

A Comparison of Heartbeat Detectors for the Seismocardiogram

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Abstract

The study aimed to study the accuracy in RR time series derived from the seismocardiogram when employing different heartbeat detectors in subjects measured in a quiet environment. The ECG and seismocardiogram of 17 healthy volunteers was recorded at a sampling frequency of 5 kHz using a Biopac acquisition system. The seismocardiogram was acquired using a triaxial accelerometer (LIS344ALH, ST Microelectronics). Four detectors of the heartbeat from the seismocardiogram were employed relying either on the Continuous Wavelet Transform or bandpass filtering. The detectors adapt their parameters to the morphology of the signal by estimating mean heart rate and the bandwidth of the signal associated to the heartbeat. For all detectors, the standard deviation of the error in the obtained RR time series is in mean slightly higher than 2 ms and the percentage of obtained RR time intervals that have an error higher than 30 ms is around 3.5%. The seismocardiogram, when measured in a quiet environment, can be used instead of the ECG to obtain reliable RR time series when using proper heartbeat detectors.

1. Introduction

The analysis of heart rate variability (HRV) has been established during the past few decades as a valuable non-invasive tool to assess the status of the cardiovascular autonomic function and it has been frequently used in the analysis of physiological signals in different clinical and functional conditions [1, 2]. Over recent years, there has been interest into using unobtrusive methods to monitoring heart rate without electrodes. The seismocardiogram (SCG) is the study of body vibrations induced by the heartbeat. This term was popularized in the 90s by Salerno and Zanetti [3]. However, the recording of body movements associated with cardiac activity is much older [4]. The ballistocardiogram (BCG) records the movements of the body as an effect of the

blood mass ejected by the heart with each contraction. Usually the BCG is recorded in a supine position over a mobile platform that moves with each beat. The SCG usually records the sternal acceleration and has higher frequency content than BCG. Recently, the interest in SCG has been revitalized by the availability of low cost MEMS sensors and portable devices that include them (smartphones, PDA, etc.)

Some authors have proposed the SCG signal to study changes in the cardiovascular system [5,6,7]. Friedrich et al [8] have estimated the RR intervals from the ballistocardiogram and compare them with the ECG RR intervals. Hence the interest to compare the quality of RR time series obtained from the SCG with a gold standard time series obtained from the ECG.

The aim of this work is to propose an algorithmic approach to the detection of heartbeats from the SCG robust and accurate enough to obtain RR time series that can be used for HRV analysis. With this approach, we define four heartbeat detectors and compare time series with those obtained from the ECG.

2. Materials and methods

2.1. Heartbeat detectors from the SCG

Because the morphology of the SCG can differ from subject to subject and with differences in the positioning of the sensor over the body, adaptive algorithms for the heartbeat detection have been created. The proposed heartbeat detectors are based on two basic assumptions: the measured accelerations associated with the heartbeat are narrowband processes and the heartbeat is nearly periodic. Then, the first step in all the proposed heartbeat detectors is to find the appropriate frequency band that contains the most of the energy of the SCG. In order to estimate the mean of the heart rate, the power spectrum of the SCG is computed by using the periodogram and a Hanning window. The mean heart rate is computed as the frequency that has a maximum power between 0.5 Hz and 2 Hz (these limits could be adapted when bradycardia or tachycardia is suspected). The next step is to analyze at

random segments of the SCG containing a few heartbeats in order to provide a “central frequency” around which most of the energy of the signal is contained. This step can be achieved in several ways. In this work, after bandpass filtering the SCG with a bidirectional Butterworth filter of order 4 and cutoff frequencies of 5 and 30 Hz, we have computed the continuous wavelet transform (CWT) of segments spanning four times the mean heart period previously estimated. The chosen wavelet has been the complex Gaussian of order 4. The CWT has been computed for scales whose central frequencies lie between 5 Hz and 30 Hz (for the chosen wavelet and a sampling frequency of 5 kHz these scales go from 84 to 500). For each scale, the standard deviation of the magnitude of the CWT is computed and the appropriate scale is chosen as the one that maximizes the standard deviation. Moreover, the central frequency of this scale is also computed. The process is repeated in as many segments containing approximately 4 heartbeats as desired and finally the mean of central frequencies (cf_{opt}) as well as the rounding of the mean of appropriate scales (s_{opt}) are computed. Figure 1 shows an example with a segment of the filtered SCG, the evolution of the standard deviation with the scale and the magnitude of the CWT using the appropriate scale.

After estimation of cf_{opt} and s_{opt} , we have defined four heartbeat detectors:

- Detector 1 (DET1) computes the CWT using s_{opt} and the complex Gaussian wavelet of order 4. If C is the obtained complex signal, $\text{Re}(C)$ and $\text{Im}(C)$ its real and imaginary parts respectively, then and in order to maximize the visibility of the heartbeat, the form factor (ratio between maximum and standard deviation) of $\text{Re}(C)$, $-\text{Re}(C)$, $\text{Im}(C)$ and $-\text{Im}(C)$ are computed. The signal that maximizes the form factor is chosen to detect the heartbeats. This detection has been achieved using an adaptive threshold with a time constant of 2 s. The heartbeat is located at the maximum of the signal in a window of 200 ms centered at the intersection of the signal with the threshold.
- Detector 2 (DET2) starts with the heartbeats detected with DET1 and refines the position by maximizing the correlation of the signal with the first detected heartbeat.
- Detector 3 (DET3) filters the SCG using a bandpass bidirectional Butterworth filter of order 4 with cutoff frequencies equal to $cf_{opt} \cdot 2^{-1/2}$ and $cf_{opt} \cdot 2^{1/2}$. If fSCG is the filtered signal, if the form factor of $-\text{fSCG}$ is higher than the form factor of fSCG then $-\text{fSCG}$ is used for detection instead of fSCG. The detection has employed once again an adaptive threshold with a time constant of 2 s and a window to locate the maximum around the intersection points.
 - Detector 4 (DET4) starts with the heartbeats detected with DET3 and refines the position by

maximizing the correlation of the signal with the first detected heartbeat.

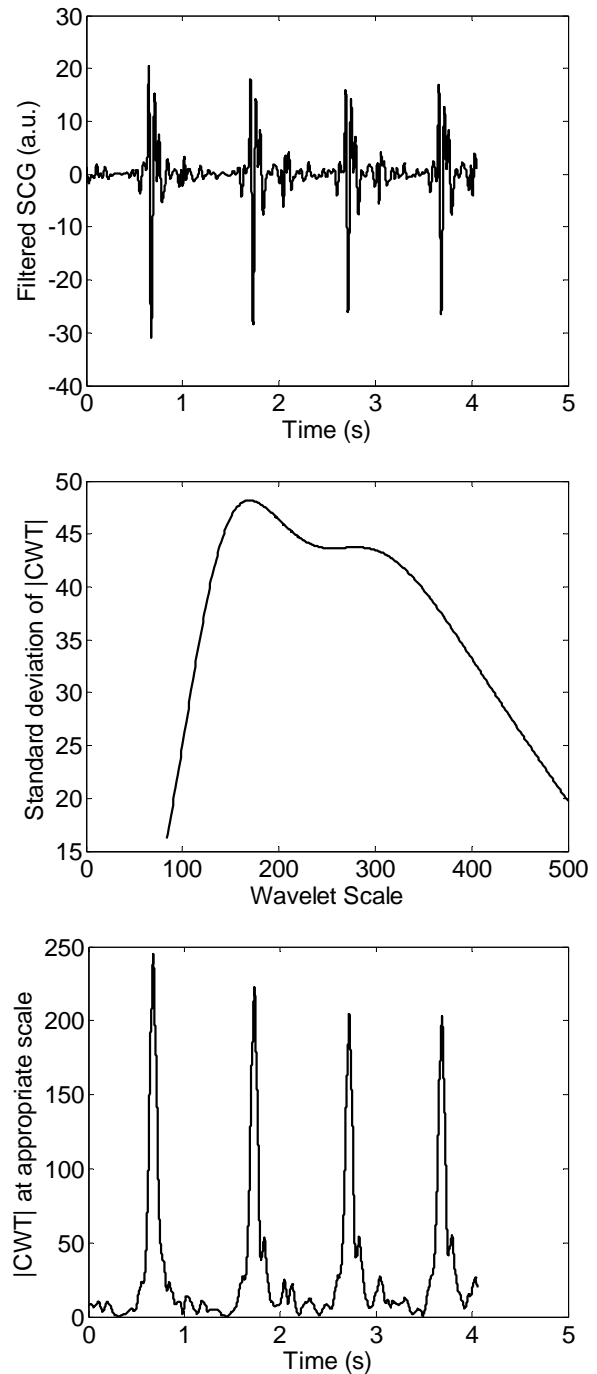


Figure 1. Example of the choice of the best scale to detect the heartbeat. The maximum of the standard deviation of the magnitude of the CWT corresponds in this case to the scale 169 that it is associated with a central frequency of 14.8 Hz

2.2. Database description

For the study we measured the ECG, breathing and SCG in 17 healthy subjects (age: 24.7 years \pm 3.9 years, sex: 6 females/11 males, body mass index: 24.7 kg/m² \pm 3.9 kg/m²). Data was acquired using a Biopac MP36 data acquisition system (Santa Barbara, CA, USA). Channels 1 and 2 of the system were devoted to measure conventional ECG (leads I and II respectively) with a bandwidth between 0.05 Hz and 150 Hz, channel 3 was employed to measure the respiratory signal obtained from a thoracic piezoresistive band (SS5LB sensor by Biopac, Santa Barbara, CA, USA) with a bandwidth of 0.05 Hz to 10 Hz and channel 4 was devoted to acquire the SCG using a triaxial accelerometer (LIS344ALH, ST Microelectronics) and a bandwidth between 0.5 Hz and 100 Hz. For the ECG measurement we used monitoring electrodes with foam tape and sticky gel (3M Red Dot 2560). Each channel was sampled at 5 kHz.

During the measurement, the subjects were asked to be very still in supine position on a comfortable conventional single bed and awake. After attachment of sensors, we recorded the basal state of the subjects by measuring during 5 minutes. After that, the subjects started to listening music during approximately 50 minutes. Finally, we monitored all subjects 5 minutes more after the music ended.

2.3. Comparison assessment

For each of the recordings, the QRS complexes were detected for the standard lead I. A first rough fiducial point was obtained by using the Pan-Tompkins QRS detector [9] but was further refined by maximizing the correlation between any detected QRS complex and the first detected QRS complex using templates of 200 ms duration centered on the rough fiducial point. From these QRS locations, the reference RR time series was computed (\mathbf{RR}_{ref}). On the other hand, from the outputs of the four detectors were used to obtain four RR time series from the SCG (\mathbf{RR}_1 , \mathbf{RR}_2 , \mathbf{RR}_3 and \mathbf{RR}_4). Due to misdetections, the error between the reference and the detector n (σ_{dRRn}) was assessed by the standard deviation of the differences between \mathbf{RR}_{ref} and \mathbf{RR}_n when these differences are lower than 30 ms. The percentage of rejected differences (higher than 30 ms) were accounted as an indicator of the quality of the measurement ($\%M_n$). Figure 2 shows an example using the detector 3.

3. Results

Table 1 shows the results for the error between time series and the percentage of misdetections for each detector. As seen by the results, the four detectors provide quite similar RR time series when compared with that

obtained from the ECG. Detector 1 has the lowest error while detectors 2 and 4 (based on matching pattern) have a slightly higher error.

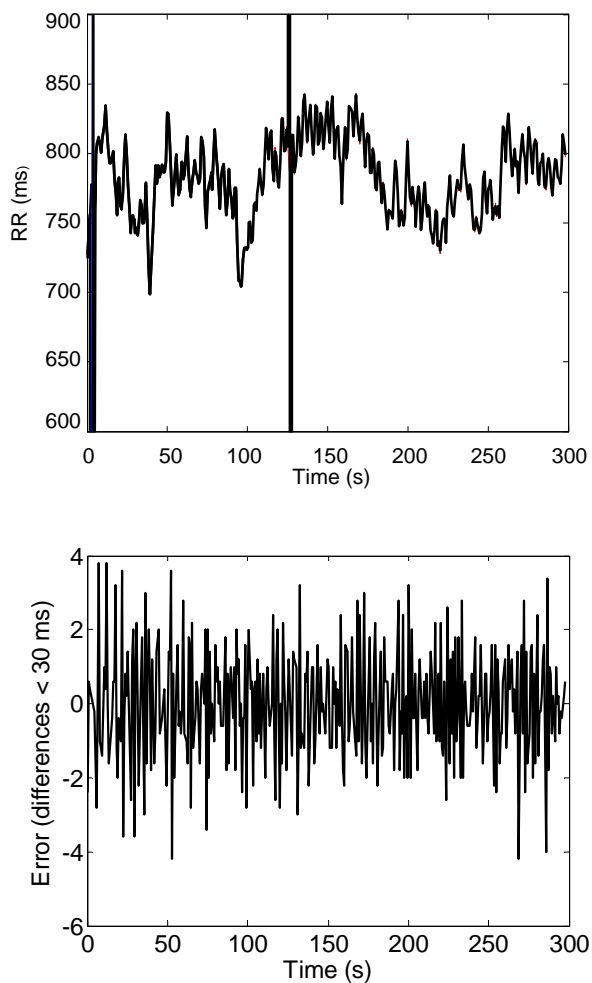


Figure 2. Example of comparison of two RR time series. The upper panel shows the RR time series of reference and that obtained from the third detector (that has some misdetections). The lower panel shows the differences between time series without the misdetections ($\sigma_{dRR3} = 1.47$ ms, $\%M_n = 1.57\%$)

Table 1. Results for errors and misdetections (mean \pm standard deviation)

Detector	σ_{dRRn} (ms)	$\%M_n$
1	2.27 \pm 0.81	3.34 \pm 5.69
2	2.34 \pm 0.82	4.29 \pm 8.06
3	2.30 \pm 0.80	3.87 \pm 6.69
4	2.33 \pm 0.85	4.78 \pm 8.79

Detector 1 has also the lowest percentage of misdetections.

4. Discussion

Because all the proposed detectors provide quite similar results, the best choice is detector 3 because it is easier to implement. On the other hand, the detectors can be further optimized by taking into account that detectors 1 and 2 use a complex Gaussian wavelet of order 4 and detectors 3 and 4 rely on a simple bandpass filter. Choosing another wavelet (or combination of wavelets at different scales) or defining other cutoff frequencies of the filter can improve the detectors. Nevertheless, the accuracy of the detection is high enough for most HRV applications.

The recordings have been obtained in a very controlled and quiet environment with the subjects lying still. Maybe some of the proposed detectors are more robust than the others in front of movement or other artifacts. This question will be answered in future works. Moreover, the visual inspection of the error between RR time series suggests that the difference between both time series is modulated by breathing. A future work will study how much of the error can be explained by breathing.

5. Conclusion

We have proposed some heartbeat detectors to obtain the RR time series from the seismocardiogram. The detectors adapt their parameters to the morphology of the signal by estimating mean heart rate and the bandwidth of the signal associated to the heartbeat. For all detectors, the standard deviation of the error in the obtained RR time series is in mean slightly higher than 2 ms and the percentage of obtained RR time intervals that have an error higher than 30 ms is around 3.5%. Because all the proposed detectors have quite similar performances, the best detector, for its simplicity, is based on a narrowband bandpass filter.

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