be divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT). DWT is often used to process discrete experimental data of physiological signal.

This paper uses DWT to analyze gastric slow wave signal. After using DWT to decompose EGG signal, the signal of EGG is decomposed into different frequency subbands. Through analysis of frequency bandwidth of slow wave, researches on variations of bandwidth of slow wave from fasting to meal verify the effectiveness of detection method of slow wave. The proposed method also can be used as a clinical tool to analyze bradygastria and tachygastria of human stomach.

II. WAVELET TRANSFORM

Wavelet transform is a method using a series of basic translated and compressed wavelet function to describe the sampling signal. Signal analysis is used in order to obtain the relationship between time domain and frequency domain of signal. The time information of signal can be obtained through shifted transform of wavelet transform, characteristics of frequency is available through scaled transform of wavelet transform. WT using scaling factor and translating factor is called two-scale wavelet transform, which is a representative form of discrete wavelet transform.
The meaning of continuous wavelet transform is that mother function of wavelet does inner product with analyzed signal under different scale parameter \(a\) after displacement parameter \(b\). The CWT of a signal \(x(t)\) is defined as,

\[
WT_s(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*(\frac{t-\tau}{a}) dt, \quad a > 0
\]

\(x(t)\) is the sample signal and \(\psi^*(x)\) is the mother wavelet function. CWT can be expressed as equivalent in frequency domain as following,

\[
WT_s(a, \tau) = \sqrt{\frac{a}{2\pi}} \int_{-\infty}^{\infty} X(\omega) \psi^*(a\omega) e^{j\omega \tau} d\omega
\]

The essence of WT is that any function \(f(t)\) in \(L^2(R)\) space is expressed as superposition summation on \(\psi_{a,b}(t)\) with different scale factor \(a\) and shift factor \(b\). Fourier transform only mapping \(f(t)\) into frequency domain, wavelet transform mapped one-dimensional time signal to two-dimensional time scale domain signal, therefore \(f(t)\) has multi-resolution features unwrapped on mother wavelet. By adjusting the expansion factor \(a\) and translation factor \(b\), we can get wavelet with different time-frequency bandwidth to match any data of original signal. And analysis of time-frequency localization will be available on sampling data.

For the discrete case, with respect to the wavelet \(\psi(t)\) can be discretized as follows,

\[
CWT_s(iT_s, a) = T_s \int_{-\infty}^{\infty} x(nT_s) \psi^* \left( \frac{n-\tau}{a} \right)\]

Where \(T_s\) is the sampling interval, and \(i\) is the integer sample number.

The relationship of the wavelet coefficients, scaling factor and frequency obtained from discrete wavelet analysis are shown in figure 1, \(S\) represents an original input signal, and frequency range of these two signals is half of the bandwidth of original signal. Signal decomposition can be realized by multi-level iterative decomposition. We can obtain high resolution in low frequency components. As shown in figure 2 and 3, EGG signal getting off noise is the trend A9 signal with low frequency. The D1 and D5 are wave signals with high frequency.

The signal D1 and signal A1 are produced by \(S\) through highpass and lowpass filters of WT. A1 is the trend signal in low frequency, D1 is the detail signal with high frequency. The

\[
\begin{align*}
S & (0-100Hz) \\
A1 & (0-25Hz) \\
A2 & (0-12.5Hz) \\
A3 & (0-6.25Hz) \\
A4 & (0-3.125Hz) \\
A5 & (0-1.5625Hz) \\
A6 & (0-0.78125Hz) \\
A7 & (0-0.390625Hz) \\
A8 & (0-0.1953125Hz) \\
D1 & (25-50Hz) \\
D2 & (12.5-25Hz) \\
D3 & (6.25-12.5Hz) \\
D4 & (3.125-6.25Hz) \\
D5 & (1.5625-3.125Hz) \\
D6 & (0.78125-1.5625Hz) \\
D7 & (0.390625-0.78125Hz) \\
D8 & (0.1953125-0.390625Hz)
\end{align*}
\]

Fig.1 Wavelet decomposition figure
variation of slow wave frequency spectrum and power spectral analysis from fasting to meal is used to obtain quantitative digested peristaltic slow wave.

III. EXPERIMENTS AND RESULTS ANALYSIS

Experimental apparatus are shown in Figure 4, the experimental system includes: skin surface electrodes, amplifier with two channels (500X, 20Hz lowpass filter), data collection card with eight channels (NI BNC-2110) and PC. Labview 8.5 was used to get experimental data. The positions of the skin sampling electrodes are shown in figure 5.

Reference electrode R is located in xiphoid. A3 is located in mid-point of the xiphoid and the navel, A4 and A3 is at the same horizontal line, the distance between A3 and A4 is about 4-5cm. A1, A2 is about 45 degree angle to the horizontal line, the interval is approximately 4-5cm. Two-channels scheme is adopted in experiments, only takes positions R, A1 and A3 [12]. Talking is not allowed during experiments to maintain testee stable and sitting comfortably to prevent movements. The recording of EGG data is still going on without getting off electrodes during test meal. So the same experimental condition of EGG character would be affirmed in this way. Ten groups of experiments were done for analysis. Each sampling time is about 80-100 minutes.

First, wavelet transform of MATLAB was used to decomposed initial sampling data into 9-layers, A9 (f: 0 -0.098 Hz) signal was obtained. Then, the signal A9 was processed with Fourier transform filter and inverse-Fourier transform to obtain signal of slow wave (0.040-0.062Hz).

Then, through analysis of frequency spectrum and power spectrum of slow wave activity, shown in figure 6 and 7 above, it can be observed that the frequency spectrum and the power spectrum had significantly increased after meal, which indicated that the energy of slow wave bandwidth strengthened significantly.

From analysis of power spectrum of time windows, the energy of slow wave frequency bandwidth of time windows increased clearly after starting of test meal. As shown in figure 8, the energy levels of fasting and meal are also different obviously.

Finally, through the slow wave bandwidth we get above, inverse-Fourier transform was used to reconstruct the slow wave in time domain. Slow wave after meal is as shown in figure 9.

In order to evaluate filter method proposed in this paper with Chebyshev II filter. The index SNR and RSE are achieved to evaluate these two filters. The SNR of filter is defined as follows,

\[
\text{SNR} = 10 \times \log \left( \frac{\sigma_x}{\sigma_n} \right)
\]
Where \( \sigma_s \) represent variance of original EGG signal and \( \sigma_n \) represent variance of noise.

The RSE of filters were calculated as follows,

\[
RSE = \sum_{i=0}^{L-1} (X_r(i) - X_0(i))^2
\]  

(5)

Where \( X_r \) is a reconstructed signal and \( X_0 \) is an original EGG signal with noise with L sample length. The larger the SNR, the better the filter performance is. Also the performance of filter is better while RSE is smaller.

From comparison of filter proposed in this paper with Chebyshev II filter, as shown in Table I, the SNR of DWT is much larger than Chebyshev II filter. More information of Chebyshev II filter, as shown in Table I, the SNR of DWT is better while RSE is smaller.

| Filter in this paper | SNR | RSE(unit: 10⁶) |
|----------------------|-----|---------------|
| Chebyshev II filter  | 51.3407 | 5.6357 |

Chebyshev II filter, as shown in Table I, the SNR of DWT is much larger than Chebyshev II filter. More information of EGG signal is included after DWT filtered. The DWT filter performed better than Chebyshev II filter.

IV. CONCLUSION

EGG signal is non-stationary signal, useful information need to be extracted from it. In this paper, EGG signal was decomposed into 9 layers with DWT. the decomposed signal A9 was obtained, its frequency range was 0-0.098Hz. Signal of the slow wave was achieved by Fourier transform and inverse-Fourier transform. Comparing fasting and postprandial frequency spectrum and power spectrum, energy enhancement in the slow wave bandwidth was obviously exhibited after meal. Through analysis of power spectrum of time windows, there was significant energy enhancement in power spectral density after test meal.

Analytical methods based on Wavelet Transform have been widely used in processing biological signals. Taking into account computational accuracy of the algorithm, the filtering thought this paper used, which processing rough locating on frequency firstly and then fine locating on frequency, is logic. Meanwhile, the wavelet transform can be used to obtained frequency bandwidths of slow wave and spike activity. By experimental data calculation and analysis, clear slow wave was accessed after meal. Slow wave

detection algorithm of gastric digestive peristalsis based on wavelet transform is verified to be effective. Through the comparison of SNR and RSE of Chebyshev II filter and filter method proposed in this paper, it can be proved that DWT is effective and it can be widely used in digital signal procession of physiology. Therefore, DWT has become a valid and attractive tool for the research of the physiology, electrophysiology and pathophysiology.

REFERENCES

[1] A. Akin, H. H. Sun, “Time-frequency methods for detecting spike activity of stomach,” IEEE Trans. on Med.Biol.Eng Comput., Vol. 37, 1999, pp. 381–390.
[2] Mahmut Tokmakci, “Analysis of the Electrogastrogram Using Discrete Wavelet Transform and Statistical Methods to Detect Gastric Dysrhythmia,” Journal of medical systems, 2007, Vol. 31, pp. 295–302.
[3] C. Y. Ryu, K.C Nam, S.C Kim and D.W Kim, “Comparison of Digital Filters with Wavelet Multiresolution Filter for Electrogastrogram,” Proceedings of the Second Joint EMBS/BMES Conference, Houston, USA 2002 pp.137-138.
[4] Zhao Shu, Ren Chaoshi. “Electrical bio-impedance method: a noninvasive measurement and evaluation technique of gastric motility function,” World Chinese Journal of Digestology, 2006, 14(5), pp.465-469.
[5] Daubechies, I., “The wavelet transform, time-frequency localization and signal analysis.” IEEE Trans. Inf. Theory 36(5):961–1005, 1990.
[6] Xu, H.B Zhu, JD Chen. “Pyloric electrical stimulation reduces food intake by inhibiting gastric motility in dogs,” Gastroenterology, 2005, 128(1), pp. 43–50.
[7] Price, C. N., Westwick, D. T., and Mintchev, M. P., “Analysis of canine model of gastric electrical uncoupling using recurrence quantification analysis.” Dig. Div. Sci. 50:885–892, 2005.
[8] Kara, S., Dirgenali, F., and Okkesim, S., “Estimating gastric rhythm differences using a wavelet method from the electrogastrograms of normal and diabetic subjects.” Instrum. Sci. Technolos. 33:519–532, 2005.
[9] Kara, S., Dirgenali, F., and Okkesim, S., “Estimation of wavelet and short-time Fourier transform sonograms of normal and diabetic subjects’ electrogastrogram.” Comput. Biol. Med. 36:1289–1302, 2006.
[10] J. Chen. “Non-Invasive measurement of gastric myoelectrical activity and its analysis and applications,” Proceedings of the 20th Annual international conference of the IEEE Engineering in Medicine and Biology Society, 1998, Vol. 20, pp.2802-2807
[11] Zhang, Y., Wang, Y., Wang, W., and Liu, B. “Doppler ultrasound signal denoising based on wavelet frames.” IEEE Trans. Ultrason. Ferroelectr. Freq. Control 48:709–716, 2001.
[12] B. Kruisee-Swidergel, and K. Jonderko, “Multichannel electrogastrography under a magnifying glass - an in-depth study on reproducibility of fed state electrogastrograms,” Neurogastroenterol Motil, vol. 20, pp. 625–634, 2008.