Heart Rate Estimation from FBG Sensors using Cepstrum Analysis and Sensor Fusion

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Abstract— **This paper presents a method of estimating heart rate from arrays of fiber Bragg grating (FBG) sensors embedded in a mat. A cepstral domain signal analysis technique is proposed to characterize Ballistocardiogram (BCG) signals. With this technique, the average heart beat intervals can be estimated by detecting the dominant peaks in the cepstrum, and the signals of multiple sensors can be fused together to obtain higher signal to noise ratio than each individual sensor. Experiments were conducted with 10 human subjects lying on 2 different postures on a bed. The estimated heart rate from BCG was compared with heart rate ground truth from ECG, and the mean error of estimation obtained is below 1 beat per minute (BPM). The results show that the proposed fusion method can achieve promising heart rate measurement accuracy and robustness against various sensor contact conditions.**

I. Introduction

Ballistocardiogram (BCG) has gained increasing research interests recently due to the advancement of vibration sensing technology and the feature of unobtrusiveness of the sensing devices. Unobtrusive and continuous monitoring of heart rate has wide applications at homes or hospitals.

A key challenge in BCG analysis is the presence of strong variation of morphology of individual heart beats [1]. Position and posture of a subject in bed could be the factors of such variation. As a result, beat-to-beat interval or heart rate detection in time domain is very difficult.

Finding heart rate from BCG signals in frequency domain has the advantage of not relying on specific peaks or templates in waveform. However, BCG is a nonstationary signal, thus a prominent frequency component may not always present in a fixed window of BCG signal. In [2], an adaptive window auto-correlation approach was proposed to detect beat-to-beat interval, and a dynamic programming method is used in the extraction of smooth interval track.

On the other hand, multichannel BCG can provide redundancy for improved detection performance. One example of such sensors is Fiber Bragg grating (FBG) sensor. A number of sensors on a single optical fiber could pick up BCG at different locations, and presumably some of the sensors could provide good quality signals. There have been different ways of fusing the multichannel BCG signals. In [3], signals from sensors are summed together before A/D conversion. In [4], spectra from different sensors are averaged, before cepstrum is derived. In [5], heart rate readings are first obtained from different sensors and then fused with Bayesian fusion, of which one of the sensors is capacitive ECG.

This paper presents a method of estimating heart rate from multichannel BCG using FBG sensors. A cepstral domain smoothing and peak detection technique is proposed to reliably estimate heart rate. The multiple sensors are fused naturally in the cepstral domain, as a higher value of cepstrum coefficients reflect higher signal to noise ratio. We believe the fusion method is advantageous to the current approaches using value averaging. Experimental results have demonstrated the accuracy of heart rate estimation, and the effectiveness of the fusion method.

II. Overview

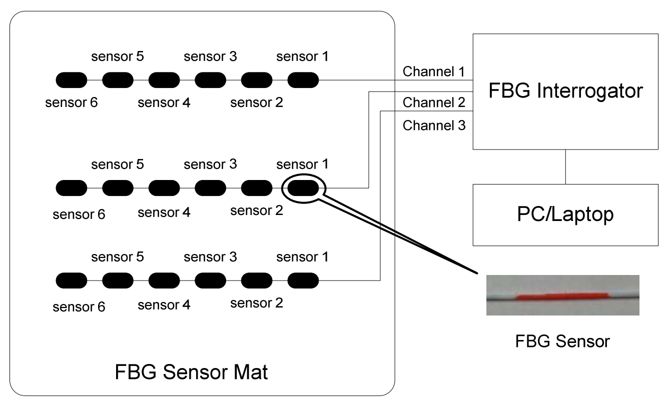

Figure 1. FBG heart rate monitoring system

In our heart rate monitoring system, the FBG sensor mat is connected to an optical interrogator and PC as shown in Figure 1. Each sensor mat consists of 3 FBG sensor arrays with 6 sensors each. The sensor arrays are further packaged onto a Polycarbonate (PC) sheet and connected to the FBG interrogator using three optical channels. BCG signals from the channels/sensors are transferred to the PC, and heart rate estimation is performed on the PC in real-time.

Figure 2 shows the major steps of the proposed heart rate estimation method. First, the signal from each sensor is transformed from time domain to cepstral domain with a smoothing process. Second, the signal from different sensors of a same array is fused by utilizing the cepstrums. And finally, the heart rate is estimated from the fused signal by detecting peaks in the cepstrum. Details of the algorithm are presented in the following sections.

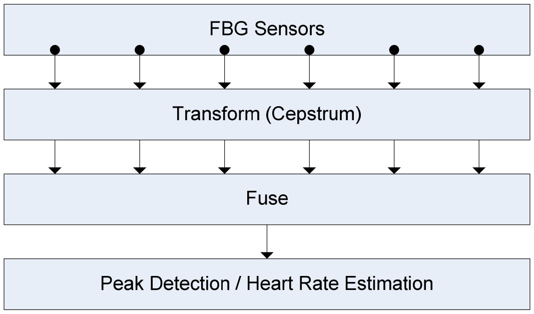

Figure 2. Basic algorithm flow of the heart rate estimation method

III. CEPSTRUM WITH SMOOTHING

A. BCG Signal

The FBG sensors can pick up the body movement due to heart beat as well as respiration of the human subject. The BCG signal is typically obtained by bandpass filtering the raw signal from sensors. We used cut-off frequency of 0.5Hz and 20Hz for the bandpass filters. Figure 3 illustrates BCG (lower subplot) together with simultaneously collected ECG (upper subplot).

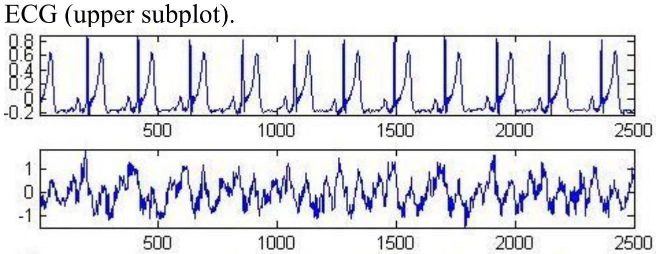

Figure 3. ECG and BCG signals

Unlike ECG, the repeating pattern of each heart beat is not so obvious, and it is difficult to use a uniform time-domain landmark for automatic heart beat identification.

B. Cepstrum with smoothing

For heart rate estimation, we are interested in finding the repeating rate in the BCG instead of identifying each heart beat pattern. This is similar to detecting pitch from audio signals. We hence looked into cepstrum of BCG for heart rate estimation, as Cepstrum is typically used for pitch detection in audio or speech [6,7].

BCG is however a non-stationery signal and periodicity changes from time to time or even from beat to beat. The peak in the cepstrum of BCG signal is usually not very prominent. We thus propose a smoothed cepstrum for heart rate estimation. By applying low pass filtering on the cepstrum, the main peak becomes more prominent and easier to be detected and tracked. Figure 4 shows the cepstrums of a 3 second BCG signal after applying low pass filtering of different cut off frequencies. The x-axis is the lag-time in cepstrum measured in number of samples (sampling rate is 250Hz). We observed that the lower is the cut off frequency, the more prominent the peak becomes. In this scenario, the lag-time range is from 0.4 second to 1.5 seconds (the normal human heart beat duration).

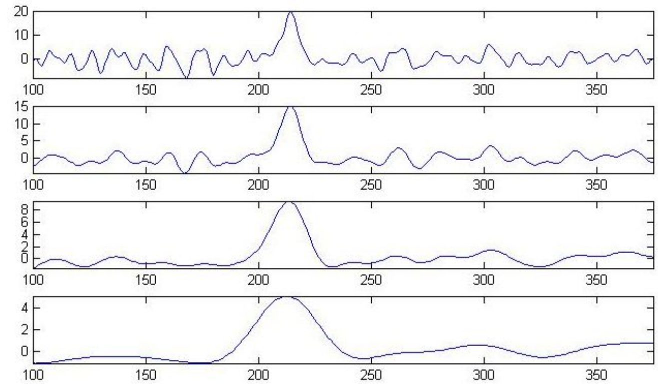

Figure 4. Cepstrum with smoothing (lower plot with lower cut off frequency of low-pass filtering).

IV. SENSOR FUSION

Sensor fusion is important in our system, since the contact condition of different sensors in an array can be different. The variation can be due to the position or posture of a human on the bed. Adding up the signals of all the sensors in time domain may not result in good performance, because the dynamic range of different sensors may not be related to signal quality or noise levels. However, in cepstral domain, the magnitude of cepstral coefficient is naturally related to periodicity of the signal, which is the focus in heart rate estimation.

We fuse the signals by taking the maximal value of each lag time bin among all the sensors to be fused, and in our case the 6 sensors in an array. Figure 5 illustrates the cepstrogram of a few minutes of FBG data. The 6 small images show the cepstrogram of 6 sensors, and the bigger image on the right shows the fused cepstrogram. In the plots of cepstrogram, the x-axis corresponds to lag time, and y-axis corresponds to time of the cepstrum analysis window.

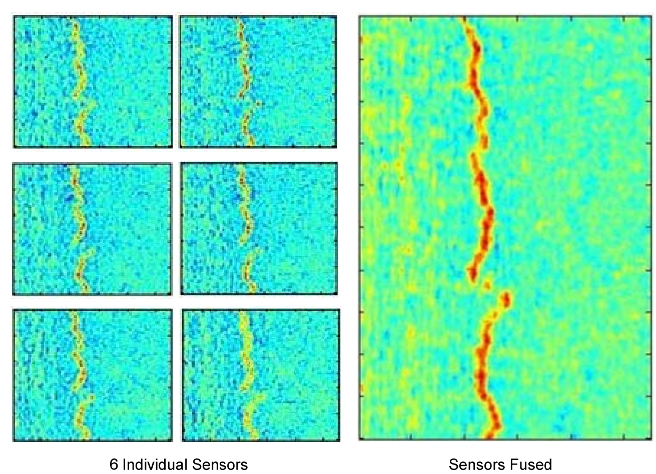

Figure 5. Sensor fusion based on cepstrum

V. HEART RATE ESTIMATION

Heart rate estimation could be performed in the fused cepstrum or in the cepstrum of any individual sensor.

A. Multiple Level Cepstrum Peak Detection

A peak in the cepstrum corresponds to a lag time that a heart beat signal repeat itself in the time domain. Thus for heart rate estimation, the goal is to find the right peak in the cepstrum. We propose to detect the peak from multiple level cepstrum. The detection starts from a more smoothed cepstrum, where it finds the smooth major peak, and then proceeds to the finer smooth level, where the peak is detected within a range that is defined in the earlier stage. We used a simple peak detection method at any level, where the peak magnitude and steepness of the peak are measured. By using multiple level cepstrum peak detection, the likelihood of detecting wrong peak is reduced compared to detecting peak directly at the finer level of cepstrum.

B. Heart Rate Estimation

In the actual heart rate monitoring applications, the heart rate is normally estimated from a time window. In this study, we used 10 second window, and collate the ceptrum peaks detected within each window of the cepstrogram. The time lag values of the peaks are used in calculating heart rate, and the magnitude values of the peaks are used to measure the confidence of the detection.

Heart rate is calculated as below:

$$A[i]=mean(log(L[i])) \quad \text{for i=1 to n} \quad (1)$$

$$B=exp(sum(A[i]) \quad \text{i=1 to n} \quad (2)$$

$$R=60*SR/B \quad (3)$$

where i is the index number of the ceptrum in the 10 second cepstrogram window, n is the total number of cepstrum in the cepstrogram, and $L[i]$ is the peak lag time measured in number of samples. SR is the sampling rate, and the heart rate R is measured in beat per minute.

The confidence of estimation (weight) is calculated as below:

$$W=sum(M[i]) \quad \text{for i=1 to n} \quad (4)$$

where $M[i]$ is the magnitude of i^{th} cepstrum peak.

Figure 6 illustrates the heart rate estimation of a 10 minute FBG data. The upper subplot shows the heart rate ground truth from ECG (in blue) and estimated heart rate from FBG (in red). The middle subplot shows the heart rate difference between FBG and ECG. The lower subplot shows the weight value. For this particular estimation, a threshold of 8.5 is used in weight, thus there is no heart rate reading from FBG if the weight value is below the threshold.

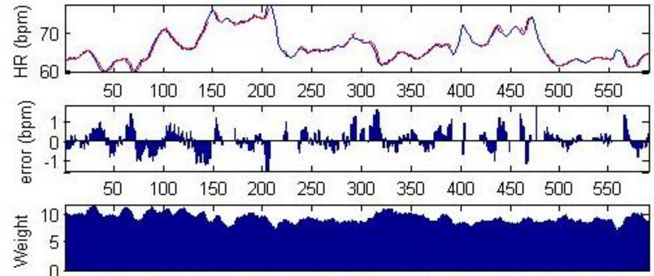

Figure 6. Heart rate estimation from BCG and error against ECG

VI. EVALUATION

Evaluation of the proposed method was conducted by collecting both BCG and ECG simultaneously for multiple subjects with various sleeping postures. The heart rate from ECG serves as ground truth for the correctness of the heart estimation from BCG.

A. Data Collection

In the experiments, a FBG sensor mat with 3 arrays of sensors was put on a bed, below a thin bed sheet. Each array contains 6 sensors, and the locations of the arrays are 1) under the pillow; 2) upper chest; and 3) lower chest. Ten subjects with both genders and ages from 20s to 50s participated in the data collection. There were 2 sessions for each subject: 10 minutes of lying flat posture, and 10 minutes of sideway posture. A subject was presumed not to move during a session. ECG is recorded along with FBG with time synchronized.

For cepstrum transform, a window of 3 second is used, and a cepstrogram is derived by sliding the window by a stepsize of 0.04 second. A heart rate reading is estimated from every 10 second window of the cepstrogram. The step size of the window is 1 second. Heart rate from ECG is calculated by detecting the R-peaks and getting the mean R-R intervals within the 10-second-window. The heart rate reading from FBG sensors were estimated for each sensor array independently, i.e. there are totally 3 readings from the 3 sensor arrays on the bed.

B. Results

The heart rate reading from FBG and ECG are compared in beat per minute (BPM). The mean as well as standard deviation of the absolute error is calculated for each 10 minute session. In addition, the acceptance rate of the estimation method for each session is measured by taking the ratio of valid heart reading against total number of estimation windows.

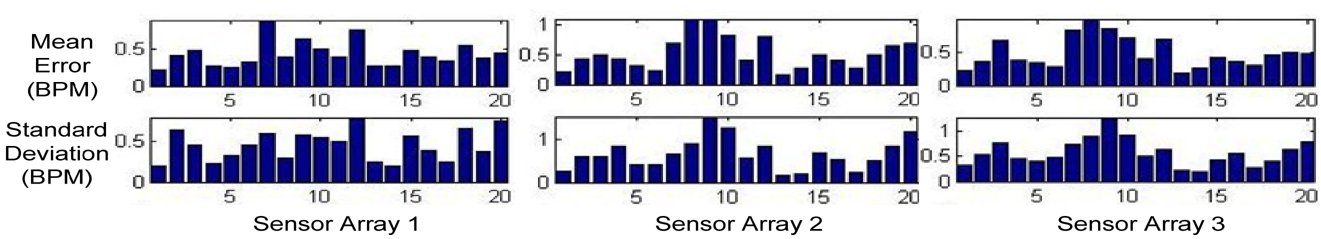

Figure 7. Mean and standard deviation of heart rate estimation errors

Figure 7 shows the heart rate estimation results of the 3 sensor arrays, with signal fusion among the 6 sensors in an array. Sensor arrays 1 to 3 correspond to the location of the sensor array in the bed. For each sensor array, the upper subplot shows the mean absolute estimation error for each session. The lower subplot shows the standard deviation of absolute estimation error. The session sequence number (1-20) in the plots corresponds to the 10 subjects (each subject has 2 sessions); the odd number is for flat lying posture and the even number is for sideway lying posture.

From the results in Figure 7, it can be seen that the average heart rate estimation error is below 1 BPM for all the sessions and all the sensor arrays. The standard deviation of the error is also mostly below 1.

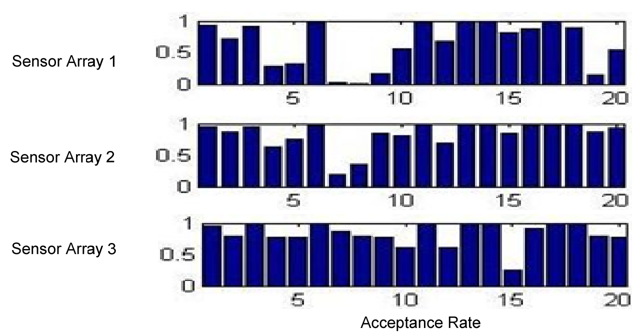

Figure 8. Acceptance rate of heart rate estimation

The acceptance rate of the estimation is shown in Figure 8. The average acceptance rates for the 3 sensor arrays are: 0.64, 0.83 and 0.83 respectively. It can be seen that sensor array at chest positions in general has higher acceptance rate than the head/pillow position.

In addition, we evaluate how the sensor fusion improves the estimation. Table I shows the average results of 20 sessions for individual sensor in the sensor arrays against fused sensor. In the table, only the best sensor (lowest mean error) out of the six is shown. From this result, we could see that the difference of accuracy between fused sensor and non-fused sensor is small. Table II shows the comparison of average acceptance rate. It can be seen that the acceptance rate improves significantly after fusion.

TABLE I. ACCURACY COMPARISON (FUSION VS NO-FUSION)

Sensor Array	Sensor	**Mean Error (BPM)**	**Error STD (BPM)**
Array 1	Best	0.4739	0.3815
	Fused	0.4275	0.4503
Array 2	Best	0.4264	0.4256
	Fused	0.5291	0.6731
Array 3	Best	0.4172	0.4191
	Fused	0.4821	0.5778

From the experiment, we could see that the proposed estimation method can achieve promising accuracy in heart rate measurement and robustness against low signal quality. Furthermore, the signal fusion improves the estimation results particularly the acceptance rate.

TABLE II. ACCEPTANCE RATE COMPARISON (FUSION VS NO-FISION)

Sensor Number	**Sensor Array Positions**		
	Sensor Array1	***Sensor Array 2***	***Sensor Array 3***
1	0.3913	0.5199	0.4415
2	0.5008	0.5940	0.6126
3	0.4550	0.6248	0.6015
4	0.4996	0.6270	0.5984
5	0.4434	0.5329	0.5687
6	0.4589	0.4608	0.5307
Fused	0.6414	0.8320	0.8306

VII. CONCLUSION

A method of estimating heart rate with promising accuracy and robustness from FBG sensor arrays is presented. The signal analysis is done in the cepstral domain using smoothing and peak detecting techniques. To obtain high signal to noise ratio, the cepstrum of signals of multiple sensors are fused, as the magnitude of cepstrum reflects the quality of the signal. Experimental results validated the performance of the proposed method. Our future work consists of dynamic sensor selection for fusion and adaptive threshold setting for higher acceptance rate.

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