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Heart and Respiratory Rate Detection on a Bathroom Scale Based on the Ballistocardiogram and the Continuous Wavelet Transform

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Abstract—**Ballistocardiography is a non-invasive technique that yields information about the cardiovascular system that is not available in other external signals such as the electrocardiogram (ECG). In the last years, several research groups have obtained the ballistocardiogram (BCG) by using instrumentation methods simpler than those available in the 1950s and that did not progress because of their complexity as compared to ultrasound and other noninvasive techniques that are in common use nowadays. We describe a novel method for real-time robust heart- (HR) and respiratory- (RR) rate detection from a subject that stands on a common electronic bathroom scale. BCG signals from the scale are wirelessly sent to a PC where algorithms based on the continuous wavelet transform (CWT) extract the HR and the RR. HR results are compared to those obtained from the ECG. To better assess the RR results, subjects have been asked to synchronize their breathing rate to an on-screen bar-graph set at a constant rate of breaths per minute. This method to obtain the heart and respiratory rates is simple, compact, non-invasive and passive, and can be applied to any person able to stand on an electronic weighing scale, even if wearing shoes.**

I. INTRODUCTION

BALLISTOCARDIOGRAPHY is a non-invasive measurement method to obtain cardiovascular information. It has been known since the late 18th century but seldom used in medical practice because of technological limitations. The ballistocardiogram (BCG) arises from the body reaction to the forces exerted by cardiac contraction and rapid blood acceleration in major blood vessels. During ventricular systole, left ventricle's contraction accelerates blood towards the ascending aorta and the carotid arteries and, according to the action-reaction law, the subject's body moves in the opposite direction (towards the feet). Similarly, blood acceleration in the descending and abdominal aortas results in a reaction force pointing to the head.

Fig. 1 shows a theoretical BCG waveform, whose main waves and the time intervals between them depend on the physiological condition of the heart and main blood vessels, and the peripheral cardiovascular resistance. The signal divides in three zones: pre-ejection (FGH), ejection (IJK) and diastole (LMN). The most studied wave is the I-J complex, which is proportional to the blood acceleration in the ascending aorta and then in the descending and abdominal aorta. The I-J amplitude has been shown to reflect sub-clinical abnormalities resulting from drugs and other therapies, and pathologies related to the aortic valve and the coronary artery, among other [1].

Because forces resulting from the cardiovascular activity are very small, the BCG is a low-amplitude signal susceptible to interference from breathing, muscular temblors, vibrations, etc. Nevertheless, several research groups have recently obtained the BCG in domestic furniture such as beds, chairs and weighing scales [2-6].

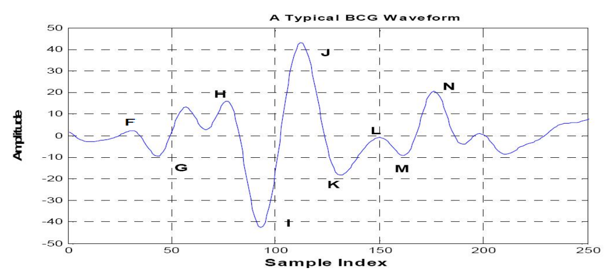

Fig. 1. The BCG is a record of mechanical cardiovascular activity that includes three groups of waves: pre-ejection (FGH), ejection (IJK) and diastolic (LMN) waves.

If any of the BCG peaks is prominent enough, the cardiac frequency can be obtained by simple peak detection or by comparison with a voltage threshold. But if there is not any clearly defined peak, the results are uncertain. This is the case, for example, for very low-amplitude BCGs and for trembling subjects. Noise reduction, for example by using artificial neural networks and discrete wavelet transforms (DWT) [7, 8], improves the sensitivity and specificity of common algorithms to detect maxima.

The BCG is a non-stationary random signal that can be analyzed in the time-frequency domains by using the wavelet transform (WT). This is a mathematical tool based on the decomposition of a signal on a set of waves that differ from a common wavelet function in a scale factor and a position factor [9]. The scale coefficient reflects the profile information of signal at a single frequency. This allows us to identify changes in a signal and at the same time to remove low- or high- frequency components.

DWT yields a series of discrete coefficients without any loss of information and without introducing any redundancy,

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at a reduced computational load as compared to the Continuous Wavelet Transform (CWT). Nevertheless, the computational load of the CWT can be reduced by processing only a few scales to obtain a map of coefficients called scalogram, which describes the time-frequency energy distribution better than DWT. CWT has also the advantage, through the scalogram of the signals, of giving a clearer information about the range of scales from which it will be possible to obtain HR and RR, and therefore about the robustness of the method. Once the right scales have been determined, the numerical complexity of the method reduces because it is enough to calculate the convolution of the signal with the numerical coefficients of the mother wavelet at the selected scale, which can be easily performed by a standard microcontroller.

Several research groups have obtained the BCG in chairs and wheelchairs in order to derive the HR [10] and RR [11] from it by using the DWT. We have obtained the BCG on a common electronic bathroom scale and processed it to obtain the HR and RR using the CWT. In this work, the results in six people with dissimilar physical condition show that HR and RR can be obtained from separate ranges of scales that may be similar for different people.

II. Materials and Methods

A. BCG and ECG acquisition

Common electronic bathroom scales include several strain gages connected in a Wheatstone's bridge. When a person stands on a scale, the strain gages will detect both the weight and the force due to the beating heart, hence the BCG. The amplitude of these two force components is dissimilar: the weight results in signals in the range of 100 mV whereas the pulsatile component is in the range of 10 µV. For a group of 20 people, we found that pulsatile force to be from 0.24 N and 8 N [4]. Usually, this second component is filtered out and the dc component is displayed to indicate weight. Instead, we high-pass filter the force signal with a differential second order filter at 0.2 Hz which offers a better CMRR than other filters using only four components [12]. Then, we amplify the signal with a gain ranging from 10^4 to 10^5, and we band-pass filter it with a first order filter between 0.8 Hz and 8.7 Hz to reduce noise and interference.

The ECG has been simultaneously acquired for reference by using a custom-made system with dry electrodes placed on a plastic steering wheel. When each hand touches the respective electrode, we obtain lead I of ECG without any need to prepare the skin.

A separate 10 bits microcontroller with an RF module connects each signal to a PC where signals are processed in real time. Fig. 2 shows the block diagram of the system implemented.

The user interface has been designed by using LabView® 8.6 and the signal processing algorithms for the BCG and ECG have been implemented by using the Advanced Signal Process Toolkit. The same wavelet-based algorithm used to detect HR from the BCG is used to detect RR from the same signals; only the scale factor is changed.

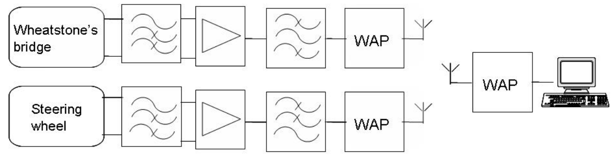

Fig. 2. Hardware block diagram to BCG and ECG acquisition

The sample rate was 100 Hz and there were 10 samples on each packet sent, so that the refresh rate of the displayed data was 10 Hz. This frequency is high enough for the data reception to be perceived as a continuous process.

The user interface has been divided in two parts, the main panel and the configuration panel, separated by a tab control. The configuration panel was used to set the parameters to read the serial port, heart rate detection algorithm and save data. The main panel was used to display data and to change the wavelet family or the scale in real-time signals.

B. HR measurement protocol

Six volunteers (S1 to S6), three that usually do not play any sport and three that do on a regular basis, were asked to stand in the scale while holding the steering wheel without making any excessive effort, and avoiding talking or moving. After 5 s, the system recorded 10 s of data (a total of 1000 samples).

C. RR measurement protocol

Volunteers were asked to stand on the scale and to synchronise their respiratory rate to an on-screen bar-graph set at a constant rate of 15 breaths per minute (250 mHz). After 10 s, the system recorded 20 s of data.

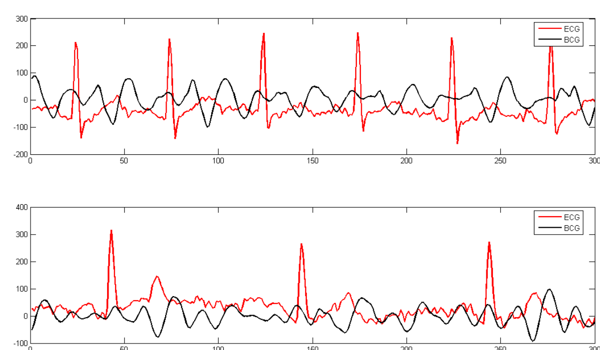

Fig. 3. 300 samples (out of the 1000 acquired) from BCG and ECG (arbitrary units) for subjects S1 (top) and S6 (bottom).

III. Results

A. HR results

Fig. 3 shows 300 samples of the BCG and ECG for S1 at HR = 120 beat/min and for S6 at HR = 63 beat/min. R waves from the ECG and I-J waves from the BCG (here shown with inverted polarity with respect to that in Fig. 1) are always synchronous. The same was obtained for the other subjects.

Several mother wavelets at different scales were tried to find the one most tolerant to unavoidable (small) subject's movements, which was daubechies 10, subsequently used to analyze signals acquired in different days, hence different HR even for the same subject. Subject S1 was measured in four instances: before and after a meal, before a meal another day, and after a meal a third day. The average HR was 84, 108, 86 and 120.

Fig. 4 shows the results from the 1000 samples of the BCG (arbitrary units) acquired when HR = 84. The coefficients line at scale 50, shown at the bottom graph, was obtained from the range of scales enclosed by the rectangle in the central graph. BCGs acquired in different days and different conditions, hence different HR, yield similar results: scalograms are periodic in a wide range of scales and the line of coefficients at scale 50 is an oscillatory signal whose frequency corresponds to the HR value. The scalogram for slower HR values looks like a stretched version of the scalogram for faster HR values.

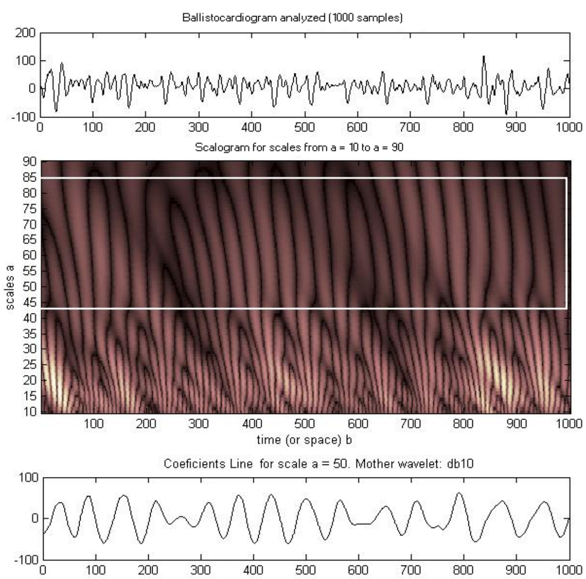

Fig. 4. BCG signal (top), scalogram (center) and coefficients line at scale 50 (bottom) for S1 when HR = 84 beats/min. The rectangle on the scalogram shows the scale's range where the wavelet coefficients for HR are obtained.

Table I shows subject's features and scale ranges in which coefficients lines are a periodic repetition that correspond to HR. It can be observed that the scales where HR can be obtained from depend on the subject's HR, but, as a general trend, we observe that for each subject, when HR diminishes, the minimal scale to obtain the HR increases, as expected, because higher scales correspond to lower frequencies in the scalogram.

Subject S4 was recorded before and after doing some physical exercise. HR increased from 81 to 96, and its value could be obtained between scales 45 and 73 for HR = 81, and between scales 38 and 78 for HR = 96. Hence, like in S1, when HR diminishes, the minimal scale with periodic coefficient values increases.

TABLE I
RESULTS FOR HR TEST

Subject	Features	HR	Scale ranges
S1	Female, 36 years, 1,75 m, 77 Kg	84	43 to 85
		86	43 to 78
		108	37 to 65
		120	35 to 63
S2	Male, 34 years, 1,80 m, 77 Kg	84	48 to 75
S3	Male, 33 years, 1,67 m, 67 Kg	79	48 to 78
S4	Male, 27 years, 1,90 m, 85 Kg	81	45 to 73
		96	38 to 78
S5	Male, 26 years, 1,90 m, 68 Kg	84	40 to 90
S6	Male, 44 years, 1,73 m, 75 Kg	51	77 to 112
		63	55 to 90

By chance, the average heart rate for three different volunteers after a meal was 84 beat/min. The range of scales to obtain the beat-to-beat HR was different in each case: (1) from 43 to 83 for S1; (2) from 48 to 75 for S2; and (3) from 40 to 90 for S5. Therefore, HR can be obtained from scale 48 to scale 63 for any of those subjects.

We observe that BCG signals like those of S6 (before a meal) for a very slow heart rate (HR = 51) and those of S1 for a very fast heart rate (HR=120) may result in scalograms where ranges that reflect the HR do not overlap. This drawback can be overcome by obtaining the CWT at more than one scale, so that HR can be obtained regardless of its low/high value.

Notice that, although S6 has a very slow heart rate (HR=51, corresponding to 0.85 Hz), which is close to the low cut-off frequency of our system (0.8 Hz), as it corresponds to a first order filter, the slight attenuation of the signal does not avoid obtaining the HR from the scalogram.

B. RR results

We have recorded the BCG of five volunteers: four of them (S1, S2, S3 and S4) were the same as in the HR analysis, and another one (S7) that does not practice any sport. We tried to find a scale whose coefficients displayed the same periodicity as the respiration, when using the same daubechies 10 mother wavelet.

Figure 5 shows the results for 2000 samples recorded from S4. The BCG signal (top graph) shows an amplitude modulation that results from inspirations and expirations, similar to the well-known modulation of the R wave in the ECG. The coefficients in the bottom graph belong to the scale 400, and display a periodic behaviour whose frequency is 250 mHz, which was the respiratory frequency of the subject.

Table II summarizes the results obtained for all the volunteers. We observe that, similarly to HR, a sinusoidal signal whose frequency agrees with RR could be obtained from the same scales for different subjects, here 285 to 320.

TABLE II
RESULTS FOR RR TEST

Subject	Features	HR	Scale ranges
S1	Female, 36 years, 1,75 m, 77 Kg	75	270 to 560
		78	250 to 430
		84	250 to 360
S2	Male, 34 years, 1,80 m, 77 Kg	81	285 to 440
S3	Male, 33 years, 1,67 m, 67 Kg	75	240 to 320
		81	240 to 380
S4	Male, 27 years, 1,90 m, 85 Kg	75	245 to 460
S7	Male, 33 years, 1,67 m, 59 Kg	66	250 to 400

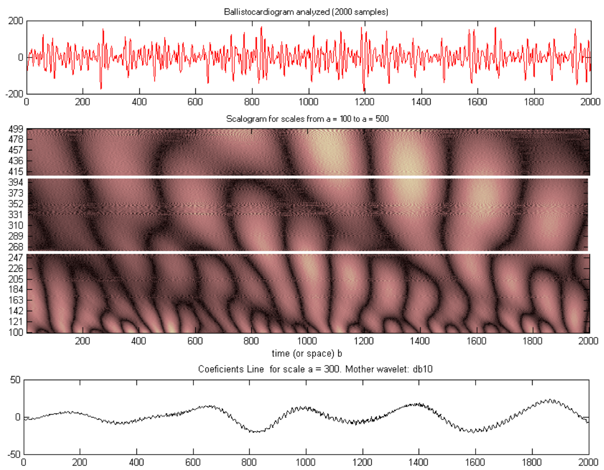

Fig. 5. BCG signal (top), scalogram (center) and coefficients line at scale 400 (down) from S4. The rectangle on the scalogram indicates the ranges of scales where the periodicity of coefficients agrees with that of the coefficients of the respiratory rate RR. The noise in the scalogram results from the limited time resolution of the CWT for such a low-frequency signal as RR.

IV. Conclusion

We have presented a compact and non-invasive system to obtain the heart rate and the respiratory rate using a common electronic weighing scale. The system relies on analyzing the BCG using the continuous wavelet transform CWT and looking for particular scales in the scalogram that reflect the same periodicity as the HR or RR. To validate the HR results, the ECG (lead I) was simultaneously obtained. To validate the RR results, volunteers were asked to breath at 250 mHz (once each 15 s).

For the HR study, we have analyzed six subjects. Although results for a reduced number of people and similar HR values may suggest that it is possible to derive HR from any of a relatively narrow range of scales in the scalogram, for very different HR values, two ranges must be explored. In the RR study, we have analyzed five subjects at rest. For this group and periodic respiration, it was possible to find a range of scales common to them all where RR could be obtained from. However, more subjects and different respiration conditions must be analyzed.

If the results obtained were confirmed in a broader population, it would be possible to implement a system for on-line detection of the HR and RR in a weighting scale using the BCG signal. Results in the small sample of people studied suggest that it may be necessary to obtain the CWT at more than one scale. Nevertheless, these calculations are simple enough to implement them in a microcontroller in the weighing scale itself.

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