Research Article

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Cardiac and respiratory signal extraction methods from ballistocardiography signal sensed using fiber bragg grating sensor

Abstract

This work presents a simple, efficient and an easy-to-build ballistocardiography sys-tem using Fiber Bragg Grating (FBG) sensor and a comprehensive assessment of relevant digital signal processing algorithms to simultaneously extract respiratory and cardiac frequency components from a cluttered mix Ballistocardiography (BCG) signal. The primary purpose of the current study is two-fold: first- to build an analog circuit for BCG signal amplification, and second to evaluate the performance of three state-of-the-art methods, namely: lowpass-highpass filter, weiner filter and ensemble empherical mode decomposition to simultaneously extract respiratory and cardiac frequency components from the BCG signal. BCG measurements from test subjects were used in this study and a commercial digital stethoscope was used to validate the performance of methods used in this study. In addition to the effective amplification of the BCG signal through proposed analog circuit configuration, we demonstrate that a simple low pass high pass filter configuration can be used for accurate measurement of cardiac and respiratory frequencies. Due to its simplicity, the proposed system can be suitably tailored to process BCG signal for simultaneous extraction of respiration and heart rate which can aid as an effective diagnostic tool for identifying critical disorders associated with lungs and heart dysfunction.

Keywords: optical ballistocardiography, BCG signal processing, FBG sensor, cardiac signal extraction

Volume 4 Issue 1 - 2020

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Received: January 10, 2020 | **Published:** February 24, 2020

Introduction

Accurate administration and monitoring of patients vital signs is important in hospital care.[1] Ballistocardiog-raphy (BCG) is a popular non invasive technique which records the movements of the body due to left ventricular pump activity in synchrony with the heartbeat.[2,3] Several studies have demonstrated the effectiveness of BCG signal in clinical diagnosis.[4–7] Though BCG technique is surpassed by advanced techniques such as ECG, digital stethoscope, it is still not widely used to monitor patients conditions in clinical environments and remains primarily a research methodology.[8–10] BCG signal is a combination of the signal from domi-nant respiratory activity and the meniscus cardiac activity measured on the wall of the chest.[11] Among the several critical signals of interest in healthcare, measurement of respiratory and cardiac frequencies are of prime importance to monitor patients due to its substantial influence on the patient's outcome. However, these critical parameters are generally measured using devices in electrical domain which have several limitations including synchronization for specific event extraction, electromagnetic interference in hospital environment, high signal to noise ratio etc.[11,12] Use of multiple devices for monitoring of cardiac and respiratory signals of patients in a hospital is also laborious and can delay the disease management and prognosis, especially during emergencies and critical illness situations.

To overcome these complications, several researchers have used optical fiber based systems to acquire these vital signals as they do not contain any conductive parts and in sensitive to electromagnetic artifacts.[13–15] This paper is an extension of the work reported earlier, where Fiber Bragg Grating Heart Beat Device (FBGHBD) was used for the measurement of BCG signal.[16] Heart is enclosed within the mediastinum; the medial cavity of the thorax, the heart extends obliquely from the second rib to the fifth inter costal space.[17] Hence the effect of cardiac activity on the chest/burst wall is faint and it becomes extremely difficult to measure it during any possible movements of the patients which induce undesired noise/artifacts in the nascent BCG signal. Present work aims at proposing and demonstrating suitable signal processing algorithms for effective extraction of cardiac and breathing activities from the obtained mix BCG signal. The scope of the present work is to compare the performance of several state-of-the-art signal processing methods to simultaneously extract cardiac and respiratory frequencies from the mix BCG signal acquired from FBGHBD.

Experimental details

Experimental setup

The experimental setup depicting the position of FBGHBD and digital stethoscope used in this work is shown in Figure 1 which is similar to the setup designed by Chethana et al.[16] However present work is unique in its objectives as it focuses on assessing methods for con-sistent and simultanious extraction of heart beat and cardiac components from mix BCG signal. SM130-700 FBG interrogator from Micron Optics Inc is used for real-time recording of change in wavelength from the FBGHBD. FBG sensor used in FBGHBD undergoes a mechanical deformation along with the silicone diaphragm. Due to this mechanical deformation, the Bragg wavelength of the FBG sensor changes notifying the signatures of the heart beat and respiration which are used for extracting its frequency components.

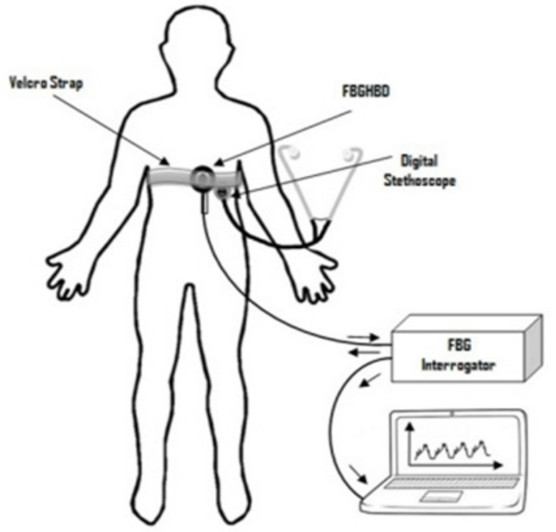

Figure 1 Experiment architecture.

Data acquisition

Healthy subjects free from any cardiac and respiratory disorders volunteered for this study. For the set of trial conducted, necessary ethical committee approval was obtained along with the consent of the subjects. These subjects were advised not to consume alcohol or any sort of medication, 24 hours prior to the commencement of the experiment. After explaining the experimental procedure, each subject was given a trial run before the readings were taken. Subjects were made to rest in supine posture condition before the start of the experiment. Both FBGHBD and digital stethoscope were mounted on the chest of the subject. Data was acquired simultaneously from both de-vices in normal breathing for 1 minute, with the interim gap of around 15 seconds and with valsalva maneuver (breathing with closed glottis) for 15 sec for all trials. A typical mixed signal obtained from FBGHBD with time on x -axis and wavelength converted strain on Y- axis is shown in Figure 2. This mixed signal has both cardiac and respiratory activities with an evident interim valsalva phase for about 10 seconds (15-25sec). A suitable method is thus essential to extract these components for further analysis.

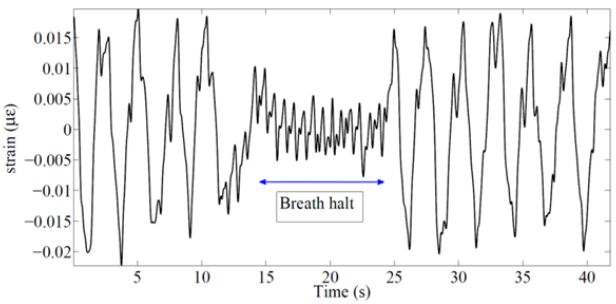

Figure 2 Examples of a raw signal with breath halt.

Method

This section provides the description of the signal processing algorithms evaluated in this work for extraction of cardiac and respiratory frequencies from the FBGHBD mixed signal.

Lowpass-highpass configuration (LP-HP)

Figure 3 shows the block diagram of the proposed ar-chitecture. The raw data obtained from the FBGHBD is initially subtracted from its mean value to remove any DC bias and then passed through a 5th order Butterworth low pass filter set at 10Hz. The peak frequency (fp) from the Power Spectral Density (PSD) of the resulting signal was obtained. A low pass filter set at fp+0.2 provides the res-piratory frequency and a high pass filter set at fp+0.2 was used to obtain cardiac frequency.

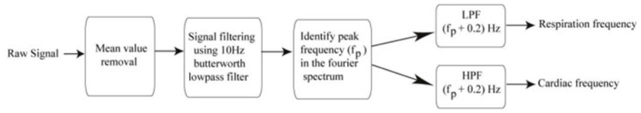

Figure 3 Proposed signal processing architecture.

Ensemble empherical mode decomposition (EEMD)

Empherical Mode Decomposition (EMD) proposed in 1998.[18] decomposes a given time domain signal into several "intrinsic mode functions" (IMF's). The decomposi-tion of the signal using EMD is data driven and is adaptive in nature, making it very flexible and adoptable. Given an input signal.

$$x(t) \in R^{1} * N,$$

Where N is the number of samples, the IMF's are obtained using EMD such that:

$$x(t) = \sum_{k=1}^{n} ck(t) + rn(t) \tag{1}$$

Where $ck(t)$ = IMF's and $rn(t)$ is the residual of x(t) after extracting n IMFs components. More details about the EMD can be found in.[18] The main disadvantage of EMD algorithm is that it is sensitive to noise in the input signal leading to mode mixing.[19] Due to this limitation, an extension to the EMD algorithm known as Ensemble-EMD (EEMD) was proposed in literature to eliminate mode-mixing problem.[20] In EEMD, prior to EMD decomposition, white noise is added to x(t) and the optimum choice of IMF's are obtained (IMF1- IMFk) as an average of a number of ensembles of the EMD algorithm. Compared to EMD, EEMD can effectively solve the mode-mixing problem and end effects in EMD method.[21] The following procedure was used to obtain heart rate and respiration rate using EEMD:

A. The raw signal segment was filtered using a 5th order low pass butter worth filter set at 10Hz.

B. After adding white noise to the raw signal, the resulting signal was decomposed using EEMD.

C. The respiration and heart rates were calculated from the local maxima of their respective decomposed components corresponding to respiration and cardiac cycles, respectively.

Wiener filter

The Wiener filter is another popular noise-reducing method used in this study. Wiener filter is a class of optimal filters, which uses the available signal and noise characteristics.[22] The Wiener filter minimizes the difference between the filtered output and desired output. In the present study, the coefficients of the Weiner filter were adjusted using a least mean square method to reduce the square of the difference between the desired and the actual signal after filtering.

There are several applications of Weiner filter in ECG signal analysis, such as on stress ECG,[23] time frequency ECG representation, and filtering. In frequency domain, the transfer function of a non-causal Wiener filter is defined as:

$$H[f] = S[f]^2 / \left(S[f]^2 + N[f]^2 \right) \qquad (2)$$

Where, H[f] is the frequency response of the filter, N[f] the frequency spectra of the noise and S[f] the frequency spectra of the signal. The Wiener filter takes into account the amount of signal and noise at each frequency point. The Wiener filter is different from adaptive filter and it maximizes the ratio of the signal power to the noise power. In the present work, N [f] corresponds to the frequency spectra of the raw input signal and S[f] is the frequency spectra of the raw signal when the subject was made to hold the breath which corresponds to the cardiac signal.

Experimental results

Respiratory frequency

Figures 4&5 shows the frequency spectra of the raw signal obtained from the sensor which clearly shows a main frequency peak between 0.1 and 0.5Hz. There is also a possibility of the presence of several high-frequency components superimposed on the normal respiratory signal due to involuntary body movements. By using the low-pass filter set at fp+ 0.2 Hz, the detected exterior perturbations in the signal were removed with a low noise signal ratio. Figure 6 represents filtered data of a typical subject to extract respiratory component. The same respiratory frequency (e.g. 26 inhalations per minute) was obtained when compared with the measurement obtained using digital stethoscope, validating the measurements of the proposed method. Similar performance was obtained for all different trials as shown in Table 1.

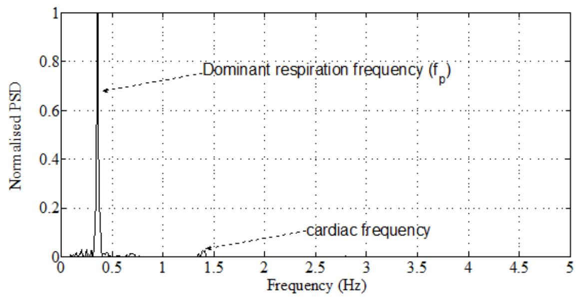

Figure 4 Frequency spectrum of the raw signal.

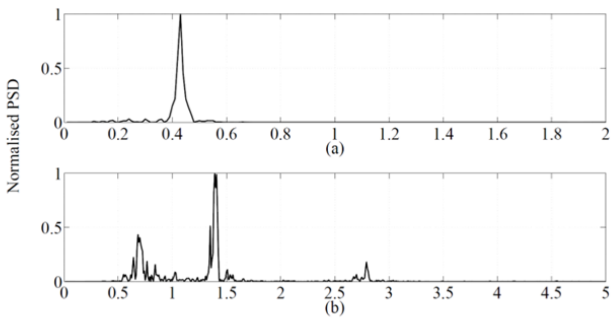

Figure 5 Extracted signal frequencies (a) is respiration, (b) is cardiac.

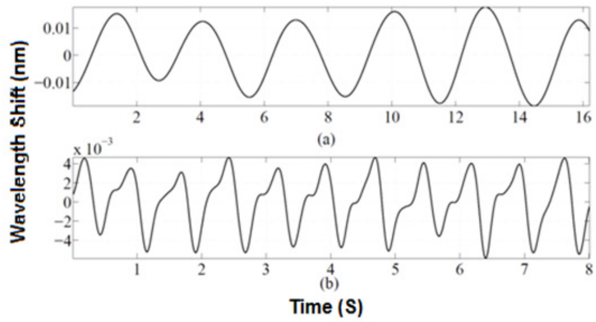

Figure 6 Extracted clean signals (a) is respiration, (b) is car-diac.

Table 1 Quantitative tabulation of respiration and cardiac components extracted results from BCG signal

Type	Subject1			Subject2		
	Trial 1	Trial 2	Trial 3	Trial 1	Trial 2	Trial 3
Respiration Rate	26	28	29	25	22	19
Heart Beat	83	81	83	66	65	65

Cardiac frequency

Figure 2 illustrates an example of the raw BCG signal obtained from the FBGHBD when the subject was asked to halt his or her breath. Higher frequency components can be seen in the frequency spectra Figure 4 when compared with the respiratory frequency. This led to the assumption of the presence of cardiac signal, which related to the heartbeat frequency. In order to obtain the frequency of the cardiac cycle, the processing stage as illustrated in Figure 3 was implemented, resulting in the signals of Figure 6, whose frequency spectra are illustrated in Figure 5. One can detect the region with the location of the cardiac frequency peaks (e.g. between 0.5 and1.5 Hz).

Comparing these obtained results with the digital stethoscope which is previously used in determining respiratory frequency and cardiac components. The FBG signal is initially filtered with a HP filter set at fp+ 0.2 Hz. The proposed method using the FBGHBD provided precise value of heart beats per minute and these measurements were obtained were tabulated in Table 1. From the table, it is evident that the proposed approach enables to obtain accurate simultaneous information about the cardiac and respiratory frequency from the mixed BCG signal acquired from FBGHBD.

Comparison with other methods

One of the major drawbacks of EEMD was the identification of the IMF component corresponding to respiration and cardiac cycle. It was observed that the IMF varies between test subject (subject specific) and their identification is a tedious process which cannot be achieved in real-time. An example IMF from subject 1 is shown in Figure 7. Another drawback is its increased computational complexity since EMD process should be repeated for several times before calculating ensemble average means that EMD process would repeat for several times. The major drawback of the Wiener filter is its fixed frequency

Citation: Chethana K, Guru PAS, Nagaraj SB, et al. Cardiac and respiratory signal extraction methods from ballistocardiography signal sensed using fiber bragg grating sensor. *MOJ App Bio Biomech.* 2020;4(1):15‒19. DOI: 10.15406/mojabb.2020.04.00125

response at all frequencies and the necessity to estimate the power spectral density of the clean signal and noise prior to filtering. This method is not feasible in real-time as it requires a reference signal (cardiac or respiration signal) to estimate the frequencies of the desired signal. Moreover, from Figure 8 it can be seen that both EEMD and Weiner filter fail to provide accurate heartbeat and respiration rate suggesting that the proposed LP-HP filter method is robust for accurate measurements of heart beat and respiratory rate.

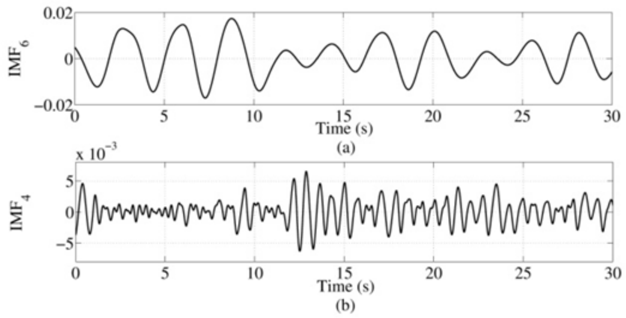

Figure 7 Extracted raw signal from EEMD.

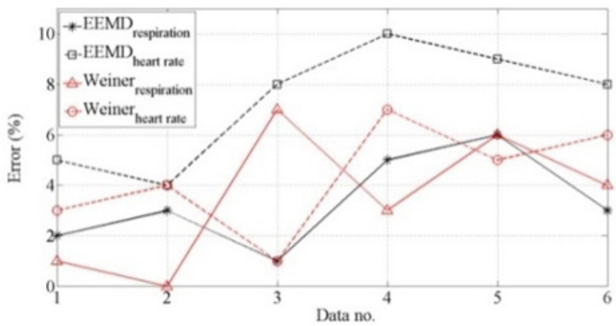

Figure 8 Error of EEMD, weiner for different trails. Error is percentage error when compare to reference from stetho-scope.

Conclusion

Several state-of-the-art methods have been imple-mented in this paper for extracting cardiac and respiratory frequencies from a BCG signal. The performance of each method has been explores based on the heart rate and respiration rate estimation. A simple lowpass-highpass filter configuration was found to be suitable for our application and the other methods had few drawbacks. EEMD method depends on the IMF component which varies from subject to subject which is not consistent. A wrong IMF component can result in a poor outcome. Poor results were obtained using the Weiner filter which requires a reference signal and cannot be used in real-time. With further validation on patients in the clinical en-vironment, the proposed system has a potential for continuous monitoring of respiration and heart rate. Since the breathing rate is usually measured manually and infre-quently, the addition of a measure of breathing rate to the pulse oximeter display could help in early recognition of deterioration in critically ill patients. In addition, the pro-posed system can also be developed as a multimodal early warning system (combining respiration rate and heart rate with pulse oximeter) if more than one of the measurements changes significantly from the normal value.

Acknowledgements

The heading of the Acknowledgment section and the References section must not be numbered. SAP Productions wishes to acknowledge all the contrib-utors for developing and maintaining this template.

Disclosures

The authors have no relevant financial interests in this article and no potential conflicts of interest to disclose.

Conflicts of interest

The authors declare, that there is no conflict of interest.

Funding

None.

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