ISSN 1750-9823 (print)
International Journal of Sports Science and Engineering
Vol. 1 (2007) No. 1, pp. 39-44

Detection and Extraction of Physiological Dielectric Characteristic Using Wavelet Analysis

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(*Received October 25 2006, accepted December 20 2006*)

Abstract. Physiological dielectric characteristic signal such as electromyography (EMG) signal or electrocardiogram (ECG) signal is the basic data of human physiology in researching and monitoring athletics training or recovery exercise. After the wave decomposition to biological signal, in order to extract the feature of signal and eliminate the noise in the superior wave, based on wavelet analysis, using global statistics and local maximum likelihood analysis to the wavelet series respectively, a method to filter the signal was given here, thus the recognition and extraction of human EMG-signal mixed with random noise and ECG-signal was achieved, at last, relevance analysis was made to the results, which test the feasibility of this method of recognition and extraction.

Keywords: Physiological Dielectric Characteristic, Feature Extraction, Recognition, Wavelet Transform

1. Introduction

Physiological dielectric characteristic signal has a wide application in the research of human movement and other field of bioengineering, especially in athletics training or recovery exercise, collecting and analyzing all kinds of bioelectric signals has become the basic method of monitoring and researching in the movement process. Biological digital signal is a non-stationary weak signal, and often is a low frequency signal in the high noise background. So to this collected biological signal, it has a practical significance to eliminate all kinds of interference components from the disturbed signals or to make extraction and analysis of the signal feature.

One of the methods used commonly in the time domain analysis of non-stationary signal is short-time (window) Fourier transform. Short-time Fourier transform can reflect the feature of local area frequency by using sliding window to analyze the signal, the sliding window processing in time domain is similar to filtering in frequency domain with filter clusters on the divided frequency band, the precondition it used in the non-stationary signal processing is supposing that the signal is stationary in the window, that is, to consider the whole signal section as pseudo stationary signal. However the shortcoming of processing global non-stationary signal by the fixed sliding window is also obviously. Because of this shortcoming, based on the feature of wavelet transform in time frequency analysis, that is it has different resolution in the different position of time-frequency plane, we discuss the recognition and extraction of the physiological dielectric characteristic signal.

2. Feature extraction of data based on wavelet analysis

Wavelet transform comes from window Fourier analysis. Define the continuous wavelet transform as

$$< f, \varphi_{a,b} >= CWT_{\varphi} f(a,b) = | a |^{-1/2} \int_{-\infty}^{+\infty} f(t) \overline{\varphi(\frac{t-b}{a})dt} \tag{1}$$

Where φ is the wavelet bases, a is the scale parameter to control dilation on the time axis, b is the translation parameter.

Wavelet bases φ should satisfy

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$$C_{\varphi} = \int_{-\infty}^{+\infty} \frac{\left|\overline{\varphi(\omega)}\right|}{|\omega|} d\omega < \infty \tag{2}$$

Let $a = a_0^j$, $b = ka_0^j$. If $a_0 = 2$, we get the basic function system of discrete wavelet transform

$$\varphi_{j,k} = 2^{-1/2}\varphi(2^{-j}t - k) \tag{3}$$

Approximate the signal $f(t)$ more and more roughly by choosing resolution from 2^{j-1} to 2^j, use $\delta^j(t)$ to denote the deviation of the two approximations, that is, it is the lost information, and can be denoted by the linear combination of $\varphi_{j,k}(t)$. Let $\varphi(t)$ and $\psi(t)$ be the wavelet function and scaling function of $f(t)$ respectively with the resolution of 2^j, its discrete approximation $A_j f(t)$ and detail part $D_j f(t)$ can be denoted as

$$A_j f(t) = \sum_{k=-\infty}^{\infty} C_{j,k}\psi_{j,k}(t), \quad D_j f(t) = \sum_{k=-\infty}^{\infty} D_{j,k}\varphi_{j,k}(t) \tag{4}$$

$C_{j,k}$ and $D_{j,k}$ denote the rough image coefficient and detail coefficient with the resolution of 2^{-j}.
According to the property of multi- resolution analysis, we get

$$\sum_{m=-\infty}^{\infty} C_{j+1,m}\psi_{j+1,m}(t) + \sum_{m=-\infty}^{\infty} D_{j+1,m}\varphi_{j+1,m}(t) = \sum_{k=-\infty}^{\infty} C_{j,k}\psi_{j,k}(t) \tag{5}$$

From this we get the Mallat Algorithm

$$C_{j+1,m} = \sum_{k=-\infty}^{\infty} h^*(k-2m)C_{j,m}$$

$$D_{j+1,m} = \sum_{k=-\infty}^{\infty} g^*(k-2m)C_{j,m} \tag{6}$$

$$C_{j,k} = \sum_{m=-\infty}^{\infty} h(k-2m)C_{j+1,m} + \sum_{m=-\infty}^{\infty} g(k-2m)C_{j+1,m}$$

Where $h(k)$ and $g(k)$ denote Daubechies filter.

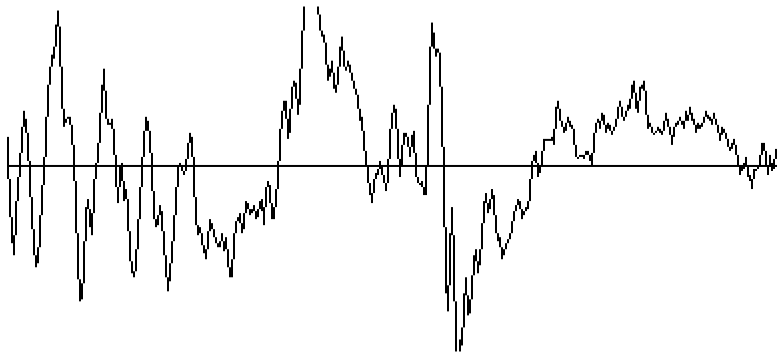

Fig.1: EMG signal

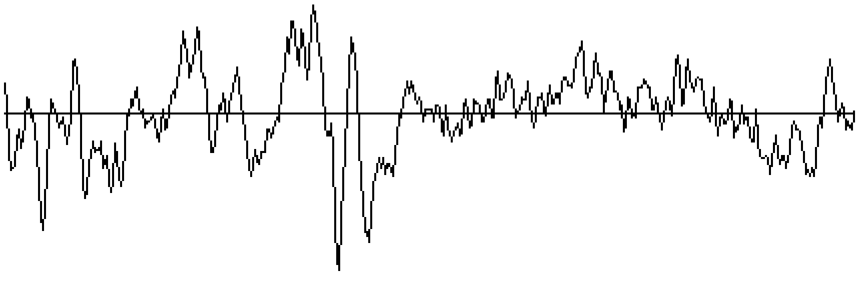

Fig.2: Disturbed EMG-ECG signal

Because biological signal has general features as randomness, nonstationarity and the complexity of background noise, this kind of signal often belongs to the low frequency weak signal in the high noise background. To some disturbed biological signal, by wavelet transform and inverse transform, we extract the signal feature first globally then locally. The biological signal processed in the numerical experiment is the EMG-signal of human back and the disturbed EMG-signal which is mixed with ECG-signal, as shown in Fig.1 and Fig.2

2.1. Extracting data global feature

The method of extracting data global feature mainly process the signal before and after the wavelet transform as well as the wavelet series in the view of statistics. This method is based on the global view, observing and extracting signal feature globally. It is the traditional method of the wavelet analysis. Analyzing the signal in the view of statistic can avoid the error caused by time delay, so it can reflect the global feature of the signal.

The global modulus maxima can express rang of signal amplitude on this frequency band. The energy of the signal $f(t)$ is

$$E_0 = \sum_{k=0}^{N-1} f^2(k) \tag{7}$$

The Zero Crossing Rate (ZCR) express the times that signal wave crosses the axis of abscissas. It can be defined as

$$Z_0 = \frac{1}{2N}\left\{\sum_{k=1}^{N-1}\left|\mathrm{sgn}\left[f(k)\right]-\mathrm{sgn}\left[f(k-1)\right]\right|\right\} \tag{8}$$

Where

$$\mathrm{sgn}(x) = \begin{cases} 1, x \geq 0 \\ -1, x < 0 \end{cases}$$

Commonly, the randomness of noise signal is big, so its ZCR should be higher. The low frequency physiological dielectric characteristic signal in the high noise background has a lower ZCR. Expediently, we remark that Di is *i*th parameters of wavelet series, Si is *i*th parameters of smooth wavelet series and Si(In) means inverse of Si after all tables.

Table 1 Wavelet series statistic feature of EMG

Signal	Modulus max	Modulus min	Expect.	Variance	Energy	ZCR
EMG	0.336	-0.372	0	0.391	/	0.108
D1	0.032	-0.029	0	0.039	0.061	0.632
D2	0.043	-0.043	0	0.086	0.149	0.600
D3	0.061	-0.044	0	0.158	0.250	0.630
D4	0.025	-0.042	0	0.201	0.203	0.460
S3	0.085	-0.099	0	0.345	1.188	0.310
S4	0.038	-0.055	0	0.289	0.417	0.380

Table 2 Wavelet series statistic feature of EMG-ECG

Signal	Modulus max	Modulus min	Expect.	Variance	Energy	ZCR
EMG-ECG	0.428	-0.456	-0.004	0.352	/	0.159
D1	0.069	-0.100	0	0.054	0.115	0.642
D2	0.090	-0.089	0.001	0.120	0.290	0.655
D3	0.078	-0.046	0.001	0.181	0.329	0.550
D4	0.026	-0.038	-0.007	0.170	0.151	0.480
S3	0.102	-0.124	-0.002	0.286	0.819	0.310
S4	0.028	-0.041	-0.001	0.217	0.238	0.400

Compare Table 1 with Table 2, the modulus maxima of the EMG-ECG signal and its detail signal after wavelet transform D1,D2,D3 is higher than EMG signal, while their modulus minima is lower than EMG-signal. Compare the modulus maxima, there exists some mutant signals in EMG–ECG signals, and this mutant signal should not belong to the noise signal caused by measuring, for mutant signal exists in the detail signal of each wavelet series. Because of the property by wavelet transform multi-resolution analysis, D1, D2, D3 take up the most part of the whole signal frequency band, and belong to the high frequency part, while S3 and S4 belong to the low frequency part.

Furthermore, the modulus maxima of D3 and D4 is extremely similar, especially the modulus maxima at D4 of the two signals have no obvious differences. That is to say some mutant signals can be filtered after wavelet transform with higher series. The noise signal--the random noise caused by measuring and the interference noise in domination wave, has already been filtered when the series of wavelet transform reaches 4.

Meanwhile, from the statistics, the ZCR of the detail signals are higher, they cross the zero point frequently, so they can be seemed as random signals. However, the ZCR of original signal and smooth signal is lower, the biological signal be measured should be a low frequency signal in the high noise background, so the smooth signal can be seemed as the domination wave need measuring. In the global view, according to the characteristic data extracted form signals, considering the method to filter the information of high frequency part, we can get the domination wave signal we needed by wavelet transform with low frequency information.

2.2. Extraction and Analysis of Data Local Feature

2.2.1. The extraction of characteristic periodicity

In the analysis of instantaneous signal, the most important information is mutant point. Ordinary digital signal processing is come into being the original signal, the extraction of mutant point is under one scale on the principle of wavelet theory. Associated the appearance of mutant point with the method of wavelet analysis, the local modulus maxima of wavelet series ($W^1_{2^j} f, W^2_{2^j} f, W^3_{2^j} f...$) appear at the mutant point of the signal. When Extracting the local modulus maxima of the signal given by the numerical experiment, considering the time delay before and after the collection of the two group of signals, and for biological signal is collected under the high noise background, the information of modulus maxima is also easily to de disturbed, so take the method of extracting characteristic cycle, that is to compute the average pitch time of the two adjacent modulus extreme value (one modulus maxima and one modulus minima), which appears to be the average distance between points when signals are discrete. In order to reflect the feature of the signals correctly, we use regression to compute the characteristic cycle.

Compute the characteristic cycle of the signals after wavelet transform, the data is shown in Table 3.

Table 3 Characteristic periodicity of the two signals

Signal	D1	D2	D3	S3(In.)	S4(In.)	S5(In.)
EMG	13.827	8.512	11.857	18.438	29.308	61.800
EMG-ECG	16.977	10.938	5.067	12.927	32.857	65.125

As it is shown in Table 3, the characteristic cycle has no great difference after the inverse wavelet transform to the smooth signal with the forth and fifth wavelet series. Also from characteristic cycle data of D1, D2 and D3 can get that their randomness is big, and they belongs to the random signals. This declares that S4 and S5 have same signals, while S5 belongs to the low frequency part of S4. Wavelet decomposition to the fourth or fifth series filter the high frequency part, and has a better effect.

2.2.2. local maximum likelihood analysis

Based on the existence of time delay before and after the signals collected, there should exist great error if only considering the global likelihood, so consider their local maximum likelihood.

$$\tilde{P}_{f,g}(l) = \max_{0 \le i, j \le N-l} \left\{ \sum_{k=0}^{l} \left| f_{i+k} - g_{j+k} \right| \right\} \tag{9}$$

In the expression l is the local maximum likelihood analysis parameter, it is the length of signal local comparison, and it is variable. The local analysis of GMT signal and GMT-ECG signal when the local parameter is 60, 80, 100…180 is shown in Table 4.

Table 4 EMG and EMG-ECG detail signal local maximum likelihood analysis data

Parameter	60	80	100	120	140	160	180
D1	0.221	0.183	0.149	0.130	0.116	0.103	0.095
D2	1.065	0.835	0.717	0.633	0.601	0.541	0.511
D3	3.671	3.098	2.613	2.486	2.250	2.191	2.021
D4	3.558	2.983	2.575	2.680	2.559	2.413	2.205
D5	2.741	2.254	2.103	1.925	1.754	1.604	1.471
S3	8.040	6.225	5.484	4.756	4.440	4.081	3.688
S4	5.780	4.700	4.290	3.716	3.455	3.172	2.889
S5	3.658	3.348	3.094	2.913	2.590	2.354	2.157

It can be concluded from Table 4 that the likelihood of smooth signal is greater than detail signal, this prove the feasibility of filtering detail signal again. However it can be found in Table 4 that D3 and D4 also have big values. Meanwhile, the data of S5 is obviously lower than other smooth signals, if all the low frequency parts of smooth signals in original signals are the domination wave signals needed, the result can't be like this, it means that a part of frequency band in low frequency part doesn't belong to the domination wave signals. To this situation consider the method of associating D4 with D5 or associating D4 with D5, making inverse transform to restore the signal in the lower frequency band of wavelet detail signals, thus can get the domination wave signals.

3. Data Processing and Correlation Testing

The cross correlation function of two signals expresses the dependency of the two signals, it can judge the dependency of two signals in the condition of ignoring the pitch time and the time skew level of two signals; the autocorrelation function can be used to analyze if the signals have some periodicity. Let f_i and g_i $(i = 1,2,...N)$ be two digital signals, the estimating of the cross correlation function is defined as

$$r_{f,g}(j) = \frac{1}{N-j}\sum_{i=0}^{N-j-1} f_i g_{i+j} \tag{10}$$

The estimating of the autocorrelation function is defined as

$$r_{f,g}(j) = \frac{1}{N-j}\sum_{i=0}^{N-j-1} f_i f_{i+j} \tag{11}$$

To the experiment signals, use the inverse transform signals of the third and the fourth wavelet series to restore the domination wavelet signals, the testing result of dependency of the domination wave signals shown in Fig.3~Fig.8.

The detail definition is not given here. From the comparison of the data analysis and the program running results above, it can be found that making wavelet transform till the fourth series has the best result. Due to the limitation of the length, only one filtering method with its results and correlation analysis to the clinical data is given here.

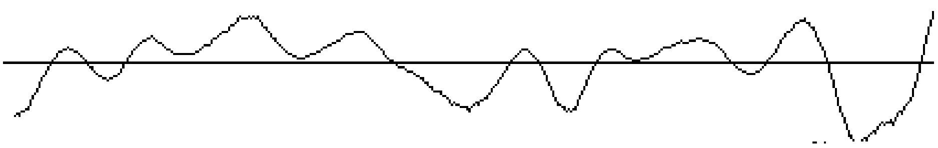

Fig.3 Domination wave restoring of the third wavelet series to low frequency smooth EMG-ECG signals

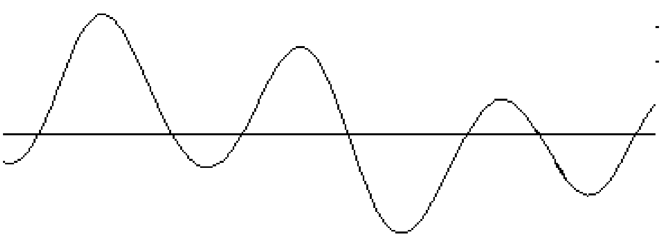

Fig.4 Auto-correlation figure of the domination wave restoring to the third wavelet series of EMG signals

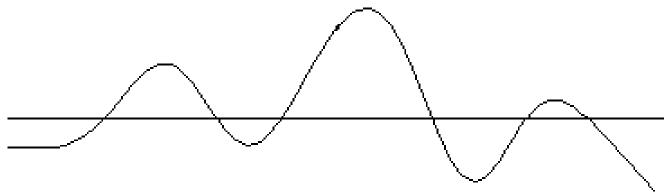

Fig.5 Cross-correlation figure of the third wavelet series to EMG and EMG-ECG signals

3.1 Filter detail signals

Using the low frequency smooth signals of the third wavelet series to restore the signals by making the inverse wavelet transform, get the domination wave signals. The filtering results are shown as following:

3.2 Fourth wavelet series to restore the signals

Using the detail signals of the fourth wavelet series to restore the signals by making the inverse wavelet transform, get the domination wave signals. The filtering results are shown as following:

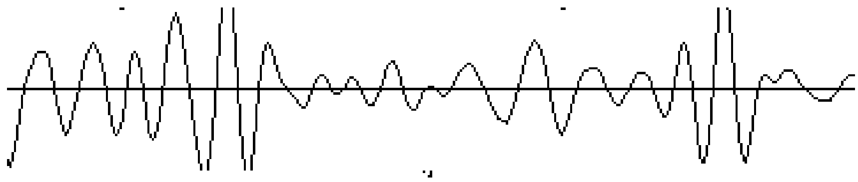

Fig.6 Domination wave restoring of the fourth wavelet series of low frequency smooth EMG-ECG signals

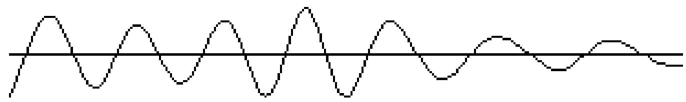

Fig.7 Auto-correlation figure of the domination wave restoring of the fourth wavelet series of EMG signals

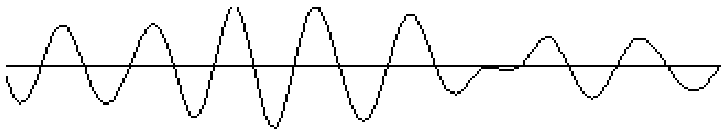

Fig.8 Cross correlation figure of the fourth wavelet series of EMG and EMG-ECG signals

To the results of the correlation processing of the filtering result above, it can be concluded from the autocorrelation figure of EMG signals that the domination wave signals after filtering have some periodicity, from the cross correlation figure of EMG and EMG-ECG signals, it can be found that the EMG and EMG-ECG signals are extremely similar, only with certain differences on time frequency. It indicates that two methods of filtering discussed above are feasible. Furthermore, it can be seen from the correlation analysis that using the fourth wavelet series to transform accord with the situation, and is a better filtering method.

4. References

[1] Jianping Li. *Wavelet Analysis & Signal Processing.* Chongqing: Chongqing Publishing House. 1997.

[2] Jianliang Li, Yong Jiang. *Computer Numerical Method.* Nanjing: SEU Publishing House. 2000.

[3] Yaqiang Shen, Xu Liu. A Language Method to Remove Noise Based on Sub-wavelet. *Signal Processing*. 2000, **16** (3): 221~226.

[4] Zhengyong Zhang, Xiaoming Cheng. The Step By Step Change of Regular Human ECG Morph. *Biophysics Paper*. **16**(1): 105~113.

[5] C. Li, C. Zheng. Detection of ECG characteristic Points Using Wavelet Transform. *IEEE Trans, On Biomedical Engineering*. 1995, **42** (1): 21~28.

[6] Mallat Zhong. Characterization of Signals from Multiscale Edges. *IEEE Trans, On Pattern Analysis and Machine Intelligence*. 2000, **14** (7): 710~732.