Application of unconstrained BCG extraction in VDT visual fatigue monitoring

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Abstract: Eye diseases caused by long times of use of visual display terminal (VDT) products is considered as a serious problem in recent years. The eye fatigue monitoring is significant for early warning. Here, an unconstrained measuring method is used to extract Ballistocardiogram (BCG) by acceleration sensor. The acceleration signals are acquired by installing the sensor on seat back. Adaptive threshold wavelet transform is processed for denosing non-linear noise interference such as power line interference, baseline drift, random movement of human body, and ground vibration. Frequency domain filtering and IFFT are applied to extract BCG from acceleration sensor. RR interval of ECG and JJ interval of BCG in time domain have the similar cycle, and the correlation coefficient is up to 0.9918, which prove the feasibility to extract BCG from vibration signals using unconstrained method.

1 Introduction

Eye diseases caused by long times of use of visual display terminal (VDT) products are considered as serious problems. The eye fatigue monitoring is significant for early warning. Researches on VDT visual fatigue are mainly divided into three categories [1]:

i. Judgment by physiological signals [2], including pulse signals, ECG, and EEG signals etc. The above physiological signals usually need to fix electrodes and other devices on fingers, wrists, head, or breast and proved high precision in detecting VDT visual fatigue. However, constraint methods are uncomfortable, which lead to mental stress and the measurement accuracy is greatly influenced. Therefore, unconstrained physiological signals monitoring methods have become hotspots in recent years. Unconstrained BCG monitoring method is the most feasible method that has been investigated in recent years with encouraging results.

The first type of research is based on Doppler effect. Heart undergoes volumetric changes during each cardiac cycle. These changes are then reflected in the periodical movement of the chest of subjects. By measuring chest displacement, ECG can be extracted using higher resolution sensors [3]. Jure Kranjec [4] established an ECG acquisition experiment by radar equipment.

The second type of research is based on audio monitoring. In every cardiac cycle, two distinctive sounds (i.e. first and second heart sounds) are generated. Kranjec [5] established a sound acquisition experiment on the basis of a condenser microphone in quiet surroundings and confirmed its validity.

The third type of research is based on monitoring acceleration signals. The principle is to extract heart beat from the periodical movement of the chest caused by the impact of the contraction of the heart. Lim [6] discovered that acceleration sensor is sufficiently sensitive for measuring subtle vibrations on the body attached to a chair. Literature [7] apply acceleration sensor installed on the bed to monitor sleep quality. The study of intelligent seat on the basis of the physiological signals measurement such as body weight, blood pressure, and respiration is researched by installing sensor on cushion, handrails, and backrest. Therefore, it is feasible to extract BCG by mounting the vibration sensor on the seat for visual fatigue monitoring.

However, the above-mentioned measurement methods to extract physiological signals from high-noise background requires further study.

ii. Judgment by subjective feelings of eyes sour, body stiffness, dizziness etc. described by VDT subjects. B. P. Koirala Lion's Centre for Ophthalmic Studies (BPKLCOS) studied VDT visual fatigue by regression coefficients analysis and proposed that long-time use of VDT could lead to eyes sour, tears etc. [8]. However, the conclusion relies on subjective feelings, it can only be used as an auxiliary verification method.

iii. Judgment using score method by task (identification of similar words, reading speed etc.). Heuer H [9] and Rafael I [10] evaluate visual fatigue by selecting different semantic words and grading scales. However, the method is easily affected by sleep deprivation and mental status. Similar as subjective evaluation method, it can only be used as an auxiliary verification method.

In view of the above problems, an unconstrained measuring method is used to extract Ballistocardiogram (BCG) by acceleration sensor. The acceleration signals are acquired by installing the sensor on seat back. Adaptive threshold wavelet transform is processed for denosing non-linear noise interference such as power line interference, baseline drift, random movement of human body, and ground vibration. Frequency domain filtering and IFFT are applied to extract BCG from acceleration sensor. RR interval of ECG and JJ interval of BCG in time domain have the similar cycle and the correlation coefficient is calculated, which proved the feasibility to extract BCG from acceleration signals using unconstrained method.

2 Experiment setup

2.1 Subjects requirements

A total of 10 college students were selected, aged from 20 to 25 years, their uncorrected visual acuity are better than 0.9 and without eye diseases, weights are in the range of 142.62 ± 10.54,
drugs or food may affect mental health are forbidden before the experiment in 3 days.

2.2 Experimental equipment

i. Apple 6s mobile phone (4.7 inches screen, Fig. 1);
ii. Acceleration sensor attach on the seat. The seat is wheel-less to reduce the noise caused by movement. LMS signal acquisition system is used to acquire vibration signals by PCB-333B30 type acceleration sensor (Fig. 2);
iii. PC-80B high-speed ECG detector, the sampling frequency is set to 512 Hz (Fig. 3).

2.3 Equipment installation

The subjects are asked to hold the mobile phone with two hands and put arms on the table to keep 45 cm distance from VDT. The angle between the VDT and the desktop is 75° to avoid discomfort of glare and neck. The acceleration sensor is closed to the contact surface between caudal vertebrae and the seat (Fig. 4). The electrodes of the PC-80B high-speed ECG detector are pasted as shown in Fig. 5.

2.4 Experimental procedure

The subjects are asked to play mobile phone games for 120 min to insure the process from normal vision to fatigue. BCG is acquired by acceleration sensor and ECG is acquired by electrodes:

i. BCG collection: acceleration signals are acquired for 5 min in every 15 min. The subjects are required to keep their back against the seat and remain still to ensure the accuracy of signals acquisition.
ii. ECG collection: ECG signals are collected at the same time for verifying the accuracy of BCG extraction.

3 Signal processing of BCG extraction from acceleration signals

3.1 First level of noise reduction of acceleration signals by adaptive threshold wavelet denoising

BCG extracted from acceleration sensor is weak that extracted in large noise background, which mainly come from power line interference, baseline drift, human movement, and ground vibration. Where power line interference and baseline drift can easily be separated because of its cyclical characteristics. However, human motion and ground vibration noise are random signals and difficult to be removed by traditional frequency domain denoising. The adaptive threshold wavelet denoising has higher resolution compared with traditional wavelet algorithm by selecting different threshold. The algorithm of adaptive threshold wavelet for denoising has four key factors (threshold function, threshold, wavelet basis, and decomposition scale, the denoising steps are stated as follows:

i. Determination of the threshold function

The threshold function is:

$$\eta(x, th, m) = \begin{cases} x - 0.5\text{sign}(x) & \frac{th^m}{\sqrt{m!^2}}, \quad |x| > th \\ 0.5\text{sign}(x)\frac{th^m}{\sqrt{m!^2}}, & |x| \leq th \end{cases}$$

(1)

where $x$ is the signal without noise pollution, $th$ is the threshold, and $m$ is the parameter, which is used to adjust the threshold function according to experience, and $\eta(x, th, m)$ is a variable threshold function.

$$m_j = 1 + 10\frac{E_{d_j}}{E_{o_j}}$$

(2)

where $m_j \in (1, 11]$. As the $j$ becomes larger, $m_j$ becomes smaller, and $E_{d_j}$ decomposes the noise energy of the $j$ layer.

$$E_{o_j} \approx \frac{1}{2^{j-1}} \sum_{k=0}^{N-1} d^2_{j,k}$$

(3)

$E_{d_j}$ decomposes the total energy of the high frequency part after the $j$ layer.
\[ E_{th} = \sum_{k=0}^{N-1} d_{j,k}^2 \quad (4) \]

d_{j,k} \text{ is the coefficient of high frequency after the signals decomposed in } j \text{ layer.}

When the } j \text{ layer is decomposed, } M \text{ is determined according to (2), and then substituted into (1). The threshold function after decomposing in } j \text{ layer is:}

\[ \eta_j(x, y, m_j) = \begin{cases} x - 0.5 \text{sign}(x) \frac{\theta_m^{m_j}}{\theta_{m_j+1}} & |x| > \theta_j \\ 0.5 \text{sign}(x) \frac{\theta_m^{m_j+1}}{\theta_{m_j}} & |x| \leq \theta_j \end{cases} \quad (5) \]

ii. Determination of threshold

The original signals is } x, \text{ the signals mixed with noise is } y, \text{ and the noise is } n. \text{ } y \text{ can be described as:}

\[ y = x + n \quad (6) \]

The wavelet coefficients of } y, x, \text{ and } n \text{ after wavelet transform are } u, u, \text{ and } v, \text{ respectively. Thus, (6) transform into}

\[ \hat{u} = u + v \quad (7) \]

Define functions:

\[ g(y) = \hat{f}(y) - y \quad (8) \]

where } \hat{f}(y) \text{ is the threshold function, } g = [g_0, g_1, \ldots, g_N] \text{ is the mapping function of the } N \text{ dimension vector. Thus, (8) can be established:}

\[ E[ \| g(y) \| ^2 ] = E[ \| \hat{f}(y) - y \| ^2 ] = E[ \| \hat{u} - u \| ^2 ] + E[ \| v \| ] \quad (9) \]

\[ E[ \| g(y) \| ^2 ] \text{ corresponds to the minimum value when the minimum value of } E[ \| \hat{u} - u \| ^2 ] \text{ is taken, } g(y) \text{ is differentiable and can be obtained according to the unbiased estimation:} \]

\[ E[ \| \hat{f}(y) - y \| ^2 ] = N + E[ \| g(y) \| ] + 2V : g(y) \]

(10)

where } V : g(y) = \sum_{k=0}^{N-1} (\partial g_k/\partial y_k).

SURE is an unbiased estimate of (10), which is defined as:

\[ R_s(t) = N + \| g(y) \| + 2V : g(y) \quad (11) \]

From (9), the minimum value of MSE corresponds to the minimum value of unbiased estimation. Therefore, the corresponding threshold is the best threshold in the minimum MSE sense when the (11) takes the minimum value. The gradient function of RS (T) is:

\[ \frac{\partial R_s(t)}{\partial \theta_h} = 2 \sum_{k=0}^{N-1} g_k \cdot \frac{\partial g_k}{\partial \theta_h} + 2 \sum_{k=0}^{N-1} \frac{\partial^2 g_k}{\partial y_k \partial \theta_h} \quad (12) \]

According to (8), } g_i = \eta(y_i, y, m) - y_i \text{, the substitution type (1) is used to calculate the partial derivative.}

\[ \frac{\partial g_i}{\partial \theta_h} = \begin{cases} -0.5 \text{sign}(y_i) \cdot m, & |v| > \theta_j \\ -0.5 \text{sign}(y_i) \cdot m \cdot \frac{\theta_m^{m_j+2}}{\theta_{m_j+1}}, & |v| \leq \theta_j \end{cases} \quad (13) \]

The optimal threshold of corresponding scale is obtained by minimising the scale of } R_s(t). \text{ The optimal threshold can be searched by the steepest descent algorithm.}

iii. Determination of the wavelet base

Wavelet base is judged by the length of support, symmetry, self-similarity principle, vanishing moment order symmetry, and regularity. Wavelet base of Sym8 is chosen as the SNR simulated by Matlab is higher than db4, meyer8, and coif5.

iv. Determination of decomposition scale

The energy of white noise is not changed after orthogonal wavelet transform, the energy is compressed to the larger wavelet coefficients in the wavelet space, after it transformed by wavelet. The wavelet coefficient of the useful signals is dominate because it contains colour noise. So, the spatial coefficients of each layer can to determine whether there are white noise characteristics. When the high-frequency coefficients of the wavelet do not show white noise, the number of decomposition layers is satisfied. Meanwhile, we achieve the purpose of removing the noise and keeping the useful signals as much as possible.

Wavelet coefficients de-correlation whitening test:

The hypothesis of original is } H_0: \{x(n)\}, \text{ it is independent white noise; Negative hypothesis: } H_1: \{x(t)\} \text{ is a related sequence.}

The estimated auto-correlation coefficient of the original sequence is } \rho_k (k = 1, 2, \ldots, m), \text{ and the auto-correlation coefficient after the wavelet de-correlation is estimated to be: } \rho_k (k = 1, 2, \ldots, m). \text{ The definition of the estimation method is used:}

\[ (\rho_1 + \rho_2 + \cdots + \rho_m) / (\rho_1 + \rho_2 + \cdots + \rho_m) = 1 - \frac{1}{\rho_m} \quad (14) \]

where } \rho_k (k = 1, 2, \ldots, m) \text{ is the auto-correlation coefficient of the original sequence, } \rho_k (k = 1, 2, \ldots, m) \text{ is the auto-correlation coefficient after decorrelated.}

\[ \rho_k = \frac{\sum_{n=1}^{N-k} (x_n - \bar{x})(x_{n+k} - \bar{x})}{\sum_{n=1}^{N} (x_n - \bar{x})^2} \quad (15) \]

where

\[ \bar{x} = \frac{1}{N} \sum_{n=1}^{N} x_n \quad (17) \]

According to the theory of mathematical statistics, it follows the } F(m, m) \text{ distribution:

\[ \rho_1^2 + \rho_2^2 + \cdots + \rho_m^2 = 1 - \rho_m \quad (18) \]

Therefore, when the value of test statistic } F(m, m) - 1 \text{ is enough, the null hypothesis should be rejected. We will get the critical value of } F_{\alpha} \text{ from } (F(m, m)) \text{ distribution table when the significant level of } \alpha \text{ given. If } F(m, m) - 1 > F_{\alpha}, \text{ we should negate the original hypothesis.}
The steps to decompose scale are as follows:
The decomposition layer number \( j = 1 \), and the extraction of high-frequency coefficient \( d_{kj} \) to form the correlation sequence of \( H_1 \{ x(n) \} \). Then, carry out \( d \)-correlation whitening test, if \( d_{kj} \) is performance white noise:

\[
j = j + 1
\]

If \( d_{kj} \) cannot show white noise, the optimal decomposition level can be obtained:

\[
N = j - 1
\]

v. The wavelet decomposition is carried out on the \( j \) layer.
vi. If \( j \) is \(< N \), then \( j = j + 1 \); if \( j > N \), the wavelet inverse transform is used to get the signals.

The adaptive threshold wavelet method is used to denoise the signals (Fig. 6a) collected by the subject in 25 s of the fourth 5 min. The signals denoised are as shown in Fig. 6b. Comparing Fig. 6a with b, the curve is smooth and noise is significantly suppressed.

3.2 Secondary noise reduction by band-pass filter and heartbeat extraction

Band-pass filter is a frequency domain analysis method to pass frequencies within a certain range and rejects frequencies outside that range. In the second step of denoising, the band-pass filter is selected according to the range of heart rate. The acceleration signals is filtered in frequency-domain after the first step of denoising, Fig. 7 is the spectrum diagram of vibration signal after band-pass filter. Fig. 8 is BCG of time domain obtained after Fig. 7 processed IFFT.

4 Analysis of experimental results

4.1 Time domain waveform comparison of ECG and BCG

Fig. 9 shows a typical R-R interval in a heartbeat cycle of ECG signal. J-J interval of BCG are found by a heartbeat cycle of BCG signal in Fig. 10 [11]. It is proved that ECG and BCG signals have the same cardiac cycle.

Fig. 8 shows BCG signal acquired by subjects 4 extracted from vibration signals. Meanwhile, ECG signal is monitored shown in Fig. 11. Same cardiac cycle is shown by comparing the J-J interval and R-R interval in Figs. 8 and 11.

4.2 Correlation analysis of ECG and BCG

Corrcoef function is used to analysis the correlation coefficient of two cycles. corrcoef = 1 in the case of a completely correlated; corrcoef = 0 in the case of completely irrelevant. 0 < corrcoef < 1 in the case of partial correlation. Calculated by (21), corrcoef = 0.9918, which means there is a strong correlation between ECG and BCG signals.

\[
corrcoef(i,j) = \frac{\text{cov}(i,j)}{\sqrt{\text{cov}(i,i) \cdot \text{cov}(j,j)}}
\]

Thus, the conclusion that the impact signal can be extracted from the acceleration signal is proved from both time domain comparison and corrcoef function.

5 Conclusion

This paper is discussed the application of unconstrained BCG extraction in VDT visual fatigue monitoring and draw the main conclusions as follows:

i. BCG signal can be extracted using an unconstrained method by installing acceleration signals on the seat back.
ii. Adaptive threshold wavelet transform is processed for denoising non-linear noise. The curve of denoised signals tends to be smooth and the noise is significantly suppressed.

iii. Frequency domain filtering and IFFT are applied to extract BCG from acceleration sensor. RR interval of ECG and JJ interval of BCG in time domain have the similar cycle and the correlation coefficient is up to 0.9918, which prove the feasibility to extract BCG from vibration signals using unconstrained method.

iv. The study laid the foundation for monitoring VDT visual fatigue by BCG in an unconstrained way. The monitoring indicators of VDT visual fatigue will be researched further, by comparing subjective evaluation conclusion (SD) to verify the effectiveness between the indicators and VDT visual fatigue.

6 Acknowledgment

This paper is supported by the National Science Foundation for Young Scientists of China (601301040); The National Key Technology R&D Program(2015BAK06B04); The key Technologies R&D program of Tianjin(15ZXZNGX00206, 17YFCZZC0027, 17KPXMSF00190, 17KPXMMMSF00180); The University Program of Tianjin University of Technology and Education(KJ1701); Funded by Scientific Research Project of TUTE(KJ1810).

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