Sensors & Actuators: A. Physical 395 (2025) 117058

Contents lists available at ScienceDirect

Sensors and Actuators: A. Physical

journal homepage: www.journals.elsevier.com/sensors-and-actuators-a-physical

A novel bed-based ballistocardiography system for non-contact monitoring of vital signs, apneas and arrhythmias via smartphone integration

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ARTICLE INFO

Keywords:
Remote ballistocardiography
Smartphone
Video processing
In-bed patient monitoring

ABSTRACT

This work presents a novel remote ballistocardiography system designed for continuous monitoring of individuals lying in bed. The system utilizes video recordings of a tracking marker placed on the side of the mattress. By processing the motion of this marker, ballistocardiographic waveforms are generated, capturing mattress displacements caused by cardiac activity, respiration, and body movements. The longitudinal and transverse axes of the mattress naturally separate the contributions of cardiac and respiratory signals within the ballistocardiography waveform. This orthogonal separation enables the independent analysis of each component, thereby enhancing the accuracy of heart and respiratory rate estimations. The system's high resolution and sensitivity enable not only the reliable extraction of the subject's vital signs, but also the detection of activity episodes—both voluntary and involuntary—alongside physiological anomalies such as sleep apnea and cardiac arrhythmias. The simplicity of the proposed setup offers significant advantages over conventional ballistocardiography systems by eliminating the need for integrated sensors and periodic calibration, and by mitigating common challenges in remote ballistocardiography applications, including susceptibility to ambient lighting conditions.

1. Introduction

Ballistocardiography (BCG) is a non-invasive technique that enables the measurement of micro-oscillations of the body generated by the mechanical activity of the heart and circulatory system. Its origins date back to the 19th century, when Gordon first described, in 1877, the bodily displacements resulting from the ejection of blood from the heart into the systemic circulation [1]. Later, in the 1930s, Starr and colleagues developed the classical ballistocardiograph, which employed a suspended platform to record these subtle body movements [2]. In the following decades, BCG experienced a surge in cardiovascular research, although its clinical use declined with the advent of alternative diagnostic techniques, such as electrocardiography (ECG) and echocardiography [3]. However, in recent years, advances in sensor technologies and signal processing have enabled a resurgence of BCG, particularly in applications related to remote and non-invasive health monitoring.

Various types of sensors and techniques have been developed for the detection of ballistocardiographic signals. Traditionally, mechanical ballistocardiographs employed floating platforms or stretchers equipped with pressure sensors [4]. With technological advancements, piezoelectric sensors, accelerometers, load cells, and photodetectors, among others, were introduced to measure body oscillations [5–9]. More recently, high-sensitivity video cameras combined with image processing techniques have emerged as a viable alternative for the remote acquisition of these signals [10]. These solutions enable contactless data acquisition, eliminating the need for electrodes or body-attached sensors, thereby enhancing subject comfort and facilitating long-term monitoring.

BCG applications span various fields, with particular emphasis on cardiac and respiratory monitoring. In the medical domain, BCG has been employed for the detection of arrhythmias, analysis of heart rate variability, and estimation of cardiac output [11]. Furthermore, its use in sleep monitoring has enabled the development of surveillance systems capable of detecting sleep stages or disorders such as obstructive sleep apnea without the need for intrusive devices [12–14]. Additional applications include the monitoring of subjects with heart failure, where

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https://doi.org/10.1016/j.sna.2025.117058
Received 14 July 2025; Received in revised form 9 September 2025; Accepted 10 September 2025
Available online 12 September 2025

BCG provides valuable insights into their hemodynamic status [15].

One of the most innovative recent developments in the field of BCG is the application of video processing for the extraction of cardiac signals from subjects, known as remote BCG (RBCG). This non-invasive approach enables continuous, contactless subject monitoring, which is particularly advantageous in clinical, geriatric, and home-care environments [16,17]. Through advanced computer vision algorithms, it is possible to detect micro-oscillations of the body caused by heartbeats and respiration by analyzing motion patterns in video recordings [18]. Various studies have demonstrated the feasibility of this technique in both clinical and non-clinical environments, employing methods such as facial displacement tracking, chest motion analysis, and the amplification of subtle changes in video intensity to highlight physiological movements [19]. In particular, video motion magnification has been widely used to enhance the visibility of minute displacements resulting from cardiorespiratory activity [20]. However, since the RBCG technique relies on direct recordings of the subject, it faces significant challenges due to variations in ambient lighting and artifacts caused by subject movement [21].

In a previous study, the authors demonstrated the feasibility of a remote BCG system using RFID sensors to obtain heart rate (HR) and respiratory rate (BR) from a subject lying in bed through contactless monitoring of mattress movements [22]. In the present work, a novel RBCG system is introduced for monitoring bedridden subjects, based on video processing and following the same general strategy, namely, generating the ballistocardiographic signal remotely from mattress vibrations induced by physiological activity. In this case, the signal acquisition system is further simplified by eliminating the need for sensors integrated into the bed and instead deriving the signal from a video recording of a marker drawn in the side of the mattress. This strategy addresses the aforementioned limitations common to RBCG systems that rely on direct recordings of the subject.

2. Materials and methods

2.1. RBCG system

The proposed system for BCG signal acquisition is illustrated in Fig. 1. A subject lying in bed generates vibrations in the mattress due to heartbeats, respiration, and other voluntary or involuntary body movements [23]. As discussed in the Introduction, various approaches have been proposed for recording these vibrations using different types

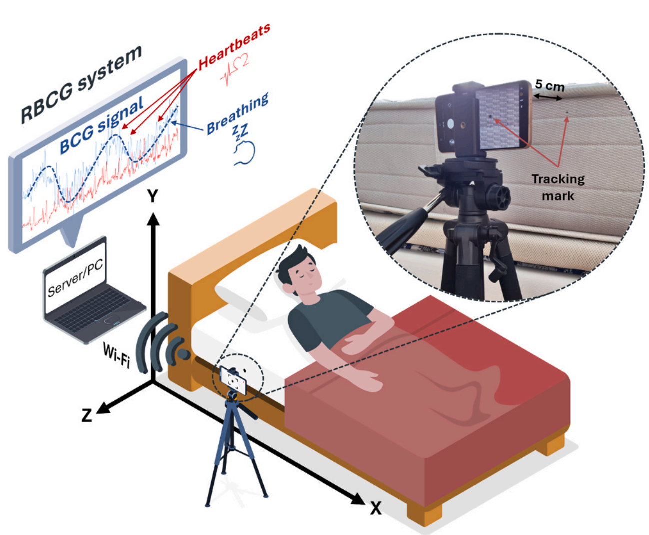

Fig. 1. Schematic representation of the proposed RBCG system. The XYZ Cartesian coordinate system used in this study is also depicted. The inset shows a photograph of the smartphone recording the marker on the side of the mattress.

of sensors. However, such systems typically require the development of a dedicated electronic measurement setup and instrumentation embedded within the mattress [24,25], which entails customized configurations for each implementation and is rarely transferable across setups due to variations in mattress type, bed frame, and overall structure. In contrast, the system proposed herein does not require the integration of specific sensors or electronic signal acquisition systems within the bed or mattress. Instead, it relies solely on a video camera—in this case, the built-in camera of a commercially available smartphone—for capturing video sequences and transmitting them to a remote server, where signal processing is subsequently performed.

The marker used for motion tracking on the side of the mattress, which may be drawn with ink or applied as an adhesive element, consists of a small black dot approximately 2 mm in diameter placed on a white surface (see Fig. 1 inset). The marker can be renewed from one trial to another, since it is not a critical parameter and does not need to be the same. The video processing described below, which is used to determine the point of interest within this marker ensures that the algorithm will be able to detect mattress displacements, regardless of the marker employed. The recording device employed in this study was a Samsung Galaxy S24 (8 GB RAM, maximum camera resolution 50 MP, image sensor size 1/57'', 4000 mAh battery, 5 G connectivity) that can be configured to capture video sequences at 30–60 frames per second (fps) with a resolution of 1920 $\times$ 1080 pixels. To avoid overloading the device, it was exclusively used for recording video segments, which were then transmitted via Wi-Fi to a remote server for storage and subsequent processing.

The smartphone is mounted on a tripod at a fixed distance of 5 cm from the mattress. The device's camera is oriented toward the marker, which is aligned with the subject's chest level on the side of the mattress. Mattress vibrations, induced by physiological activity, cause subtle displacements of the marker that are recorded in the video stream. Subsequent processing of these recording yields the ballistocardiographic signal, as detailed in the following section.

2.2. Video processing

The processing of each video sequence is conducted through the following steps:

2.2.1. Determination of mattress marker coordinates

To automatically determine the coordinates of a representative point on the marker—used for analyzing the displacements caused by the subject's physiological activity—the following sequence of operations is applied (see Fig. 2): first, the color image is converted to grayscale, and a Gaussian filter with a 7 $\times$ 7 pixel kernel is applied to reduce high-frequency noise. The filtered image is then binarized using an intensity threshold based on the standard deviation of the grayscale values. A morphological kernel filter is subsequently applied to the binary image to improve region uniformity [26]. Contour detection algorithms are then applied to this image to extract all significant contours, from which the most appropriate is selected based on geometric and photometric properties such as intensity, area, and circularity. Finally, the centroid of this contour is calculated using spatial moments with subpixel accuracy [27,28] enhancing the precision of the marker's location, thereby improving sensitivity to small vibrations in the mattress.

2.2.2. Robust optical flow analysis using pyramidal Lucas-Kanade processing

The application of optical flow algorithms for motion and velocity detection in video sequences is well established [29,30]. In this study, a four-level pyramidal implementation of the Lucas-Kanade algorithm is used, with a search window of 25 $\times$ 25 pixels. For each video frame, the algorithm updates the position of the centroid identified in step (i) and records its coordinates. This approach allows the system to discard

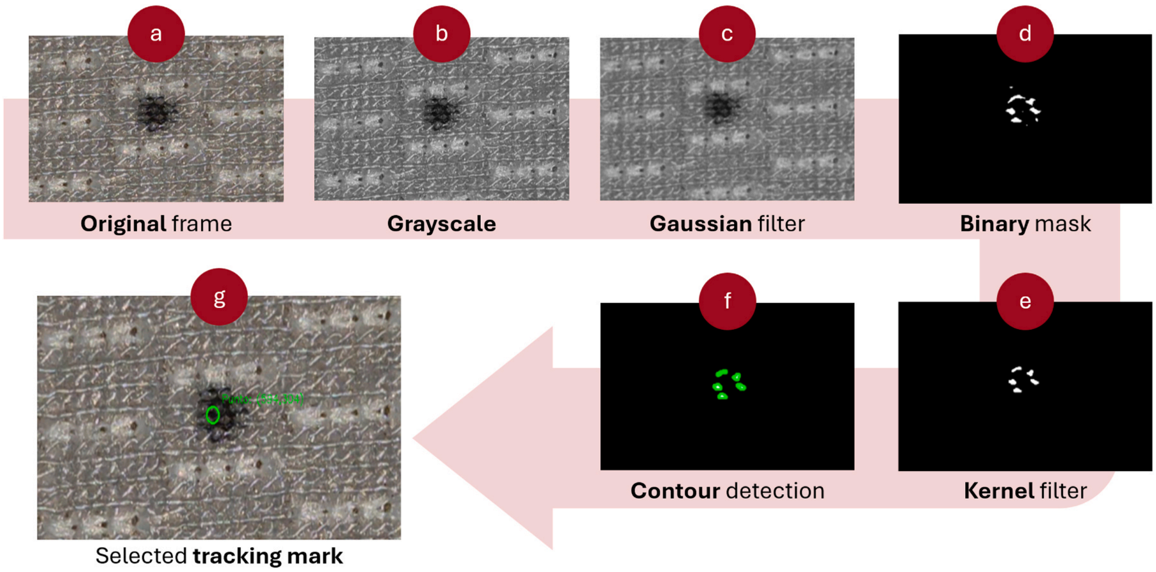

Fig. 2. Workflow for determining the coordinates of the mattress marker from the video sequence.

abrupt displacements or inconsistent coordinates caused by noise or artifacts and to recover the correct marker location in case of temporary tracking loss.

2.2.3. Filtering and parameter extraction

From the sequence of marker coordinates obtained in the previous step, two ballistocardiographic signals are derived: BCG-X and BCG-Y, corresponding to the displacements experienced by the tracked marker along the longitudinal (X) and transverse (Y) axes of the mattress, respectively. The BCG-X signal, reflecting longitudinal mattress movements, captures the dominant influence of cardiac activity, as it aligns with the direction of blood flow from head to feet [31]. In contrast, the BCG-Y signal, resulting from displacements along the mattress's Y-axis. primarily captures respiratory-induced deformations of the mattress along the transverse axis and does not register significant cardiac contributions.

To isolate the relevant physiological components, high-pass and low-pass digital infinite impulse response (IIR) filters are applied, separating the signals corresponding to cardiac pulse and respiration, respectively [22]. For respiratory signal extraction, a third-order low-pass filter with a passband frequency of 0.1 Hz and a stopband frequency of 10 Hz was designed. To extract the cardiac pulse component, a seventh-order high-pass filter with a stopband frequency of 0.1 Hz and a passband frequency of 0.5 Hz was employed. The estimation of the physiological parameters of interest, i.e., heart rate (HR) and breathing rate (BR), is performed from these filtered signals using two complementary approaches commonly adopted in BCG systems: frequency-domain analysis via the Fast Fourier Transform (FFT) [32] and time-domain analysis through peak detection [33].

In this work, peak detection for identifying individual heartbeats and respiratory cycles is implemented as follows: the cardiac signal, obtained by high-pass filtering the BCG-X signal, is further processed using the Square Wave Transform (SWT), as this technique preserves temporal alignment. A four-level SWT decomposition is conducted. The level-4 approximation parameter (S4) is normalized and enhanced with 50 % of the level-4 detail coefficients (D4). The Hilbert transform is then applied to obtain the envelope of the resulting signal, upon which peaks are detected using adaptive thresholding. Additionally, the BCG-Y signal is analyzed using the density of significant simples, a method previously reported to identify subject activity such as movements or coughing [7].

To validate the estimated heart rate, reference ECG signals were recorded using the AD8232 electrocardiograph (Analog Devices Inc., Wilmington, MA, USA). The deviation error between the reference HR and the estimated by the proposed system was computed as the absolute error between the two values.

2.3. Subjects under study

Table 1 presents the biometric characteristics of the three participants evaluated in this study. The research protocol was approved by the Ethics Committee of the University of Granada, Granada, Spain (nº 2446/CEIH/2021). Prior to data collection, written informed consent was obtained from all participants.

3. Results

3.1. BCG curves

Fig. 3(A) presents a representative example of BCG signals obtained using the proposed system from a subject lying in the supine position and a relaxed state. As observed, the BCG-X signal, associated primarily with cardiac activity, exhibits significantly lower amplitude than the BCG-Y signal, which predominantly reflects respiratory motion. These signals are subsequently processed using the algorithms described in the previous section to isolate and visualize the respective contributions of cardiac and respiratory activity. Fig. 3(B) shows the processed BCG-X signal (in blue), compared with the simultaneously recorded ECG signal from the electrocardiograph (in red). As can be seen, the cardiac activity, consisting of a series of oscillations in the BCG-X signal corresponding to individual heartbeats [34], coincides with the beats detected by the ECG system, demonstrating the expected time delay between the electrical ECG signal and the mechanical BCG signal. Fig. 3(C) shows the filtered BCG-Y signal, with non-respiratory movements removed, thereby highlighting the signal component attributable to breathing.

Fig. 4 shows the BCG curves recorded from the same subject while lying in four different positions on the bed: supine (A), prone (B), right lateral (C), and left lateral (D). As observed, the BCG-X signal, which

Table 1
Subjects' physiological characteristics.

Subject	Sex	Age (years)	Height (cm)	Weight (kg)
#1	Female	23	162	54
#2	Female	54	158	72
#3	Male	22	180	60

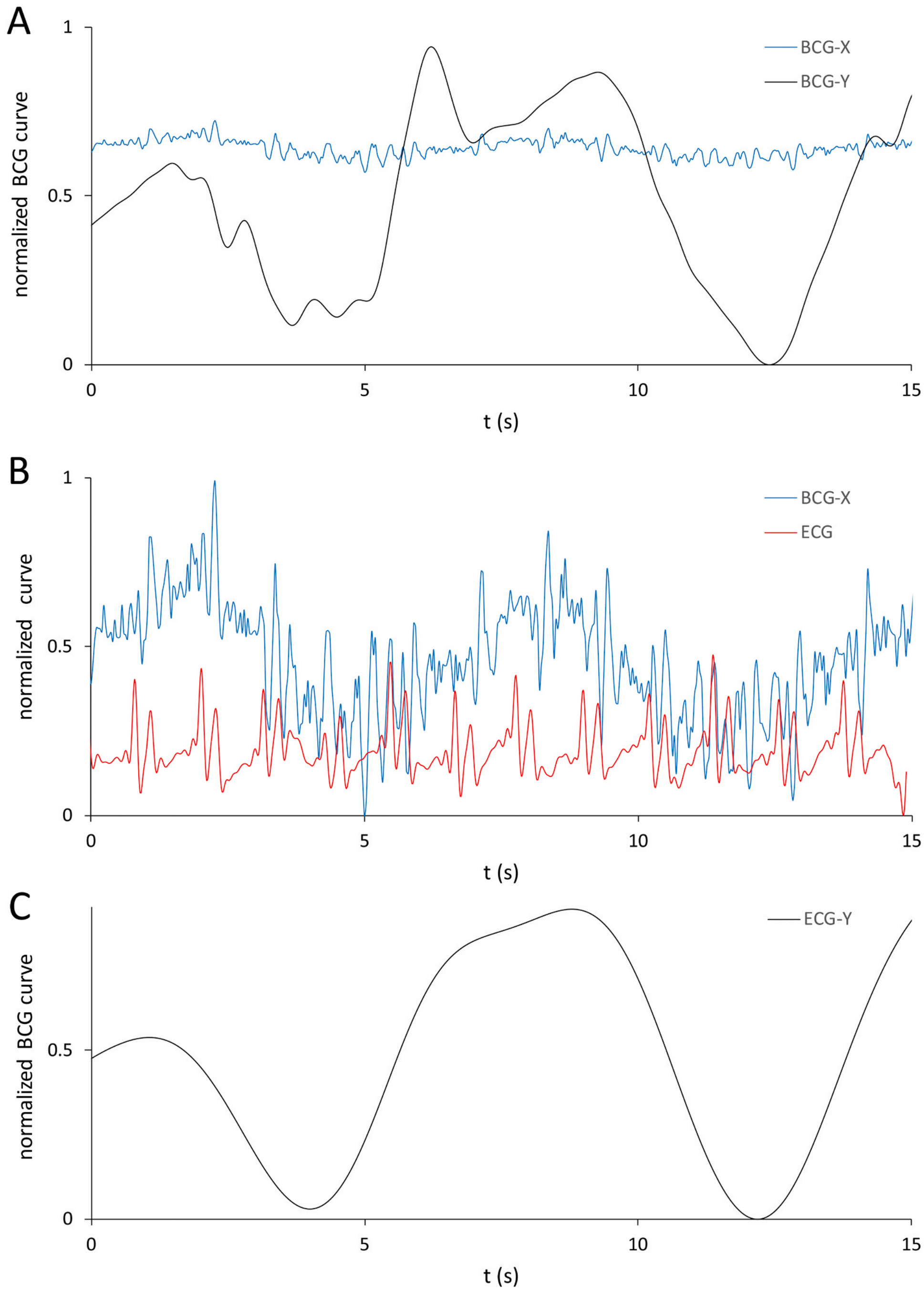

Fig. 3. (A) BCG signals acquired from a subject in the supine position. (B) Filtered BCG-X signal (blue) compared with the ECG signal (red). (C) Filtered BCG-Y signal, showing respiratory-induced motion.

reflects cardiac activity, is present across all positions. This signal also exhibits a notable respiratory component in positions (A) and (B), where the subject's chest or back is in direct contact with the mattress. In contrast, in lateral positions (C) and (D), the respiratory influence on the BCG-X signal is substantially attenuated or absent. The BCG-Y signal, on the other hand, consistently displays clear respiratory-related motion across all four postures.

3.2. Extraction of vital signs

Fig. 5 presents BCG signal sequences acquired from the three subjects in various positions and physiological states. These recordings reflect a range of heart rate and breathing rate conditions, including relaxation, elevated heart rate induced by mild physical activity, deep breathing, and forced rapid breathing. The objective is to evaluate the system's ability to estimate HR and BR under diverse physiological and postural scenarios.

The filtered BCG signals are further processed to estimate average HR and BR values for each sequence using the two proposed methods: frequency-domain analysis (FFT) and time-domain peak detection, as described in the previous section. Fig. 6 shows the peak detection results applied to the cardiac BCG-X signals from Fig. 5. In each graph, the high-pass filtered signals are shown in blue, the envelope extracted from processing this signal is displayed in black, and the significant peaks identified by the detection algorithm are marked in red.

The HR and BR values obtained from the BCG recordings presented

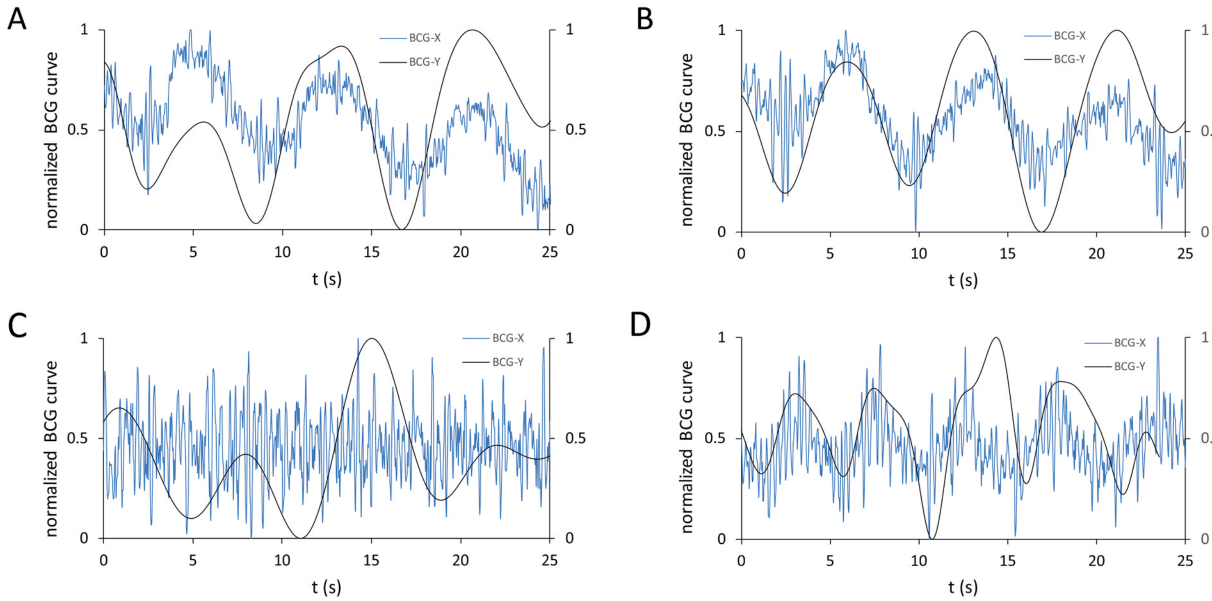

Fig. 4. BCG signals from a subject lying in the supine (A), prone (B), right lateral (C), and left lateral (D) positions.

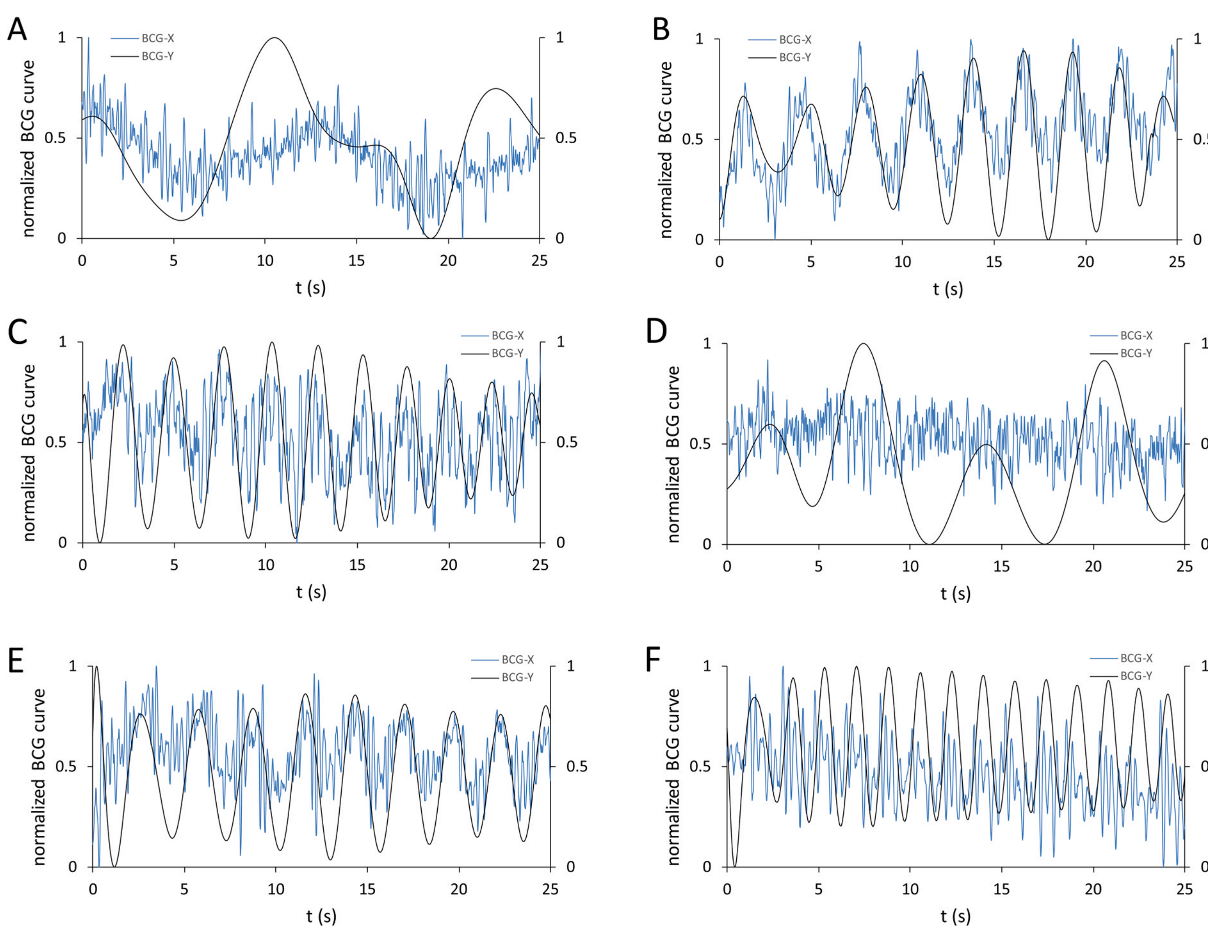

Fig. 5. BCG recordings obtained under different HT and BR conditions: (A) Subject #3, prone. (B) Subject #2, supine. (C) Subject #2, left lateral. (D) Subject #1, right lateral. (E) Subject #1, prone. (F) Subject #3, left lateral.

above are summarized in Table 2, along with the error relative to the ground-truth values. Reference HR values were derived from ECG signals, and BR values were obtained by manual breath counting.

For sequences A and D, which involved intentionally slowed breathing below the typical respiratory rates of adult subjects, yielded maximum HR errors of 2 bpm and 3 bpm using the FFT-based and peak detection algorithms, respectively. In these sequences, the BR was accurately estimated without error by both methods. Sequence B,

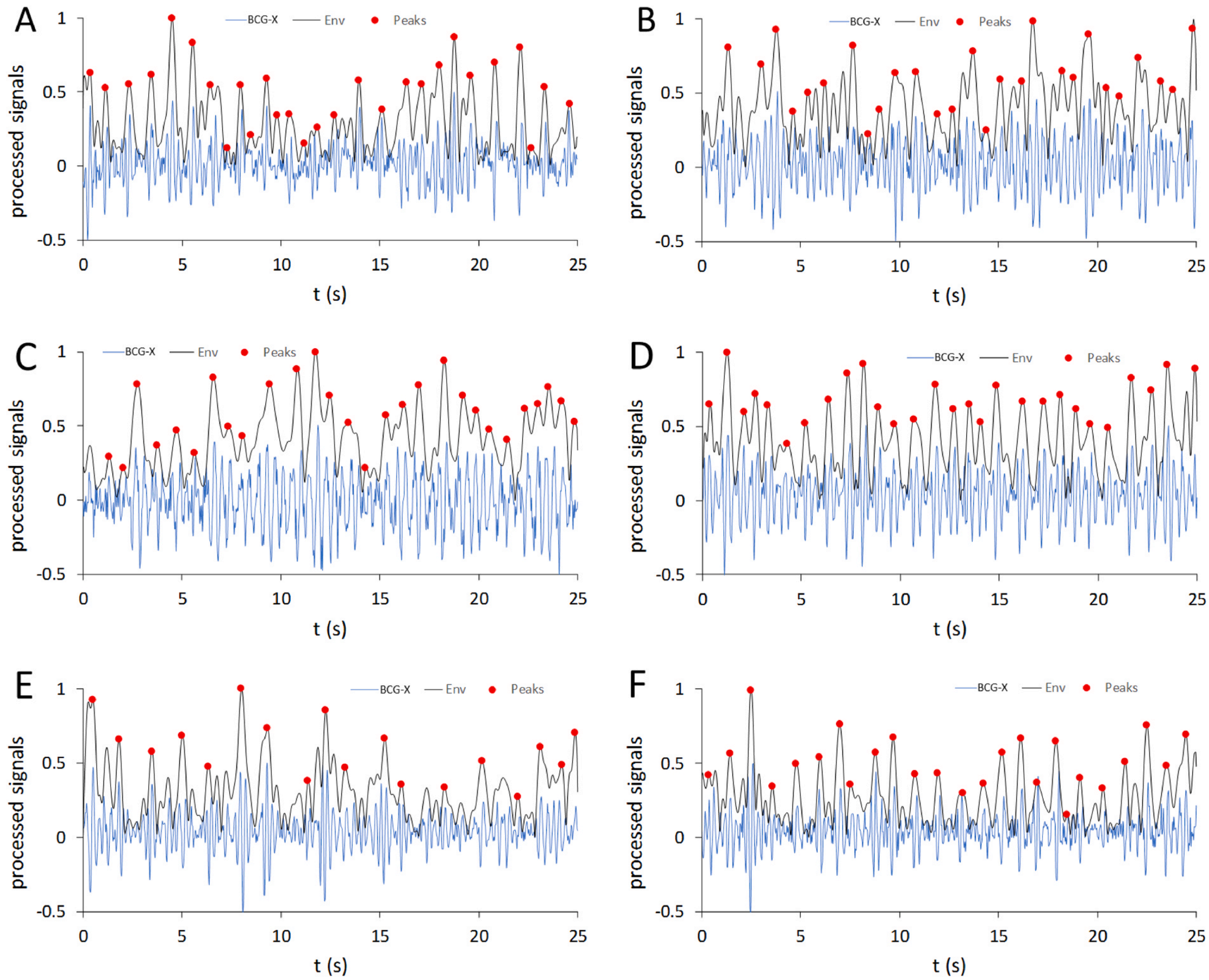

Fig. 6. Detection of significant peaks in the BCG-X signals from Fig. 5.

Table 2
HR and BR values obtained after processing sequences A–F from Fig. 6. Number between brackets represents the absolute errors.

Sequence	FFT		Peaks detection	
	HR (error) (beats/min)	BR (error) (breaths/min)	HR (error) (beats/min)	BR (error) (breaths/min)
A	57 (2)	5 (0)	62 (3)	5 (0)
B	60 (0)	20 (0)	63 (3)	19 (1)
C	62 (11)	24 (0)	67 (16)	24 (0)
D	67 (0)	10 (0)	67 (0)	10 (0)
E	41 (1)	22 (0)	43 (1)	22 (0)
F	57 (2)	35 (1)	60 (1)	34 (0)

corresponding to a subject in a relaxed state, showed no error in BR and HR estimation using the FFT-based method, while the peak detection method exhibited minimal errors of 5 beats per minute and 1 breath per minute, respectively. Sequence C, in which the subject presented a moderately elevated respiratory rate, resulted in higher HR estimation errors using both algorithms. This discrepancy may be attributed to subject position, amplified respiratory artifacts in the BCG-X signal, or mattress vibrations unrelated to the subject. Such outliers should be flagged for potential exclusion, especially when performing continuous temporal analysis, by comparing them with adjacent temporal segments. Sequence E, from a subject with naturally low HR, yielded accurate predictions for both HR and BR with negligible error. Finally, sequence F, simulating forced hyperventilation, also resulted in accurate estimations for both HR and BR using both algorithms, with a maximum error of 2 bpm (HR) and 1 breath per minute (BR).

Overall, the HR and BR prediction errors obtained with both FFT- and peak-based methods fall within the acceptable range reported in the literature for existing BCG systems [35,36] for most of the cases studied.

3.3. Activity determination

Fig. 7 illustrates in blue color a sequence acquired using the proposed RBCG system in which subject activity—specifically leg movement—is present. As can be observed in the figure, this activity causes a significant disruption in the BCG-Y signal, with amplitude components that substantially exceed those typically associated with either cardiac or

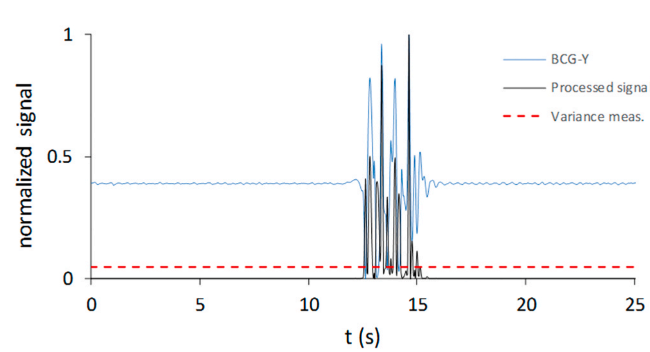

Fig. 7. BCG-Y signal containing activity-related artifacts due to leg movement (blue). Processed signal (black) and variance threshold (red).

respiratory signals.

To detect and reject sequences contaminated by subject activity, the processing method developed in [7] has been employed. This technique involves computing the density of significant samples for each sequence. This metric is defined as the normalized count of processed samples whose magnitude exceeds the variance of the overall sample set. A high density value (approaching one) indicates a clean signal, free from activity-induced artifacts, whereas a low density value (close to zero) suggests the presence of movement-related disturbances. This detection algorithm was applied to the sequences acquired using the RBCG system described in this work. The method demonstrated excellent performance, achieving a 100 % accuracy rate in identifying sequences corrupted by activity. In Fig. 7, the processed BCG-Y curve is shown in black, and the red line indicates the variance threshold used for classification. For this specific sequence, the calculated density of significant samples was 0.045, very close to zero, indicating a strong presence of subject-induced noise and correctly classifying the frame as corrupted.

3.4. Apnea detection

The proposed RBCG system, due to its ability to naturally separate cardiac and respiratory components from body-induced mattress vibrations, provides not only estimates of average BR, but also the capacity to detect apnea events, defined as involuntary interruptions or cessations in breathing.

Fig. 8 shows a representative sequence in which the subject voluntarily induced an apnea event, holding their breath approximately between seconds 18 and 35. The significant respiratory peaks, extracted from the BCG-Y signal using the peak detection algorithm described earlier, are marked in red. As shown, no breaths are detected during the apnea interval, while peaks are clearly present before and after the event. To identify such episodes, the system monitors the temporal intervals between consecutive respiratory peaks. If a prolonged period with no detected breaths is observed—exceeding a threshold derived from the subject's baseline respiratory rate, estimated from preceding sequences—the segment is flagged as a potential apnea event.

3.5. Detection of cardiac arrhythmia

One of the subjects included in this study presented a clinically diagnosed cardiac abnormality known as premature ventricular contraction (PVC). This arrhythmia is characterized by early depolarizations originating in the ventricles, resulting in heartbeats that occur earlier than expected within the normal rhythm. Fig. 9(A) illustrates this phenomenon: the red waveform corresponds to the ECG signal obtained from this subject in a relaxed state. Premature ventricular contractions are clearly visible as high-amplitude deflections, recurring approximately every six normal heartbeats. The simultaneously recorded BCG-X signal from the same subject, obtained using the system described in this work, is shown in blue. Significant peaks detected in the BCG-X signal, corresponding to both normal and premature heartbeats, are marked in black.

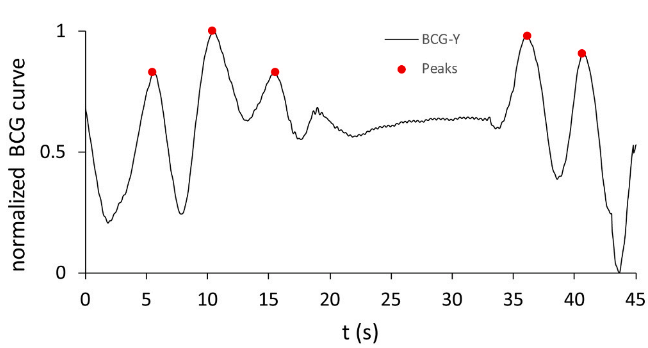

Fig. 8. BCG-Y signal exhibiting an apnea event (in black). Red markers denote detected respiratory peaks.

To assess the system's capability in arrhythmia detection, such as those exhibited by this subject, the instantaneous HR was estimated based on the time elapsed between two consecutive significant peaks. Fig. 9(B) presents the resulting instantaneous HR profile. The average HR obtained in this sequence is 67 bpm, closely matching the ground truth ECG (with a deviation of only 1 bpm). However, the instantaneous HR shows notable fluctuations, ranging approximately from 50 to 80 bpm under normal conditions. Crucially, when a PVC event occurs, it disrupts the regular heartbeat rhythm. As can be observed in Fig. 9(B), during PVC events the interval between two detected peaks becomes shorter than expected, causing a transient spike in instantaneous HR exceeding 110 bpm, as observed at 5.9 s, 12.5 s, and 19.2 s. The presence of these anomalous instantaneous HR values, which deviate significantly from the subject's baseline rhythm, are automatically flagged by the system as irregular heart activity in the subject or arrhythmic events. This result demonstrates the system's capability to not only monitor normal cardiac cycles but also detect irregular heartbeat patterns indicative of arrhythmic activity, thereby extending its potential for clinical cardiovascular monitoring applications.

4. Discussion

The video-based processing approach proposed in this study yields two orthogonal signals: BCG-X, reflecting longitudinal mattress displacements predominantly associated with cardiac activity, and BCG-Y, corresponding to transverse deformations primarily caused by respiration. This natural decoupling of cardiac and respiratory activities into distinct dimensions eliminates the need for signal separation or source isolation techniques commonly required in traditional BCG systems [12]. Consequently, the method simplifies both signal acquisition and processing pipelines, while reducing potential errors caused by signal crosstalk or mutual interference between signals, a common issue in other BCG systems.

In this study, vital signs estimation using well-established standard techniques—such as FFT analysis and peak detection—demonstrated reliable performance across various subjects and conditions. In the absence of movement artifacts, HR and BR were estimated with high accuracy, yielding maximum errors of 3 beats per minute and 1 breath per minute, respectively. These levels of precision are consistent with or better than those reported in existing literature on BCG systems. Nevertheless, certain limitations intrinsic to BCG technology persist. Specifically, external mechanical vibrations or suboptimal subject positioning can degrade signal quality, particularly for the cardiac signal (BCG-X), whose low amplitude makes it more susceptible to interference and detection loss.

In contrast to traditional RBCG systems that capture the subject's face or chest, the proposed method eliminates common limitations such as sensitivity to ambient lighting and facial movements. The system records exclusively a mattress marker, with no patient features appearing in the video. This design provides enhanced privacy, as stored recordings can be associated with subjects only through coded references, thereby ensuring protection of personal data. Additionally, it resolves the generalizability issues observed in mattress-integrated systems, where sensor characteristics, bed structure, and user variability necessitate frequent recalibration and limit scalability. Systems based on pneumatic, piezoelectric, electromechanical, or capacitive sensors often require custom integration and are difficult to extrapolate between different beds, require recalibration and adaptation for different subjects, and must be integrated into the mattress, thus precluding use with conventional beds.

In contrast, the proposed system offers a non-intrusive, low-cost, and calibration-free alternative, adaptable to various mattress types and a range of subjects without installation or calibration procedures. It enables autonomous, unattended home-based health monitoring and

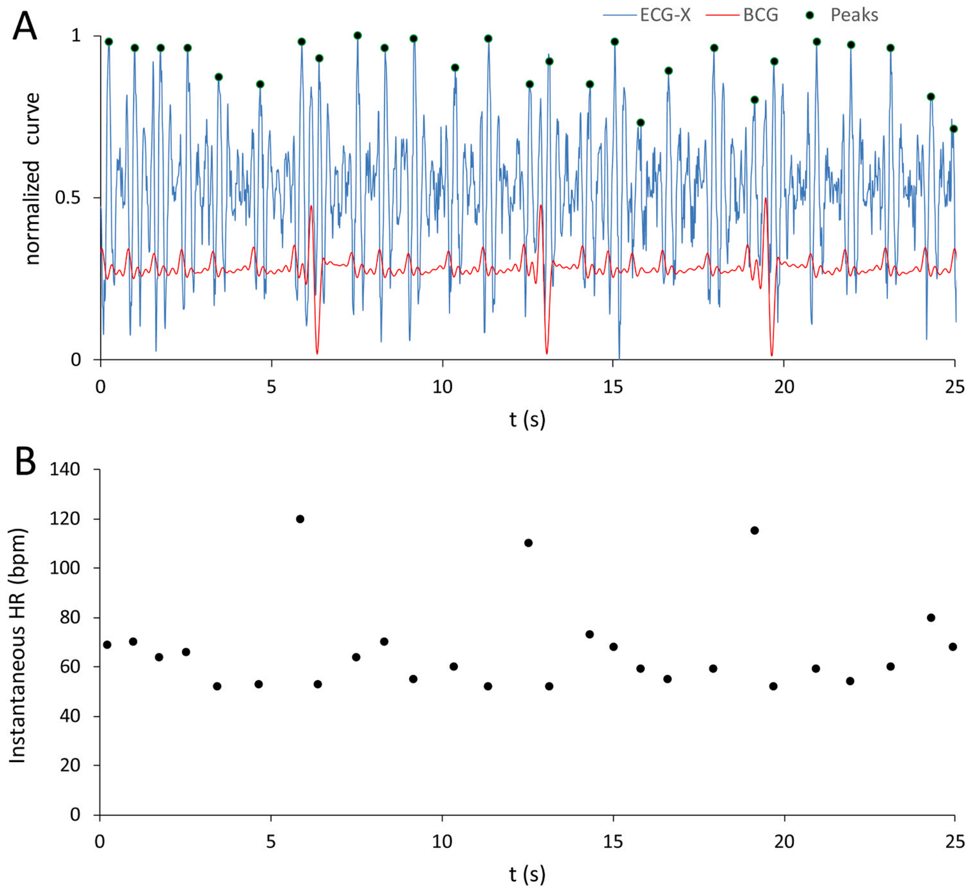

Fig. 9. (A) BCG-X (blue) and ECG (red) signals from a subject with PVC. (B) Instantaneous HR calculated from detected peaks.

subject follow-up using the subject's own smartphone. Furthermore, since the system does not process electrical signals, it is immune to electromagnetic interference. Lighting conditions—whether natural, artificial, or infrared—have minimal impact on performance, allowing for nighttime monitoring without disturbing the subject's sleep. This flexibility, combined with high signal fidelity and robust physiological parameter extraction, makes the proposed system a strong candidate for continuous, non-contact cardiopulmonary monitoring in both clinical and non-clinical settings.

In the presented work, video is recorded in short sequences of 30 s for individual evaluation. This video is transmitted via Wi-Fi to a server installed on a PC, where it is processed for parameter extraction (HR, BR, activity, etc.). The time required for the transmission and processing of each sequence is around 3 min. However, while each sequence is being processed, the system continues recording and sending new sequences that remain in a queue for later processing. This strategy inevitably entails delays in the case of long-term patient monitoring (an effect that, on the other hand, is also common in polysomnography systems, where signal processing is performed after monitoring is completed), which may affect real-time patient monitoring. The optimization of video processing can be addressed in future works based on this one where faster computation is required.

5. Conclusions

This work presents a novel remote ballistocardiography system based on video processing to monitor mattress displacements caused by a subject's cardiac activity, respiration, and movement while lying in bed. To the best of the authors' knowledge, this is the first documented approach that captures mattress motion rather than the subject directly, marking a significant advancement in non-contact cardiopulmonary monitoring. This work offers several advantages over existing BCG and RBCG systems documented in the current literature. It is completely non-invasive, requires no instrumentation of the subject or the bed, and operates under variable lighting conditions using standard smartphone cameras. In addition, unlike sensor-based mattress systems that often necessitate recalibration and integration, this solution is inherently portable, calibration-free, and compatible with a wide range of mattress types and user profiles, making it particularly well-suited for home-based or unattended monitoring.

In this study, the extracted BCG signals were processed to estimate the vital signs HR and BR using two widely recognized signal processing techniques: FFT analysis and peak detection. The resulting predictions demonstrated error rates within the expected limits for these types of algorithms, provided that the sequences were free from artifacts caused by the subject or external elements. The system also proved effective in detecting non-physiological disturbances such as muscle activity (e.g., leg movement), as well as physiological anomalies, such as apnea events and cardiac arrhythmias (e.g., premature ventricular contractions). These were successfully identified through analysis of parameters like the density of significant samples and the instantaneous HR and BR, enabling accurate classification of corrupted sequences and abnormal cardiac and respiratory events.

In summary, the proposed system represents a practical, accessible, and scalable alternative to traditional BCG monitoring, enabling reliable extraction of vital signs and detection of physiological anomalies without the limitations of direct contact or embedded sensors. Its unobtrusive nature and ease of deployment make it a promising tool for continuous health monitoring in clinical, residential, and remote care settings. Its unobtrusive nature and ease of deployment make it a promising tool for continuous health monitoring in clinical, residential, and remote care settings. The integration of this technique with wearable devices for biometric identification and other functions could provide it with greater potential in these fields.

CRediT authorship contribution statement

Nuria López-Ruiz: Supervision, Methodology, Investigation, Conceptualization. **María Agea:** Validation, Software, Methodology, Investigation. **Alberto J. Palma:** Writing – review & editing, Validation, Supervision, Funding acquisition, Formal analysis. **Pablo Escobedo:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Martinez-Olmos Antonio:** Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to translate text into English. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Antonio Martinez Olmos reports financial support was provided by Ministry of Science Technology and Innovation. Alberto J. Palma reports financial support was provided by Ministry of Science Technology and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The project was partially supported by projects PID2022–139852OB-I00 and PID2022–138727OB-I00 funded by MCIN/AEI/10.13039/501100011033 and by ERDF "A way of making Europe", by the "European Union".

Data availability

The data that has been used is confidential.

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