An Improved Estimation of Unsuitable Segments of Ballistocardiography Records Using Wavelet Transforms

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Abstract

A major challenge in BCG measurements is their high sensitivity to motion artifacts, which degrade the signal quality. Several techniques have been developed, especially for BCG measurements during sleep, to automatically discard corrupted segments. To evaluate them, the coverage factor is defined as the amount of artifact-free signal with respect to the entire recording. However, current approaches to obtain it are mainly based on the analysis of the raw signal, which may discard signal segments of acceptable quality that exhibit significant amplitude fluctuations due to factors such as respiratory rate or deviations from baseline. To overcome this drawback, a novel technique combining both the signal and its wavelet transform is proposed, which is compared to the more traditional technique based on the raw signal variance. Results obtained from the analysis of 18 recordings from the BCG Kansas public database show a 10% coverage factor increase in critical records, which may be particularly valuable for continuous monitoring applications.

1. Introduction

The ballistocardiogram (BCG) is a mechanical cardiac signal that consists of detecting the reaction movements of the body's center of gravity caused by the heart due to the ejection of blood through the vascular tree [1]. Compared to the electrocardiogram (ECG) or the photoplethysmogram (PPG), the BCG has the advantage that the necessary sensors (pressure, force, acceleration, displacement) do not require direct contact with the skin and can be integrated into everyday objects such as furniture or even clothing. However, since its inception [2], one of the problems of the BCG signal is its susceptibility to motion artifacts, unless the subject remains still and completely relaxed. These conditions are particularly difficult to achieve, especially when BCG is recorded outside clinical settings, where the goal is to make the measurement as noninvasive as possible or even unnoticed by the user, e.g., during sleep or while performing daily activities.

Therefore, various techniques have been proposed to detect motion artifacts in BCG records, like the one by Wiard et al. [3], where they proposed including an additional sensor in a modified scale to detect excessive movements in standing subjects, which thereby increased the complexity of the designed circuit. Other techniques have focused on variance-based analysis of the BCG signal to identify segments with motion artifacts. In Boger et al [4], a moving variance window of 1-second was used, and a threshold of half the average of the moving window was proposed for BCG measurements during five real-world tasks: sitting still, watching a video on a computer screen, reading, using a computer, and having a conversation.

On the other hand, Alivar et al. [5], [6] have used two distinct approaches: the first one uses a Neyman-Pearson detection test based on signal variance in the time domain, while the second approach relies on a sequential detection algorithm. However, the disadvantage of solely relying on variance analysis of the BCG signal is that in records with amplitude modulations or baseline drifts, good quality segments might be excluded. Additionally, the use of artificial intelligence models for the segmentation of BCG signals based on U-Net has been proposed [7], but this comes at the expense of increased computational complexity.

In this study, to partly overcome some of the shortcomings of the previous approaches, we propose a method that combines both the analysis of the BCG signal and its Continuous Wavelet Transform (CWT) [8]. This is a time-spectral tool that provides information on the frequency components of interest, which can help to distinguish motion artifacts more robustly. We will examine its ability to automatically discard corrupted signal segments correctly and thus improve the so-called coverage factor, that is, the proportion of artifact-free signal in relation to the total. Finally, the performance of the new proposed method will be compared, using the same database, with a more traditional algorithm based solely on the variance analysis of the signal.

2. Material and methods

2.1 Dataset

 ISSN: 2325-887X DOI: 10.22489/CinC.2023.401

To validate the proposed method, we used the database acquired by Carlson et al. [9]. These measurements were obtained with a BCG measurement system implemented in a bed and consisting of four load cells placed under each leg and four EMFi sensors distributed centrally at a sampling frequency of 1 kHz. The signals obtained from each sensor were visually examined, selecting, from the signals obtained by the EMFi sensor "Film 0", 18 records with a relevant amount of motion artifacts (Table 1). The bandwidth considered for the BCG was 0.3-24 Hz, and for the simultaneously acquired ECG (lead 3) was 0.5-40 Hz.

Table 1. Cohort characteristics

ID	Age	Height (cm)	Weigh (kg)	Gender
X1005	19	153	48.3	F
X1006	28	183.6	75.6	M
X1007	27	197.8	87.1	M
X1010	47	158.6	67.5	F
X1012	27	177.8	110	M
X1019	22	165	67.5	F
X1020	22	178.8	73.4	M
X1025	53	167.8	136	F
X1026	18	147.6	56.4	F
X1028	21	172.5	53.6	F
X1035	20	172	82.1	F
X1039	59	184.2	80.7	M
X1040	24	161.1	68.5	F
X1042	65	170.5	53.7	F
X1043	60	161.4	102	F
X1044	31	176.5	70.4	F
X1046	22	164.6	88.8	F
X1047	32	157	57.6	F

2.2 Continuous Wavelet Transform

The auxiliary processing tool used for the segmentation of BCG signals was the CWT [10], which is defined in eq 1.

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (1)$$

The Wavelet Transform (WT) involves a convolution integral between a signal *x(t)* and a wavelet function *ψ(t)*, which contains two parameters: the translation parameter *b* and the scale parameter *a*. The Wavelet Transform acts similar to a bandpass filter, with its cutoff frequencies directly linked to the scale factor *a*. For this study, the scale 16 of "Gaus2" mother wavelet function was selected, as it has demonstrated good performance in BCG detection [8].

2.3 Approach proposed

Two moving standard deviation windows of one second were used along the recordings:

$$W_1(i) = \sigma\big(S_{BCG}(i{:}\,i+1000)\big) \qquad (2)$$

$$W_2(i) = \sigma\big(CWT_{BCG}(i{:}\,i+1000)\big) \qquad (3)$$

Where $W_1(i)$ represents a moving window of standard deviation of the BCG signal (S_{BCG}) and $W_2(i)$ represents a moving window of standard deviation of its CWT (CWT_{BCG}). If only the BCG amplitude window had been used, there would have been a potential risk of segmenting parts of the recording suitable for processing, especially when the signal is modulated by respiratory rate or presents baseline drift. To ensure a more robust signal for analysis, the mean of both windows was calculated (Eq 4).

$$W_s = (W_1 + W_2)/2 \qquad (4)$$

With it, two thresholds were defined to determine the exclusion of corrupted segments. The first threshold aims to discard significant variations or signal saturation, while the second one is intended to segment weak signals or signal absence, respectively.

$$\mathrm{Thd}_{max} = \boldsymbol{mean}(W_1 + W_2) \qquad (5)$$

$$\mathrm{Thd}_{min} = \boldsymbol{mean}(W_1 + W_2) * 0.1 \qquad (6)$$

To assess the segmentation process, the coverage factor (CF) was calculated, defined as the ratio between the number of suitable heartbeats unaffected by motion artifacts and the total number of heartbeats in a recording, which can be obtained using a standard reference signal such as the ECG [11], [12]. In addition, a comparison was made between the segmentation using the method proposed and a more traditional approach based only on a variance window of the raw signal W_{var} (eq. 7).

$$W_{var}(i) = \sigma^2\big(S_{BCG}(i{:}\,i+1000)\big) \qquad (7)$$

Once the analysis windows and thresholds were obtained, the complete records were evaluated using eq. 8 to identify the areas with motion artifacts. The segmentation signal is carried out with a margin of ±150 ms when the thresholds are exceeded. The same methodology was used for the W_{var} window.

$$Seg(i-150{:}\,i+150) = \begin{cases} 2, & Ws > Thd\_max \\ 1, & Ws < Thd\_max \\ & Ws > Thd\_min \\ 0, & Ws < Thd_{min} \end{cases} \qquad (8)$$

Where 2, 1, and 0, are arbitrary values selected according to the criteria used to facilitate the visualization of the figures in the results section.

3. Results and discussion

Figure 1 shows an example of the two segmentation methods compared for the case of recording "X1039", in which a significant baseline drift of the BCG signal can be observed, whereas the amplitude of the CWT exhibits no significant variations, effectively compensating for the BCG signal window. Moreover, *Ws*, never exceeds the maximum and minimum thresholds, rendering signal segmentation unnecessary when using the method based on the two standard deviation windows for both the BCG signal and its CWT (labeled as "SD(CWT+BCG)" in the figure 1 to Figure 4). On the other hand, the segmentation method based on the variance of the BCG signal (labeled as Var(BCG) Figure 1 to Figure 4) identifies amplitude variations in the signal due to baseline drift as motion artifacts, potentially leading to the exclusion of high-quality segments.

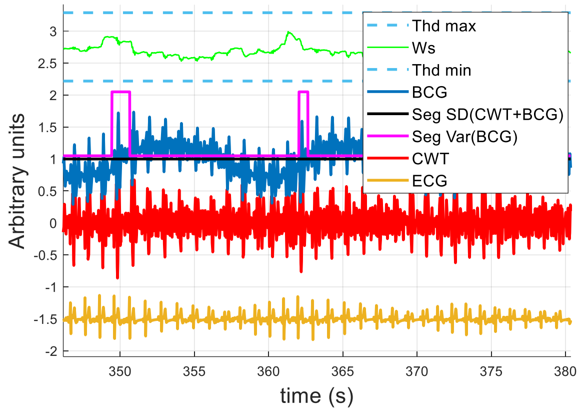

Figure. 1. Record "X1039" with baseline drift.

The records "X1005" and "X1019" (Figure 2 and Figure 3) display motion artifacts that affect both the BCG signal and the CWT, and they can be detected using both approaches. In Figure 3, it can be observed that, in certain areas, both segmentation methods coincide, while in others, Var(BCG) segmentation excludes segments with slight amplitude variations.

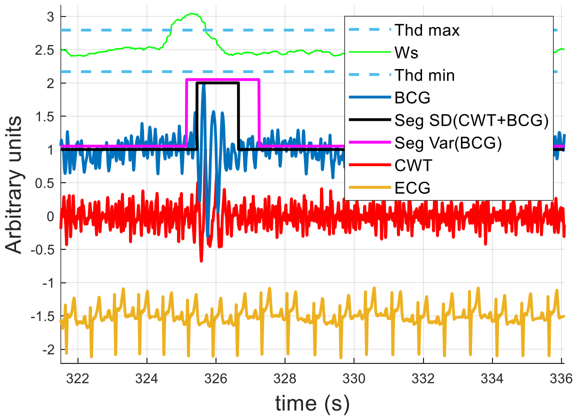

Figure. 2. Record "X1005" and the presence of motion artefacts.

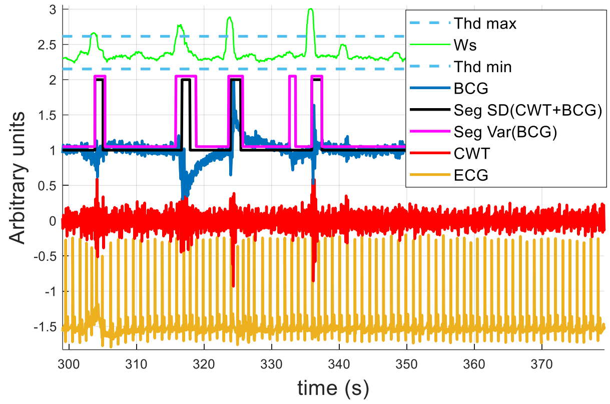

Figure. 3. Record "X1019" and the presence of motion artefacts.

Figure 4 shows the absence of BCG and ECG signals in a long segment of the "X1042" record, attributed to bradycardia, causing W_s to fall below the minimum threshold, and signal segmentation.

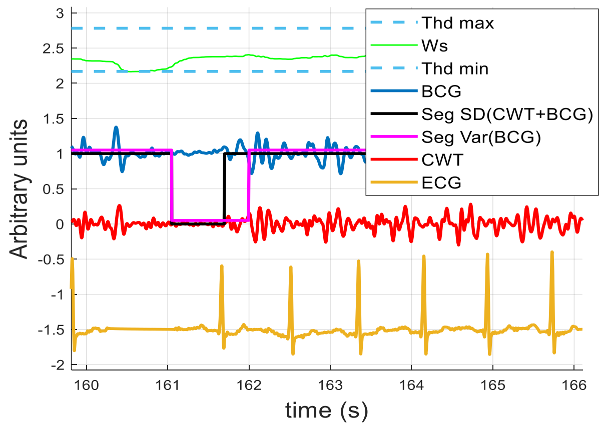

Figure. 4. Record "X1042" with absence of signal due to bradycardia.

Finally, Table 2 shows the results of the CF using the two segmentation proposals for 18 records containing motion artifacts. The results show an increase in the coverage factor with the approach that uses CWT, meaning that fewer record segments are discarded, as the CWT acts similar to a bandpass filter and is not sensitive to low-frequency variations that can modulate amplitude. Additionally, it allows for the detection of high-frequency segments with low amplitude that can lead to false detections. Although this approach was validated in bed records, where the quantity of motion artifacts is lower, it has the potential to be applied to records obtained from wearable systems, where motion artifacts would be more prevalent.

In addition to maximizing the quantity of valid recordings, quantifying artifacts in bed-based BCG records allows for the assessment of sleep quality [5], as they can provide valuable insights into sleep disruption, respiratory quality, and other important aspects of well-being during rest.

Table 2. The results of the coverage factor using the two methods analyzed for recordings of bed database.

ID	#Beats	CF (%) Var (BCG)	CF (%) SD(CWT+BG)	Difference in beats
X1005	566	98.94	99.65	4
X1006	507	99.41	100.00	3
'X1007	453	99.56	100.00	2
X1010	541	97.41	99.82	13
X1012	538	96.65	98.70	11
X1019	406	90.39	94.58	17
X1020	596	94.80	100.00	31
X1025	645	86.82	100.00	85
X1026	594	99.49	100.00	3
X1028	469	97.23	100.00	13
X1035	532	97.37	99.81	13
X1039	408	95.83	100.00	17
X1040	624	95.83	99.52	23
X1042	527	97.91	98.48	3
X1043	409	96.82	100.00	13
X1044	495	99.60	100.00	2
X1046	436	95.64	100.00	19
X1047	551	98.00	99.64	9

4. Conclusions

The proposed approach proved to be robust against interferences that can modulate the amplitude of the BCG signal or introduce a drift in the baseline, while also correctly identifying motion artifacts. It was possible to increase the coverage factor compared to an approach based solely on the variance of the BCG signal, thanks to the use of the wavelet transform, a tool that, in addition to segmenting the signal, allows for robust BCG signal detection. This makes it particularly interesting for wearable BCG applications, where motion artifacts occur more frequently, and it is necessary to maximize the amount of information that can be extracted from such records.

Acknowledgements

This work was supported in part by the Spanish Agencia Estatal de Investigación under grant PID2020-116011RB-C21 (MCIN / AEI /10.13039/ 501100011033).

Authors would like to express their gratitude to the Mexican National Council of Science and Technology (CONACyT) for the financial support and fellowship for José Alberto García-Limón.

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