Extracting Heartbeat Intervals Using Self-adaptive Method Based on Ballistocardiography(BCG)

Hongbo Ni(✉), Mingjie He, Guoxing Xu, Yalong Song, and Xingshe Zhou

School of Computer Science, Northwestern Polytechnical University, Xi'an 710072, China
{nihb,zhouxs}@nwpu.edu.cn, hmj2008mhxy@163.com,
alan19920930@163.com, 290165336@qq.com

Abstract. Ballistocardiogram (BCG) could reflect mechanical activity of cardiovascular system instead of ECG. And it is often acquired by sensitive mattress or chair without any constraints and limitations, but it contains many noise because of the impact of body and acquired equipment, those questions make heart rate detection difficult from the original BCG. In the paper, we propose an adaptive method which is used to extract heartbeat intervals (RR), and the method acquire automatically input parameters of Ensemble Empirical Mode Decomposition (EEMD) algorithm, and then decompose BCG signal using EEMD algorithm, and select adaptively decomposition component of BCG signal, whose periodicity is in accordance with the cardiac cycle completely as the target signal. Furthermore we detect the peak points and calculate the heartbeat intervals series using the target signal. In the result, the proposed method is tested using the BCG datasets from 18 subjects, including 8 females and 10 males (age 20–72). Finally, the heart rate from BCG will be compared with ECG, and the results are satisfactory and have a high accuracy.

Keywords: Ballistocardiogram · Ensemble empirical mode decomposition · Heartbeat intervals

1 Introduction

Cardiovascular disease (CVD) seriously affect the health of the elderly as the major cause of death. The World Health Organization reported that about 17.3 million people died from CVD in 2008 and the total is 30% of global deaths [1]. In recent years, as the growth of the total number of the elderly, the number of CVD deaths is expected to reach 23.6 million by 2030 [1].

Ballistocardiogram (BCG) originally was discovered in the late 19th century [2], which also could reflect the cardiac mechanical activity instead of Electrocardiogram (ECG). With the development of transducer technology, many investigators turn to apply the embedded sensors bed-frame or mattress to collect the BCG signal. The researchers [3, 8, 9] set up a smart chair embedded with EMFi-film sensors to detect BCG signal. P.F. Migeotte et al. [4] get BCG signal based on acceleration sensor. The researches [5–7] design a non-intervention mattress perception system based on piezoelectric transducer or optical fiber sensor to acquire BCG signal. As known, the RR

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intervals or heart rate variability can be extracted based on BCG signal, and the patients will not be attached with any electrodes on the surface of the skin, and there will not be any interference for the patients. However, BCG signal contains a lot of noises because of the effect of the body and acquired equipment, that makes it difficult to extract RR intervals from the BCG signal difficult. Therefore, there are many researcher in the pervasive computing community pay more attention to it.

In our paper, we propose a self-adaptive algorithm to extract RR intervals based on BCG signal. The method contains three main steps. Firstly, the input parameters of EEMD algorithm adaptively is acquired and decompose BCG signal using EEMD. Secondly, the target signal is selected automatically from the decomposition component of BCG signal, and the target signal is that its periodicity agree with the cardiac cycle completely. Finally, the peak points of target signal is detected and then we can obtain the heartbeat intervals series automatically.

The paper contains four main sections. Section 1 introduce the background knowledge and the purpose of the paper. Section 2 mainly introduce the related works about extracting RR intervals. Section 3 presents the BCG data acquired system and a novel heartbeat cycle extraction method. Section 4 test the algorithm performances based on BCG datasets from eighteen participants, and explain the experimental result. Section 5 make a summary for the paper.

2 Related Works

Many works have been completed in the matter of extracting RR intervals. Postolache O.A. et al. [9, 10, 20] design a wheelchair embedded sensors, the wheelchair can acquire BCG signal, the author use wavelet filtering and independent component analysis to remove BCG artifacts and obtain the heart rate based on wavelet transform. Mack D.C. et al. [21] develop a BCG-based sleep monitoring system, and the system can analyze noninvasively physiological signals, the system uses bidirectional recursive to filter BCG signal noise, and uses an improved variable threshold method to detect peaks. Krej M. et al. [22] acquire BCG signal based on fiber-optic vital signs sensor, and use band-pass filter, quadratic function to process BCG signal, and then use an improve search windows to detect the heartbeat peaks.

C. Bruser et al. [7] extract features from the shape of a single heartbeat, and train the feature using an unsupervised learning techniques, and then detect the occurrence of individual heartbeats in the signal using the learning parameter, and obtain beat-to-beat interval length information. C. Bruser et al. [23] design a force-sensor bed to acquire BCG signal and use a sliding window to get the intervals. Jin J. et al. [11] first use wavelet transform to remove some noise of BCG signal and then employ threshold method to get the RR intervals. Shin J.H. et al. [12] complete the heartbeat detection in two stages. Firstly, the BCG template was constructed by the expert with an empirical analysis of BCG signal and measurement device, and secondly the correlation function calculates an accuracy of template with BCG signal using a local moving window. The researcher [13, 14] preprocess the BCG signal, such as normalizing and filtering the BCG signal, and combine the threshold and power operation for BCG data to extract heartbeat intervals. Algunaidi M. et al. [15] firstly get the range of heart rate based on a lot of heartbeat data statistic, and then set the sliding window length according to the range, and get the heartbeat intervals based on sliding windows. Choi B.H. et al. [16] firstly acquire BCG signal based on a load-cell-installed bed, and combine sliding window and threshold method to get the RR intervals.

Singh B. et al. [17] propose an improved adaptive length sliding window method to get heartbeat cycle. X. Cao et al. [18] firstly decompose the BCG signal based on EEMD algorithm, and then select decomposition component seven of BCG signal as the target signal, the target signal is that whose periodicity agrees with the cardiac cycle completely, and then use the target signal to extract RR interval.

Comparing to the works discussed above, the research in this paper combine with the characteristics of biological signal that it is nonlinear and non-stationary, and improve EEMD method, and then complete to adaptively extracting the RR intervals.

3 Methods

3.1 Data Collection Platform

A nonintrusive sleep sensing system is used to collect BCG signal, which consists of a micro-movement sensitive mattress, the analog-digital (A/D) converter and a terminal PC, the system is shown in Fig. 1. The mattress is embedded with two hydraulic pressure sensors (oil tubes), one is located at the upper part of the mattress to sense the pressure of the heartbeat, the other is placed in the leg regions, and the mattress can make sure there is enough area for various subjects' physical sizes, and BCG signal is sampled with 100 Hz. The original pressure signal is recorded using micro-movement sensitive mattress, converting to digital signal by the A/D converter. Finally, we can acquire some kinds of physiological parameters datasets from the system, such as Ballistocardiogram, respiration and so on. In this work, we pay more attention to analyze the cardiac vibrations of subjects, so we only select BCG signal as our original datasets.

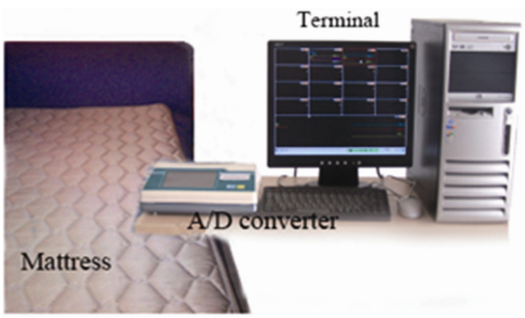

Fig. 1. Micro-movement sensitive mattress sleep monitoring system.

3.2 Signal Processing

3.2.1 Theoretical Basis and Existing Issues

Norden E. Huang came up with a method of Hilbert-Huang Transformation (HHT) in 1998 [16] which is used for analyzing nonlinear and non-stationary signals based on Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis (HSA), and the method has already been applied to many scientific research areas, including biological signal analysis. But the EMD exists many questions, such as mode mixing problem. To solve the problem, Huang propose an improved method named Ensemble Empirical Mode Decomposition (EEMD). The method is generally used for non-stationary signal, such as physiological signal.

In this paper, we will use the EEMD algorithm as a basis to deal with BCG signal, and try to solve some issues still exist, as follows:

(1) The EEMD algorithm contains two important parameters: Nstd and NE. The Nstd is the ratio of standard deviation of amplitude of the white noise signal and BCG signal, and NE is the number of iterations in the program. According to Huang theory [19], the Nstd is often set based on the working experience, so the experimental results is under the influence of parameters settings.
(2) BCG signal is different due to diverse sleep posture, person and also data acquire equipment. Different BCG signal need to set various parameters when is decomposed using EEMD. So it will be difficult to set the parameters according to different kinds of the BCG signal.
(3) X. Cao et al. [18] deal with BCG signal based on EEMD, and then select decomposition component seven as the target signal to extract RR interval, but because the BCG signal exists difference with distrinct persons, it leads to the decomposition component six or others but not seven agree with the cardiac cycle. The situation is also shown in the paper [19]. The method is suitable if we just analyze small amounts of data, but if we use it in an automatic heartbeat extraction system, it will reduce the accuracy of heartbeat cycle. Meanwhile, the decomposition effects of EEMD related to input parameters of EEMD, and the parameters is affected by BCG signal. So it is not suitable for all BCG signals to set a fixed parameter value. In order to improve accuracy of experimental data, we must select the suitable decomposition component as the target signal.
(4) Because the NE value is large, it will affect the program time efficiency. We should find a way to decease the NE value and have no effect on the decomposition effects.

3.2.2 Solving Problem Method

Based on the above contents, we can know, for the BCG signal, if we want to remove the noise perfectly, we need to add white noise signal whose amplitude is equal to the noise of BCG signal to the BCG signal. In fact, the noise of BCG signal is the high frequency information of BCG signal. So if we know the high frequency information of BCG signal, we can get the amplitude of white noise. Meanwhile, if we can extract the high frequency information that we want to remove from BCG signal, we can also calculate the parameters Nstd, and then we can complete adaptively to set the parameters Nstd of the EEMD method.

In order to remove the noise of BCG signal, we need to know that which frequency bands should be extracted as high frequency signal. According to medical field knowledge, the heart rate is 40–200 beats/min, and the maximum and minimum heart rate value is often athletes. Its corresponding frequency range is 0.67 Hz–3.33 Hz. So we should extract the high frequency signal whose frequency band is larger than 3.33 Hz.

Many methods can be used to extract high frequency information of BCG signal, such as EMD algorithm, high-pass filtering and multi-resolution wavelet transform. For the EMD algorithm, its time efficiency is relatively poor. For the high-pass filtering method, it needs to manual input the filter parameter value, different the parameter value will have different effect on the filter result. For the multi-resolution wavelet transform, it can extract high frequency detail signal adaptively, however, multi-resolution wavelet transform need to select wavelet basis.

In order to know about whether wavelet basis have seriously effect on Nstd value, we select BCG signal for 16 persons to test and select three different series of wavelet bases, they are respectively db, sym and bior, the sym and bior are select randomly, and db is often used for the wavelet decomposition of the BCG signal [39–41]. The experimental results are shown in Table 1, optional argument is Nstd parameter range that they are chose based on the artificial experience, the range is best for decomposition effect. From the Table 1, we can observe that the wavelet basis almost have no effect on Nstd value.

Table 1. The adaptive parameters compared with optional parameters.

Subject	Optional Argument	Adaptive Argument		
		db6	Sym6	bior2.8
S1	0.33–0.62	0.5115	0.5118	0.5269
S2	0.30–0.40	0.3215	0.3247	0.3233
S3	0.90–0.99	0.9820	0.9796	0.9789
S4	0.48–0.67	0.5942	0.5978	0.6012
S5	0.50–0.62	0.5648	0.5564	0.5571
S6	0.30–0.41	0.3357	0.3327	0.3460
S7	0.56–0.76	0.6340	0.6332	0.6156
S8	0.77–0.79	0.7837	0.7863	0.7896
S9	0.51–0.57	0.5367	0.5355	0.5396
S10	0.66–0.88	0.7753	0.7738	0.7745
S11	0.45–0.49	0.4702	0.4689	0.4712
S12	0.59–0.80	0.6228	0.6236	0.6230
S13	0.40–0.86	0.5863	0.5936	0.6083
S14	0.39–0.55	0.4352	0.4340	0.4279
S15	0.66–0.71	0.6904	0.6897	0.6920
S16	0.35–0.45	0.3975	0.3947	0.3898

Therefore we decide to select the multi-resolution wavelet transform to extract the high frequency signal. But we must know which decomposition scales is our need. In order to solve this problem, we randomly select an original BCG signal and a target signal, it is shown in the Fig. 2. Then we deal with the BCG signal using multi-resolution wavelet transform and get the high frequency detail signal, and then we handle the BCG signal, the target signal and the high frequency detail signal with Fourier transform. The result is shown in the Fig. 3.

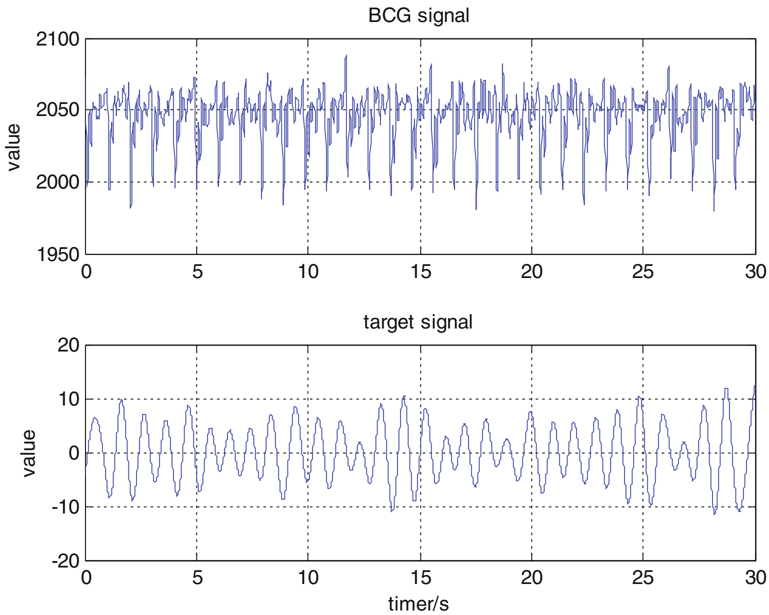

Fig. 2. The original signal and the target signal.

From the Fig. 3, we can observe that the frequency bands of the target signal is about 0–3 Hz, being consistent with the range of human heart rate. Meanwhile, so we will treat the frequency bands signal which is larger than 3 Hz as the noise signal, namely, these signals are high frequency signal that we need. From the Fig. 3, we can observe that the decomposed scale 1–4 of BCG signal is out of the bands of the heart rate of human, so we select them as the noise signal, and we should extract these high frequency signal. In order to facilitate the operation, we choose to reconstruct the decomposed scale 1–4 high frequency signal. Then we will treat the reconstructed high frequency signal as the adding white noise signal, and then compute the parameter Nstd. Now, we can complete adaptively setting of the parameters Nstd.

According to the part Theoretical Basis and Existing Problems, we know EEMD have two parameters, now we solve how to get the NE value. According to the statistical rules proposed by Huang [19], the relation of Nstd and NE is shown in the formula 1, e is decomposition error value, and which is generally set for 1%.

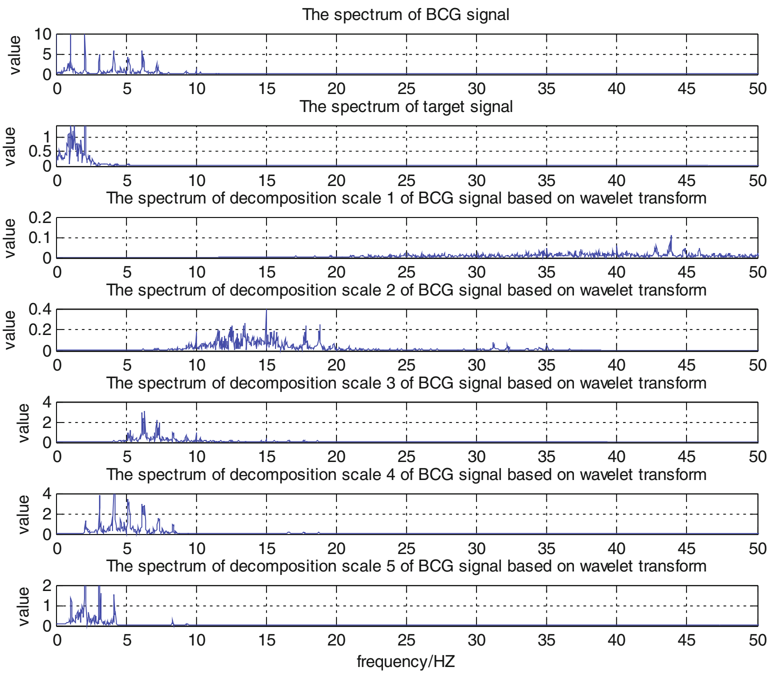

Fig. 3. The result of FFT of signal.

$$e = \frac{Nstd}{\sqrt{NE}} \tag{1}$$

However, it is not appropriate for BCG signal to let the e take 1% based on experiments experience. According to a lot of experiments, we find that it is suitable for the e taking 5%. In order to explain the question, we select an example randomly, we decompose the BCG signal using EEMD algorithm for e taking 1% and 5%, the decomposition result is shown in the Fig. 4. Although the theoretical decomposition error value is increased when e is 5%, from the Fig. 4, we can perceive that the decomposition effect is practically no difference. The Nstd value is 0.3 in this experiment, according to the formula 1, the NE value will be 900 for e being 1% and 36 for e taking 5%. So it is more suitable to set e for 5% and decreases the running time of the program. Now, we can complete adaptively setting of the parameters NE.

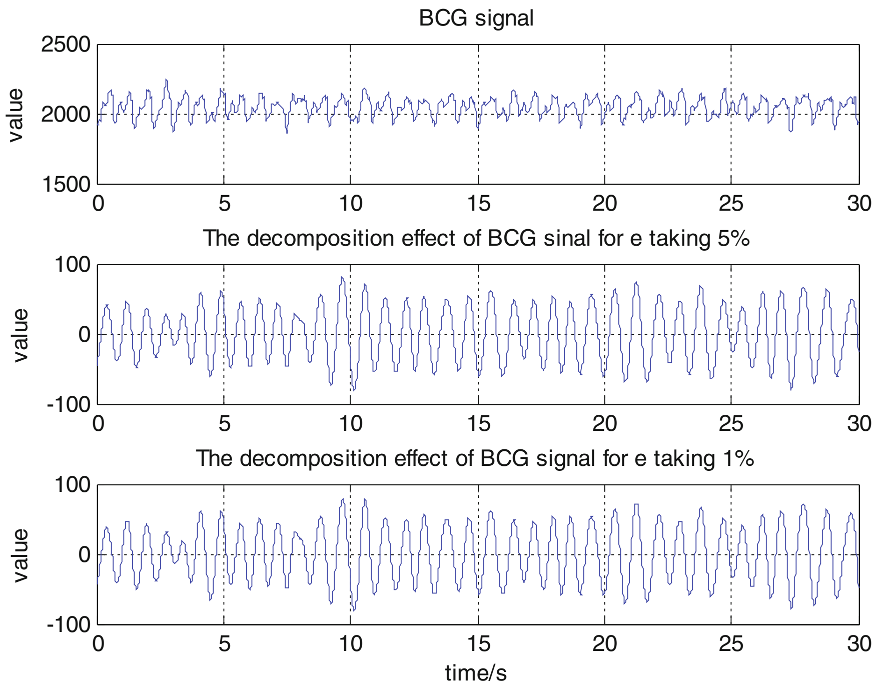

Fig. 4. The decomposition effect of the BCG signal with different e value

4 Results

In this study, we have performed experiments on each individual dataset using BCG signals from eighteen subjects, including ten males and eight females (age 20–72). The RR interval series were obtained using the proposed method.

In the procedure of extracting RR intervals, we firstly need to detect the peak points, so the procedure can be regarded as event detection, so it is possible to appear the situation that the heartbeat peak points is identified incorrectly (False Positive) and the heartbeat peak points can't be identified correctly(False Negative). In order to evaluate performance of this method. We collect the statistic data of TRR, F.P, F.N, Total Error, and calculate the accuracy value. The formula is as follow, and the statistic content is shown in the Table 3.

$$Total\ Error = TP + TN \tag{2}$$

$$Accuary = (Total\ Error/T_{RR}) * 100\% \tag{3}$$

From the Table 2, we can observe that the total error event number from the AHE algorithm is less than the total error event number from the RDS algorithm, and from the parameter Accuracy, it also reflects that the AHE algorithm has a higher accuracy and reliability for extracting the heartbeat intervals than the FDS algorithm.

Table 2. The performance comparison of the method.

Method	T_{RR}	Error			Accuracy [%]
		F.P	F.N	Total Error	
AHE	53692	273	262	535	99.00
FDS	53692	1879	3759	5638	89.49

In the Sect. 3, we know that we set e for 5% based on a lot of experiment experience, and we can improve the time efficiency of the program, so in order to evaluate time efficiency of the AHE algorithm, we start to give a test, and set e for 1% for the FDS algorithm, the result was shown in the Table 3.

Table 3. The time performance comparison of methods.

Data(min)	T_{cost}(s)	
	AHE	FDS
1	5.62	22.95
5	37.32	151.22
10	118.94	453.55
30	1054.47	4029.27

In the research filed, we often use five-minute or ten-minute datasets (such as ECG, BCG) to extract RR intervals and analyze heart rate variability. So, in this experiment, four kinds of different time-length datasets are respectively arranged to complete the test. From the Table 3, we can observe clearly that the time performance of algorithm AHE is greatly improved.

5 Conclusion

Cardiovascular disease affects seriously the health of the elderly all over the world. This study presents a novel adaptive method to obtain RR intervals based on BCG datasets. The algorithm firstly complete to acquire automatically input parameters of EEMD algorithm based on wavelet transform and signal reconstruction, and secondly complete to signal decomposition based on EEMD, and select adaptively the target signal, finally, complete to detect the peak points and calculate the heartbeat intervals series using the target signal. In brief, the method complete to adaptively extract heartbeat intervals series based on datasets.

In the result, the proposed method is tested using the BCG datasets from eighteen subjects, including eight females and ten males (age 20–72). The results of heart rate from BCG will be compared with ECG. From the Sect. 3, we can observe the precision of heart rate value from BCG is high and the accuracy of the method is 99%.

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References

1. WHO: Cardiovascular Diseases (CVDs). Geneva, Switzerland: World Health Organization (2013)
2. Giovangrandi, L., Inan, O.T., Wiard, R.M., et al.: Ballistocardiography—a method worth revisiting. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, pp. 4279–4282. IEEE (2011)
3. Junnila, S., Akhbardeh, A., Barna, L.C., et al.: A wireless ballistocardiographic chair. In: 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBS 2006, pp. 5932–5935. IEEE (2006)
4. Migeotte, P.-F., Tank, J., Pattyn, N., Funtova, I., Baevsky, R., Neyt, X., Prisk, G.K.: Three dimensional ballistocardiography: methodology and results from microgravity and dry immersion. In: Proceedings of the 33rd Annual International Conference of the IEEE EMBS, Boston, MA (2011)
5. Chung, G.S., Lee, J.S., Hwang, S.H., Lim, Y.K., Jeong, D.-U., Park, K.S.: Wakefulness estimation only using ballistocardiogram: nonintrusive method for sleep monitoring. In: Proceedings of the 32nd Annual International Conference of the IEEE EMBS, Buenos Aires, Argentina (2010)
6. Paalasmaa, J.: A respiratory latent variable model for mechanically measured heartbeats. IOP Phys. Meas. **31**(10), 1331–1344 (2010)
7. Bruser, C., Stadlthanner, K., de Waele, S., Leonhardt, S.: Adaptive beat-to-beat heart rate estimation in ballistocardiograms. IEEE Trans. Inf. Tech. in Biomed. **15**(5), 778–786 (2011)
8. Koivistoinen, T., Junnila, S., Varri, A., Koobi, T.: A new method for measuring the ballistocardiogram using EMFi sensors in a normal chair. In: Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco, CA (2004)
9. Postolache, O., Girao, P.S., Postolache, G., Pereira, M.: Vital Signs Monitoring System Based on EMFi Sensors and Wavelet Analysis. IEEE IMTC, Warsaw (2007)
10. Postolache, O., Girão, P.S., Postolache, G.: New approach on cardiac autonomic control estimation based on BCG processing. In: Canadian Conference on Electrical and Computer Engineering, 2007. CCECE 2007, pp. 876–879. IEEE (2007)
11. Jin, J., Wang, X., Li, S., et al.: A novel heart rate detection algorithm in ballistocardiogram based on wavelet transform. In: Second International Workshop on Knowledge Discovery and Data Mining. WKDD 2009, pp. 76–79. IEEE (2009)
12. Shin, J.H., Choi, B.H., Lim, Y.G., et al.: Automatic ballistocardiogram (BCG) beat detection using a template matching approach. In: 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBS 2008, pp. 1144–1146. IEEE (2008)
13. Smrcka, P., Jirina, M., Trefny, Z., et al.: New methods for precise detection of systolic complexes in the signal acquired from quantitative seismocardiograph. In: 2005 IEEE International Workshop on Intelligent Signal Processing, pp. 375–380. IEEE (2005)
14. Akhbardeh, A., Kaminska, B., Tavakolian, K.: BSeg ++: a modified blind segmentation method for ballistocardiogram cycle extraction. In: 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBS 2007, pp. 1896–1899. IEEE (2007)
15. Algunaidi, M., Ali, M.A.M.: Threshold-free detection of maternal heart rate from abdominal electrocardiogram. In: 2009 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), pp. 455–458. IEEE (2009)
16. Choi, B.H., Chung, G.S., Lee, J.S., et al.: Slow-wave sleep estimation on a load-cell-installed bed: a non-constrained method. Physiol. Measur. **30**(11), 1163 (2009)

17. Singh, B., Nagarkoti, S.K., Kaushik, B.K.: A modified algorithm for maternal heart rate detection using RR interval. In: 2011 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC), pp. 39–42. IEEE (2011)
18. Cao, X., Guo, H., Tang, J.: Heart rate extraction of ballistocardiogram based on hilbert-huang transformation. In: Long, M. (ed.) World Congress on Medical Physics and Biomedical Engineering, vol. 39, pp. 619–622. Springer, Berlin (2013)
19. Wu, Z., Huang, N.E.: Ensemble empirical mode decomposition: a noise-assisted data analysis method. Advances in adaptive data analysis **1**(01), 1–41 (2009)
20. Postolache, O.A., Girao, P., Silva, M.B., et al.: Physiological parameters measurement based on wheelchair embedded sensors and advanced signal processing. IEEE Trans. Instrum. Measurem. **59**(10), 2564–2574 (2010)
21. Mack, D.C., Patrie, J.T., Suratt, P.M., et al.: Development and preliminary validation of heart rate and breathing rate detection using a passive, ballistocardiography-based sleep monitoring system. IEEE Trans. Inf Technol. Biomed. **13**(1), 111–120 (2009)
22. Krej, M., Dziuda, L., Skibniewski, F.W.: A method of detecting heartbeat locations in the ballistocardiographic signal from the fiber-optic vital signs sensor. IEEE J. Biomed. Health Inf. **19**(4), 1443–1450 (2015)
23. Bruser, C., Kortelainen, J.M., Winter, S., et al.: Improvement of force-sensor-based heart rate estimation using multichannel data fusion]. IEEE J. Biomed. Health Inf. **19**(1), 227–235 (2015)