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Research article

Air-mattress system for ballistocardiogram-based heart rate and breathing rate estimation

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ABSTRACT

Sleep-related problems are widespread. Numerous devices for sleep monitoring are increasingly available, including smartwatches, sleep monitoring rings, etc. These devices accumulate and analyze a substantial quantity of physiological data. In this study, we develop a smart air-mattress system that can effectively aid health measurements. The proposed system adopts an air-mattress system to detect subtle changes in pressure and thereby collect micro physiological signals, including ballistocardiography (BCG) and breathing signals. The system uses ultrasonic signals to detect the subject's turning movements. To increase the signal recognition accuracy, the BCG signal is processed effectively to reduce noise interference engendered by the body movement during sleep and is processed using regression analysis for heart rate and breathing rate estimation. Accordingly, the proposed system is unconstrained and can be used to collect micro BCG signals, breathing signals, heart rate signals, and turning movements for the long-term healthcare.

1. Introduction

The recently global outbreak of the COVID-19 disease has inspired the strong need for remotely measuring platforms able to monitor the quality of patients' healthcare with affordable prices [1]. Continuous heart heat monitoring is essential for early detection of cardiovascular diseases, which would be key factors for the evaluation of human's health status. In addition, sleep-related problems, including insomnia and sleep apnea, are becoming increasingly extensive and affect modern people's daily lives. Sleep apnea has a causal link to high blood pressure, coronary heart disease, arrhythmia, heart rhythm failure, and stroke [2]. Heartbeat and breathing are crucial health indicators. Long-term heart rate measurements can enable the monitoring of heart status and signs of heart disease while respiratory monitoring can provide further information for tracking health over time.

Polysomnography (PSG) systems have been used in sleep tracking for a long time. Such systems use electrode pads stuck to the patient's body to acquire physiological signals [3]. PSG systems are highly accurate but can affect sleep quality. Accordingly, numerous unconstrained systems have been developed for acquiring and assessing human physiological data; examples of such systems include liquid mattresses [4], acoustic sensors [5], pillow sensors [6], pressure pads [7], and hydraulic beds [8]. Compared with intrusive measurement systems, unconstrained measurement systems offer improved convenience and safety.

Multiple studies have developed unconstrained physiological measurement systems in the recent decade. In Ref. [9], the authors presented a review of various signal processing methods as applied to the specific sensors, to analyze ballistocardiography (BCG)

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signals and extract heart rate and breathing rate, as well as determining sleep stages. Recent research efforts have shown that smart air mattresses can be effectively used to track physiological signals over time, including body movement, breathing signals, and BCG signals, and eventually to measure the tiny vibrations produced by the human body.

There are a variety of advanced sensing mechanisms integrated with the smart mattresses for the purpose of BCG measurement, for example, the polyvinylidene fluoride (PVDF) sensors [10,11], the piezoelectric pressure sensor [12], the electromechanical flm (EMFi) sensors [13], the strain-gauge based sensors [14], and accelerometers [15]. In the above approaches, added-on sensory and complicated signal processing is needed. In Ref. [16], a pressure sensor was used to measure vibrations caused by human movement in pressure. In some advanced approaches, detecting heart rate variability using millimeter-wave radar technology has also been tried [17,18]. However, as the reflected radar wave has to be measured, which is invasive to the subject in some sense.

To tackle the issue, in this study, we developed a smart air-mattress system based on the BCG-based measurement for monitoring the physiological characteristics of the human body. BCG can produce graphical representations of the mechanical activity of the heart and lungs [19]; it is adopted here to measure heart rate and breathing rate. The measurement systems are not invasive without the issues of electromagnetic interference. It is convenient to use with extreme low cost. The user does not require wearing any monitoring instruments and extra sensors attached with the mattress. Practically, it is appropriate to be used for long-term measurements of breathing rate and heart rate behavior of the subjects.

Body position or posture considerably affects sleep quality [20]. Three methods have recently been developed for measuring body position or turning movements during sleep; these methods entail the use of a pressure sensor in a mattress, motion sensor on a wearable device, or image recognition. In addition, multiple inertial sensors [21] accelerometers [22] and radar systems [23] have been used for body position or turning monitoring. Body position and turning monitoring during sleep is crucial because experts recommend that specific groups of people should avoid certain sleeping positions. For example, babies are not suggested to sleep on their stomach, pregnant women should not sleep on their back, and patients with sleep apnea are recommended to sleep on their sides.

2. System description

The air mattress considered in this research task is inflatable and can support the users with high sensitivity. The mattress can be inflated to support the weight of the subject up to 150 kg. The air pressure is controlled using a relief valve. This valve ensures that no air escapes the mattress and reduces experimental errors. There is a mattress-integrated air pressure sensor which is the only sensor needed to collect the necessary information.

The proposed approach possesses the following advantages for long-term care or therapy of sleep disorder.

- It is portable; the air mattress can be deinflated and folded for ease of transport and can autoinflate when plugged.
- Low cost. The mattress is mostly made of rubber and requires fewer electronic components and without the need of extra sensors.
- It can collect multiple types of physiological data, including sleeping time, breathing signals, BCG signals, and body movement information.
- It is noninvasive, no concern of radiative influence, and is able to detect all time for bedridden subjects' heartbeats and to consequently extract breathing rate, heart rate and heart rate variability.

The use of the proposed system for estimation based on the linear and random forest regression analysis of micro movement of heart activity with respect to 10 participants is realized and verified. The regression tresses can be used as a tool for heart rate estimation.

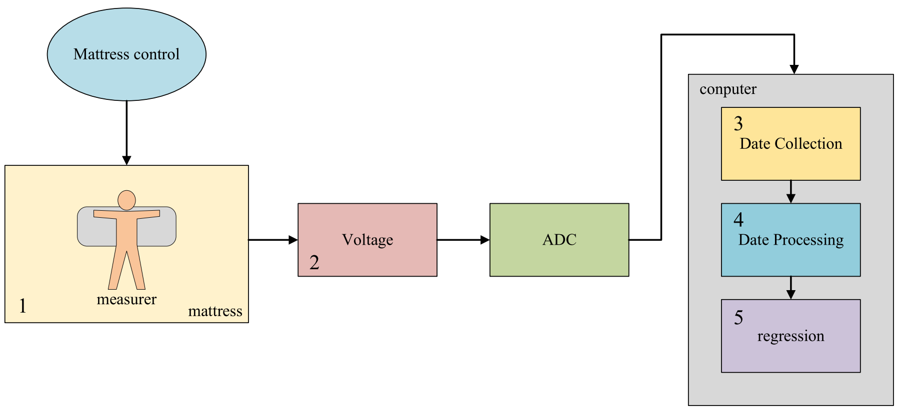


Figure 1. Illustration of the signal acquisition architecture.

3. Experimental setup

The smart air-mattress system has a compact architecture for monitoring physiological signals during sleep. For the development stage, signals collected by the air mattress are transmitted to a computer through a data acquisition system. The acquisition system consists of an interface and module for data processing, which saves data and uses it for subsequent processing. Pressure changes generated by the subject lying on the mattress are received by the air pressure sensor chip and converted into a differential voltage signal sent to the data acquisition system. The signal captured by the data acquisition system is input to an analog-to-digital converter (ADC) for conversion, and the signal is processed then. Because body movement noise may affect measurement precision, appropriate filters are used to remove interference to improve the subsequent recognition. To avoid body movement–induced false information, an outlier is applied to filter out the noisy signals that differs substantially from the rest of the data. Figure 1 displays the signal acquisition system. Table 1 lists key specifications of the air mattress.

This study fulfilling the established ethical guidelines has been approved by the Research and Development Committee of National Chung Hsing University. Informed consent was obtained from each subject before experiments.

3.1. Air-mattress system

The experimental air-mattress system is composed of an air mattress, a tube, an air pressure sensor, a unidirectional valve, a relief valve, a pump, a digital processor, and a controller, see Figure 2. The air mattress is made of lightweight rubber. Its length and width are 75 and 37 cm, respectively. Because of its rubber construction, it can be easily folded into a smaller size and carried in a bag.

The air mattress contains 128 air cells. Each air cell has no air and is not affected by the inflation system. The cell unit remains in the vacuum state with the length and width of 2 cm and 2 cm, respectively. When the subject lies on the air mattress, the air cells can automatically increase the contact area between the body and the mattress through the compressible characteristics of air. This is designed to improve measurement accuracy.

If the mattress is unoccupied, it will undergo a decompression process; it is inflated again when an individual lies down. The process is slow to prevent the inflator pump from running continuously, thus reducing power consumption.

3.2. Data acquisition

The system acquires differential voltage signals captured by the air pressure sensor. The acquisition card extracts tiny voltage signals and features a 24-bit high-resolution ADC (delta–sigma) unit and support for the NI DAQ-9178. We collected expansive samples of physiological signals and conducted validation to determine quality of the row data. Data were collected through a continuous sample acquisition process.

3.3. Signal filtering

Finite impulse response (FIR) filters are commonly used to process digital signals. Four types of digital filters are commonly used: low-pass, high-pass, bandpass, and band-rejection filters. A FIR filter is a dynamic linear system describing the dynamic relationship between input and output as

$$y(n) = \sum_{k=0}^{N} h_k x(n-k) \tag{1}$$

where $x(n)$ represents the n-th sampling input signal, $y(n)$ represents the output signal, $h_0, h_1, \ldots, h_N$ represent the impulse response values, and N represents the filter order.

Because of the low frequency of the BCG signals, in our experiments, a FIR characterized by (1) up to three order ($n = 3$) is good enough to extract meaningful signals while filtering out undesirable noises.

3.4. Signal processing

In general, acquired signals are affected by various types of interference. To obtain accurate data, the system must preprocess the acquired signals to remove unnecessary noise and outliers. In the experiment in this study, a boxplot was used to eliminate erroneous signals generated by body movement.

The system executes further processing to extract heart rate and breathing rate signals. The processing steps include time-domain analysis, peak enhancement, peak detection, erroneous peak rejection, and heart rate and breathing rate calculation.

Table 1
Fundamental features of the smart air mattress.

Operating voltage (V)	Sensitivity (mV/kPa)	Response time (ms)	Frequency (kHz)	Air pressure range (kPa)
2.7–3.3	54	1	1	0–50

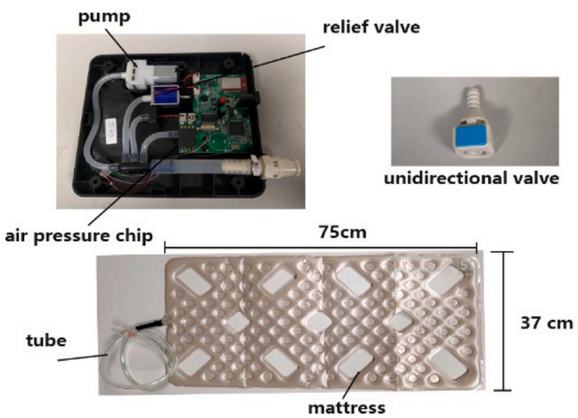


Figure 2. The air-mattress system under consideration.

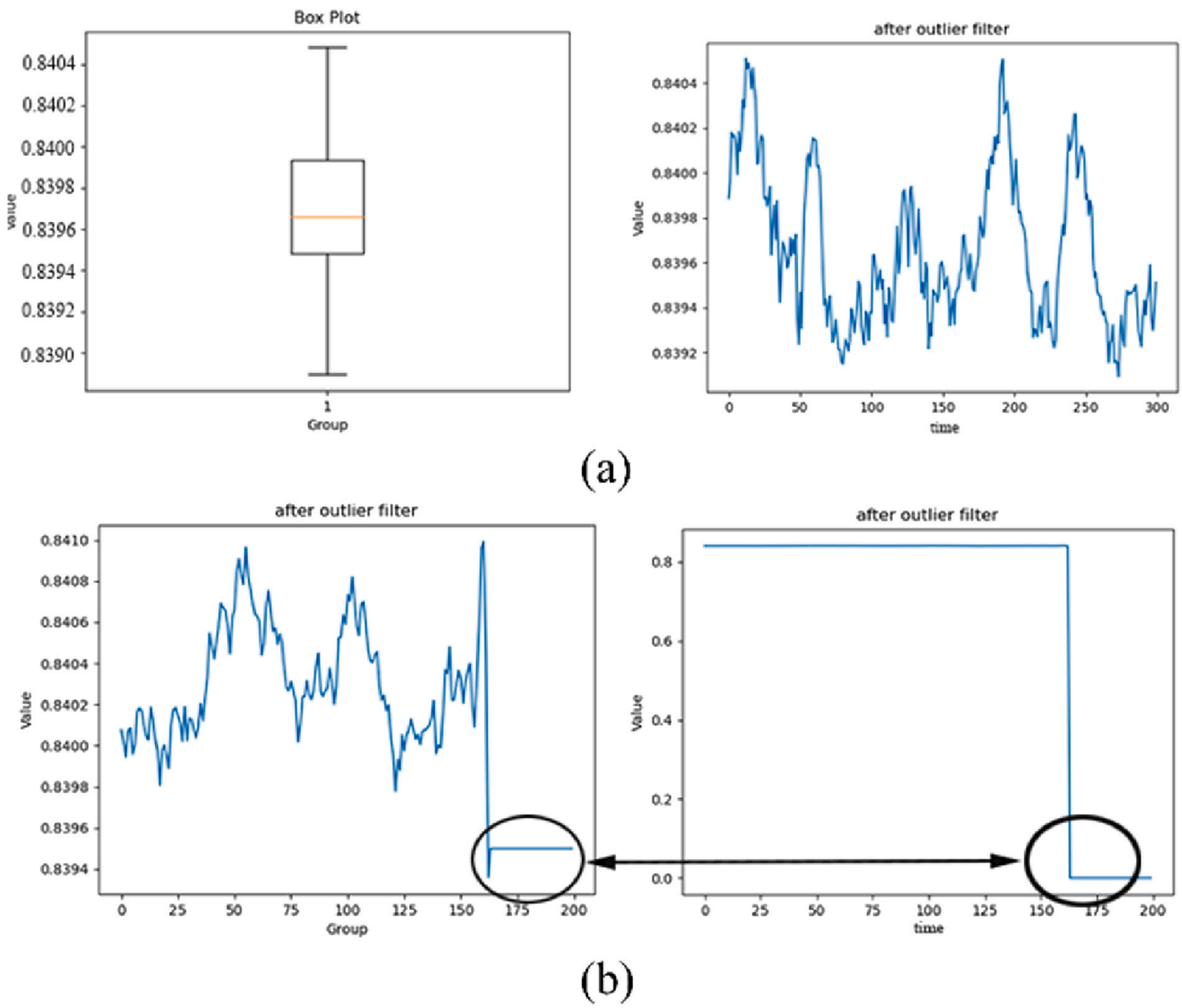


Figure 3. Signal before and after filtering. (a) Normal signal. (b) Signal after outlier filtering. The time unit is 0.1 s.

3.5. Ultrasonic detection of turning movements

People often turn over while sleeping. According to estimates, people turn over as many as 20–30 times per night. An air-mattress system alone can detect substantial changes in air pressure but cannot accurately perceive turning movements. Accordingly, we developed a module comprising ultrasonic sensors to detect turning movement signals. The installation location of the sensor module is crucial. We have tested various installation locations on the human body. The results of detection with respect to various locations were compared and the most appropriate location was set.

3.6. Regression analysis

Regression is a data analysis method that mainly explores the relationship between independent variables and dependent variables, whether the relationship is linear or nonlinear. Inferences or predictions can generally be made through the establishment of regression models.

Many types of regression analysis methods commonly seen include linear regression, logistic regression, polynomial regression, stepwise regression, and ridge regression. Choosing a suitable regression method is not easy because whether the relationship between the independent and dependent variables is linear or nonlinear is unknown in advance. Here, two regression methods, namely linear and random forest regression, were used to analyze and compensate for errors in the input and output values.

4. Experiments

4.1. Outlier

We proposed a boxplot to eliminate undesirable errors caused by extraneous body movements. The box-whisker plot is a method of using five statistics to describe the data including minimum value, maximum value, median value, the 75^{th} percentile (Q3) and the 25^{th} percentile (Q1). IQR denotes the box length between Q1 and Q3, i.e. Q3-Q1. The minimum and maximum values are defined, respectively, Q1-1.5*IQR and Q3+1.5*IQR. A point outside the boundary is regarded as outlier. For the current experiment, before and after performing the outlier detection are illustrated in Figure 3(a) and (b) respectively.

4.2. Time-domain analysis

We set up appropriate band-pass filters based on the natural frequency discrimination of breathing and heart rate signals [24,25] to separate both signals from the micro air pressure change of the smart air mattress.

The acquired signals were filtered to smooth analysis in this study. The sample results of the filtration process are illustrated in Figure 4 for 30 s with the time unit being 0.1 s. The upper panel illustrates the original signal; the second panel illustrates the signal

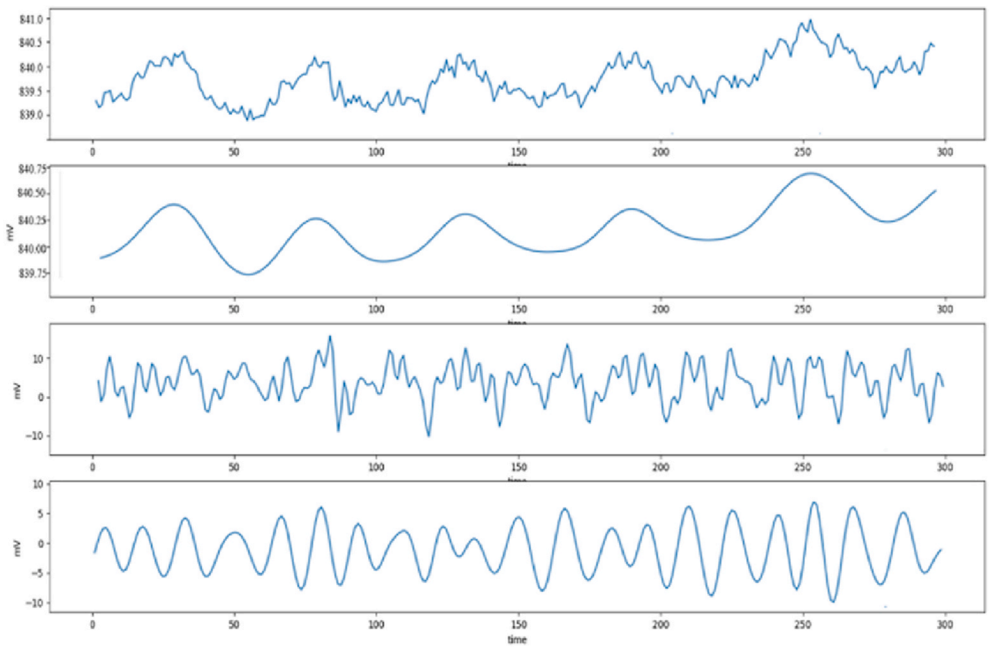


Figure 4. Sample extraction of the measured BCG signals where the time unit is 0.1 s. From the top to the bottom, the measured signal, the extracted breathing signal, the ambiguous BCG signal, and the extracted BCG heart rate signal.

filtered by a 0.2–0.5 Hz bandpass filter, which was regarded as the breathing signal; the third panel illustrates the signal filtered by a 0.5–4 Hz bandpass filter, which was regarded as the ambiguous BCG signal; and the bottom panel illustrates the signal filtered by a 0.7–2 Hz bandpass filter, which was regarded as the final BCG heart rate signal.

4.3. BCG and ECG signal comparison

During the BCG signal measurement process, we also recorded ECG signals for comparison. Figure 5 illustrates the results of comparison of signals collected over a 20 s period; the blue plot represents the ECG signals recorded by an ECG acquisition system, and the black plot represents the BCG signals detected from the proposed air mattress.

4.4. Peak enhancement

Peak enhancement [26] can be executed to improve signals and normalize signals to the same reference point. A peak detection approach ensures effective signal detection. Such an approach involves only linear conversion; thus, the position of the signal point is not affected. Different iteration times can be selected in each system, but more iterations are not necessarily better. In the iterative process, a large signal can easily be over enhanced. We have applied different iteration times and compared the results.

The peak enhancement results are illustrated in Figure 6. The upper panel presents the origin signal, the middle panel presents the results obtained after only one iteration, and the bottom panel presents the results obtained after two iterations. When two iterations were used, the peak of the weak signal was eliminated. We noted that applying only one iteration was sufficient to enhance the signal.

4.5. Peak detection

We used one-dimensional data to identify the highest peak. The local maximum was identified between neighboring values. If a special signal was encountered, a specific method was used to find its peak.

Because the original signal peak was enhanced, all peaks became more obvious and easier to identify. After conducting peak detection, we can accurately identify the J peak position of the BCG signal. After fulfilling the step for determining the peak position, we proceeded to calculate the corresponding heart rate. We used a compensation approach to address problems associated with the missing peaks. The results of the peak detection process are illustrated in Figure 7.

4.6. Erroneous peak rejection

Signal preprocessing can reveal the BCG signal peak in each band. If the original data contain missing values, the corresponding peaks may be wrongly enhanced and thus eliminated.

In the proposed system, an average JJ interval is determined for a signal. Subsequently, a signal value that is within ±30% of the average JJ interval value is considered reasonable. If the signal value is not within this interval, it would be considered invalid. If the exact value is less than 30% of the total value, then the corresponding data was ignored (Figure 8).

Figure 9(a) and (b) show, respectively, the BCG heart rate compared with the ECG heart rate (as the ground truth) for a male subject at age 24 and a female subject at the same age. The data were collected for around 2.5 min with 10 s as a sampling period. The average heart rate for the male subject is lower than that of the female. The average errors are, respectively, 5.68% and 5.60%.

4.7. Ultrasonic detection of turning movements

The installation location of the ultrasonic sensor module is crucial (Figure 10). In the previous academic studies, turning movement signals were measured from the upper body, mainly in the chest, hands, waist, buttocks. In the present study, we have explored different installation positions by considering several factors including signal quality and reliability, installation difficulty, cost, etc. It was observed that considering measurement sensitivity the best positions for the installation locations were the places where the chest and the buttocks touch the mattress. The testing subject rests for 5–10 min to reset the physical status. We wait for the measurement panel to display stable data and commence data collection. When lying down, the subject sleeps on one's back 15 min, then on left decubitus 10 min and finally on right decubitus 10 min. Total measurement time is then 35 min.

If a subject is lying down, the ultrasonic signal is theoretically unchanged. Three sleeping positions under consideration is shown in

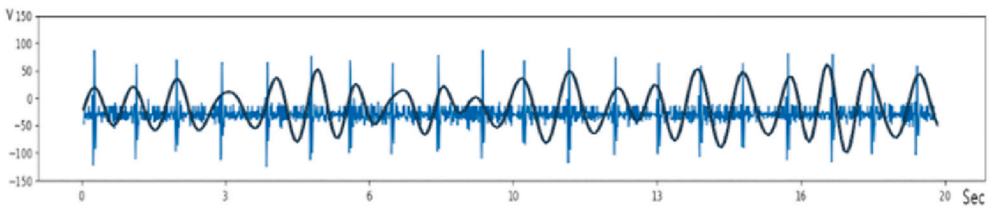


Figure 5. Comparison of BCG (in black) and ECG (in deep blue) signals.

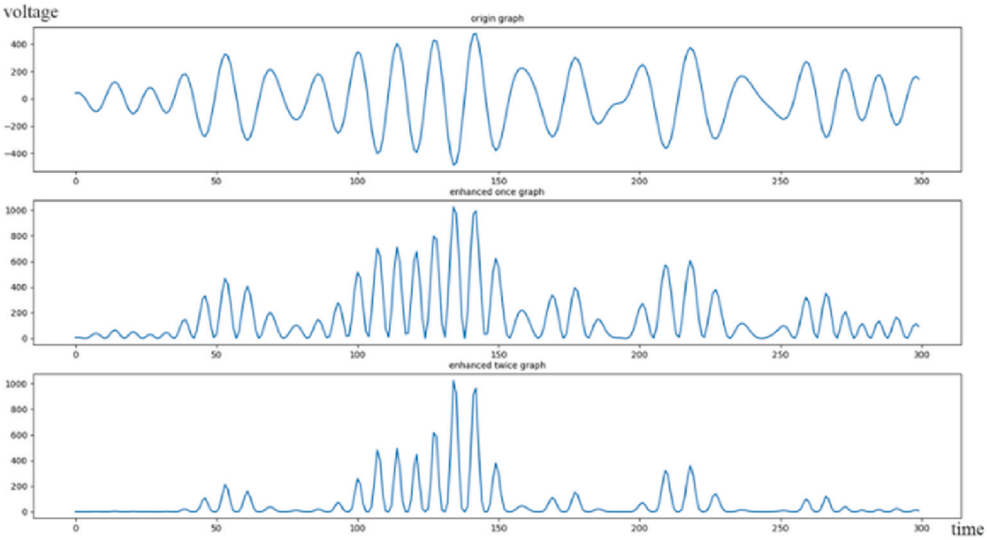


Figure 6. Signal peak enhancement where the time unit is 0.1 s.

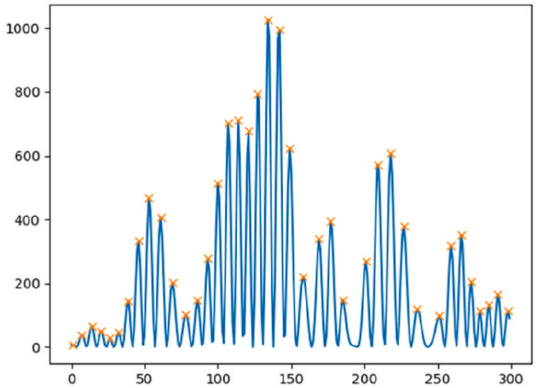


Figure 7. Signal peak detection where the time unit is 0.1 s.

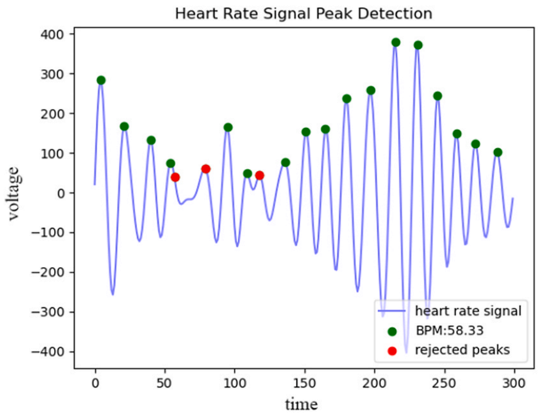
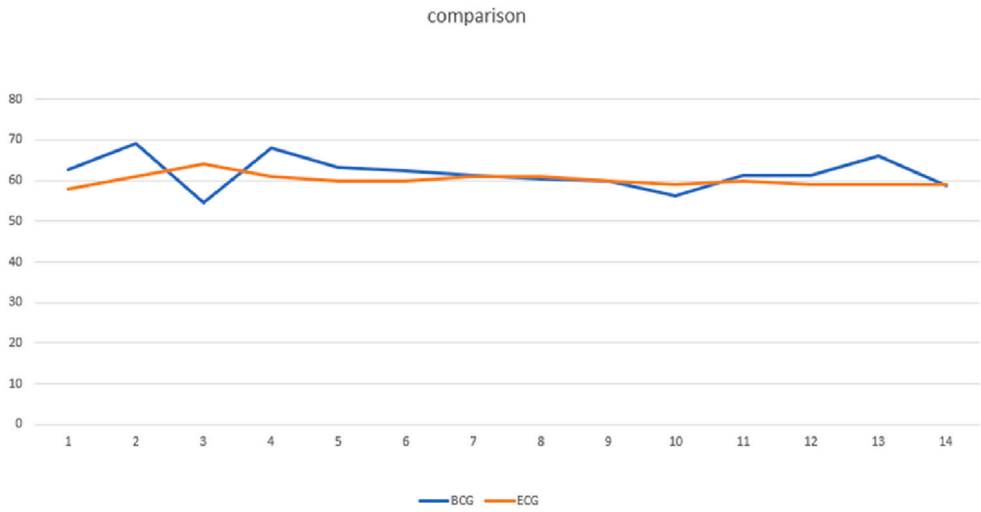
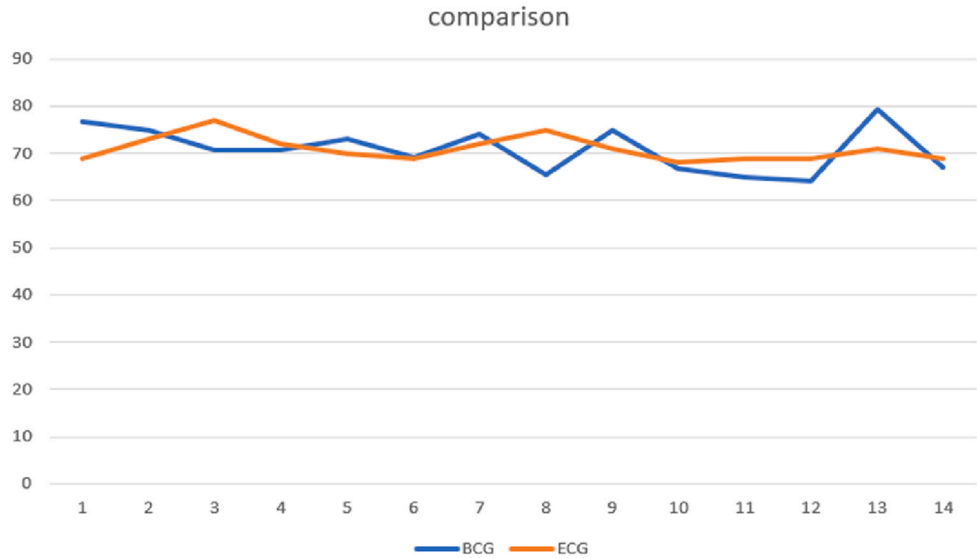


Figure 8. Heart rate estimation where the time unit is 0.1 s.



(a)



(b)

Figure 9. Comparison of BCG and ECG heart rate measurements of the (a) male and (b) female subjects with the same sampling period.

Figure 11. When the body moves, the distance between the sensor and the subject would change (Figure 12(a) for male subjects and 12 (b) for female subjects). In this study, the sampling frequency was set to 10 Hz. Every signal change was determined to be accompanied by a small change in the subject's position. We calculated the average value of movements every 3 s and compared it with a predetermined value (i.e. 5). When the value exceeded 5, the subject was judged to have turned over. The starting reference point was the lying status.

4.8. Linear regression

Traditional linear regression is used first to model the relationship between the response-ECG signal, and the explanatory (independent) variables-BCG heart rate, breathing rate and sleeping position. One is referred to Ref. [28] regarding details of applying the regression analysis. Ten volunteers with 5 females and 5 males aged 20–30 joined the experiment. The regression equations for two and three independent variables are obtained by running Python, respectively, by

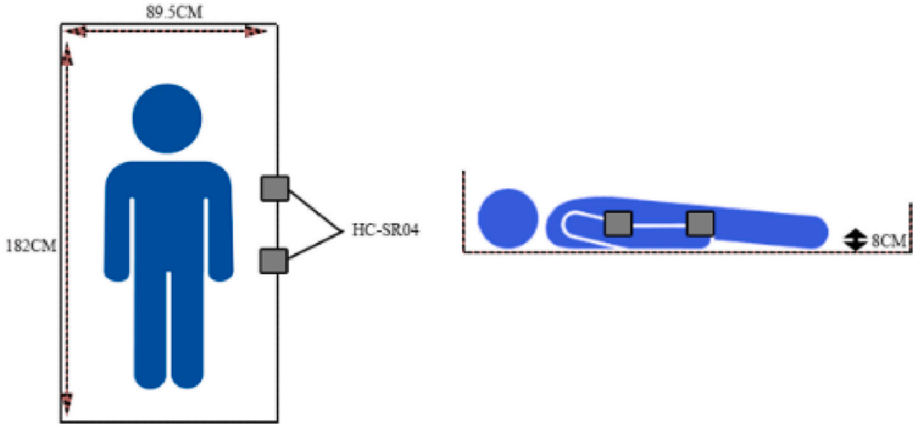


Figure 10. Installation locations of ultrasonic modules.

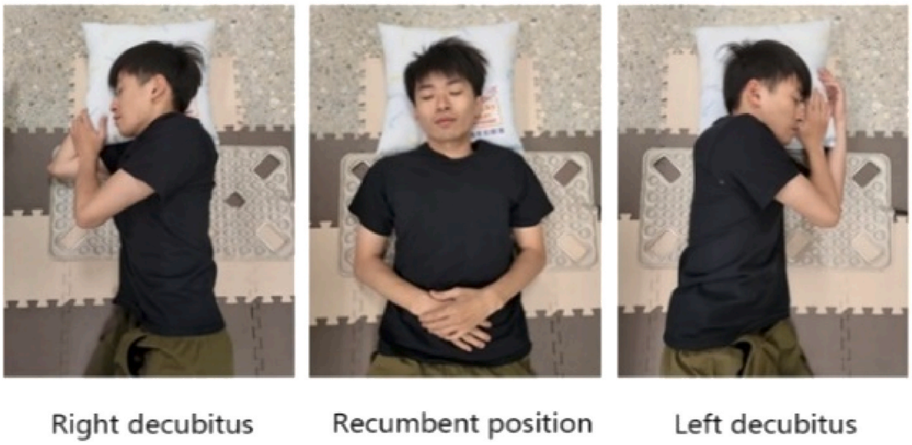


Figure 11. Three sleeping positions under consideration.

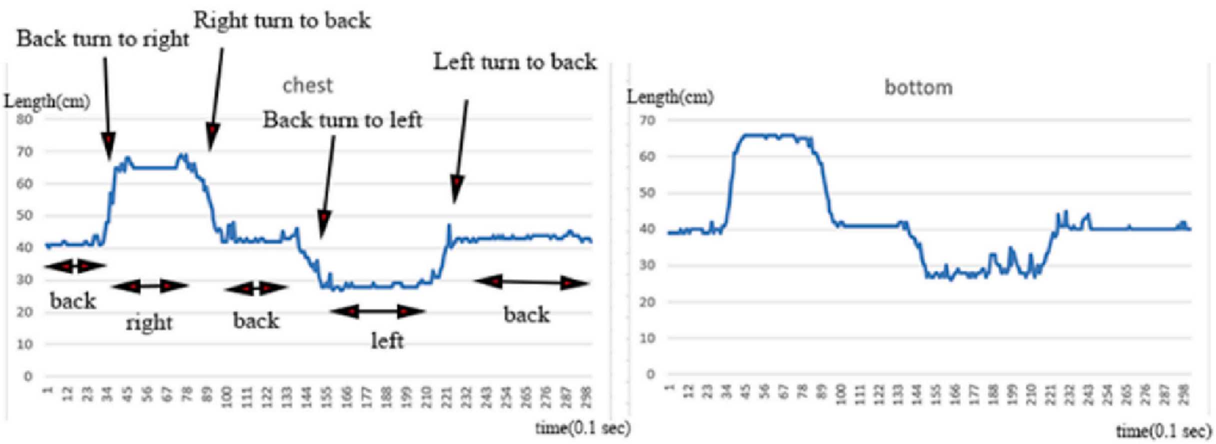


Figure 12. Turning movement signals.

$$ECG = 0.968 \cdot BCG - 0.203 \cdot breath + 7.363 \quad (2)$$

$$ECG = 1.007 \cdot BCG - 0.0958 \cdot breath + 0.333 \cdot position + 1.822 \quad (3)$$

Table 2
Linear regression results.

(a) Results of two independent variables (*BCG* and *breath*).					
Regression Design					
R value			0.886		
R-squared			0.786		
Adjusted R-squared			0.783		
Standard deviation			5.80		
Number of observations			179		
Analysis of variance (ANOVA)					
Degree of freedom		SS	MS	F	Significant value
Regression	2	21748.53	10874.26	322.74	1.32E-56
Residual	176	5930.134	33.694		
Sum	178	27678.66			
	Coefficient	Standard Error	*t*-statistic	*p*-value	
Intercept	7.364	4.665	1.578	0.116	
BCG	0.968	0.041	23.505	3.55E-56	
Breathing Rate	−0.203	0.153	−1.324	0.187	
	Lower limit 95%	Higher limit 95%	Lower limit 95%	Higher limit 95%	
Intercept	−1.843	16.577	−1.843	16.591	
BCG	0.887	1.050	0.887	1.050	
Breathing Rate	0.187	0.10	−0.506	0.10	
(b) Results of three independent variables (*BCG*, *breath* and *position*)					
Regression Design					
R value			0.857		
R-squared			0.735		
Adjusted R-squared			0.736		
Standard deviation			5.805		
Number of observations			373		
ANOVA					
Degree of freedom		SS	MS	F	Significant value
Regression	2	460532.213	15351.07	455.492	1.20E-123
Residual	369	12436.096	33.7021		
Sum	372	58489.308			
	Coefficient	Standard Error	*t*-statistic	*p*-value	
Intercept	1.822	2.995	0.608	0.543	
Position	0.333	0.3888	0.857	3.92E-01	
BCG	1.007	0.028	35.958	1.20E-122	
Breathing Rate	−0.096	0.113	−0.851	0.395	
	Lower limit 95%	Higher limit 95%	Lower limit 95%	Higher limit 95%	
Intercept	−4.067	7.711	−4.067	7.711	
Position	−0.431	1.098	−0.431	1.098	
BCG	0.952	1.062	0.952	1.062	
Breathing Rate	−0.317	0.126	−0.317	0.126	

*For briefness, BCG denotes the BCG hear rate.

where *BCG* denotes BCG heart rate, *ECG* denotes ECG hear rate, *breath* denotes breathing rate and *position* refers to sleeping position. Statistical results corresponding to (2) and (3) are presented in Table 2, indicating that the *p*-values for the BCG heart rate and body position are smaller than 0.05 (Table 2(a)) but that for breathing rate is greater than 0.05 (Table 2(b)). Here, *p*-value is defined as the step to accept or reject a null hypothesis. That's is, the prediction that holds a lower *p*-value (such as <0.05) is likely to be more meaningful addition to the model as a change in the prediction values are related to the changes of the response variable. This indicates that the breathing rate might not be fully supported by a complete regression. Thus, breathing rate and heart rate are not necessarily directly related in human beings. This is consistent with the results of recent medical research [27].

R^2 values indicate the proportion of the variance explained by variables in a regression model. The R^2 measure can provide an estimate for judging the performance of a model. In the case of involving three inputs to one output, the model variables explain approximately 73% of the variance.

After including sleeping position as a variable in the model, we observe that the regression result is worse than it was when two independent variables were adopted. These results thus indicate that estimation via the air mattress decreases if high-level noise is present or the subject is side sleeping. It is quite nature that when the subject doesn't sleep on the recumbent position, micro heart movement is hard to be directed to the air mattress leading to the inferior measurement sensitivity.

4.9. Random forest regression

Random forest regression analysis [28–31] was used in this study and involved into two parts. In the first part, the random forest regression model compared BCG heart rate and breathing rate with ECG heart rate values. In the second part, the regression model compared BCG heart rate, breathing rate, and position with the ECG heart rate values.

For the training part, we adopt the weighted impurity function to split nodes given by

$$G(y, N_s) = \frac{1}{N_s}\left(\sum_{y_i \in y_{left}} \left(y_i - \bar{y}_{left}\right)^2 + \sum_{y_j \in y_{right}} \left(y_j - \bar{y}_{right}\right)^2\right) \tag{4}$$

where N_s is the number of training samples of the current node, y_i and y_j are, respectively, the values of left and right nodes, $\bar{y}_{left}$ and $\bar{y}_{right}$ are, respectively, the mean values of left and right nodes. The data selection method based on the cost (4) used in the training process is bootstrap. Bootstrap is a kind of uniform sampling with replacement from a given training set. It reselects data and add to the training set. When the sample is normally distributed, the sampling method is suitable for the situation of normal distribution of samples.

The following parameters were set for the analysis: the maximum number of trees was set to 100, the measurement quality indicator of the split point was mean square error, the minimum number of samples required to split internal nodes was 2, and the minimum number of samples required for leaf nodes was 1. For regression tree construction, we used 70% of the data as the training set and 30% as the testing set.

To analyze the importance of variables, we import three conditions listed in Table 3 to generate three models. Figure 13(a-c) show convergence of the final regression with respect to one, two and three independent variables after performing random tree regression, where the measured BCG heart rate values have gradually converged to the ECG heart rate values, i.e. the near ground truth values, after the decision tress developed completely. The full-sized figures of the decision trees can be viewed by accessing

https://drive.google.com/drive/folders/1VIBT4rV9bVu4EUncjkeuSGJh_AWzoFg3?usp = sharing.

The computer program for executing the heart rate estimation can be accessed via the following link:

https://drive.google.com/drive/folders/1zWBIZKigb_pFbUMVLqroCZ_YeltRKUZC?usp = sharing.

The results of random forest regression are superior than the results generated by linear regression. As mentioned, breathing rate and heart rate are not directly related to human beings. Although the third tree develops more branches, breathing rate accounted for only 3% of the feature importance. Therefore, the impact of breathing rate is insignificant, and the results obtained after including breathing rate and sleeping position are inferior than other results. Under this situation, the importance of BCG is reduced substantially.

It is reasonable to recognize the fact that the subjects sleep on sides decrease measurement sensitivity and thus reduce estimation accuracy. Rather, lying down would be a better choice for measurement to aid an accurate estimation. However, it is impractical to ask the subjects to keep sleeping the way during a normal sleep period.

There are still technical issues needed to improve for real-world experiments. For example, the regression tree analysis cannot filter out extremal values in an active manner. A pre-data processing such as a data smoother would be beneficial to the subsequent data training and estimation under this situation.

5. Conclusion

This study has developed a noncontact air-mattress system for monitoring physiological signals and body movements of users. It is demonstrated to be able to detect breathing rate and heartbeat rate of the subjects with reasonable accuracy for the health care purpose. The air-mattress system equipped with a high-sensitive signal processor to sense subtle breathing signals and heart rate signals by sensing the micro air pressure change. The results were verified by conducting real-world experiments. Compared with the advanced approach adopting mmWave radar or Lidar to detect heartbeat movement of patients, the proposed approach is inactive and non-intrusive and without the issues of EMI or EMC. We have also presented linear and random forest regression analyses to develop the model for heart rate estimation. The results support the fact that breathing rate and heart rate are not necessarily directly related in human beings. Error analyses based on regression analyses are provided and discussed.

The proposed system is combining with other noncontact sensors, including blood pressure monitors and thermometers, to allow for comprehensive physiological monitoring. When combined with internet connectivity, the system is expected to provide users with a convenient health monitoring option.

Table 3
Results of variable importance analysis.

Input	Output	Mean absolute error	Mean squared error	R^2 valued score	Ratio of relative importance
BCG	ECG	3.403	19.786	0.846	NA
BCG, Breathing rate	ECG	3.423	20.041	0.844	BCG: 0.967 breathing: 0.033
BCG, Position, Breathing rate	ECG	3.818	27.978	0.816	BCG: 0.63 breathing: 0.261 position:0.109

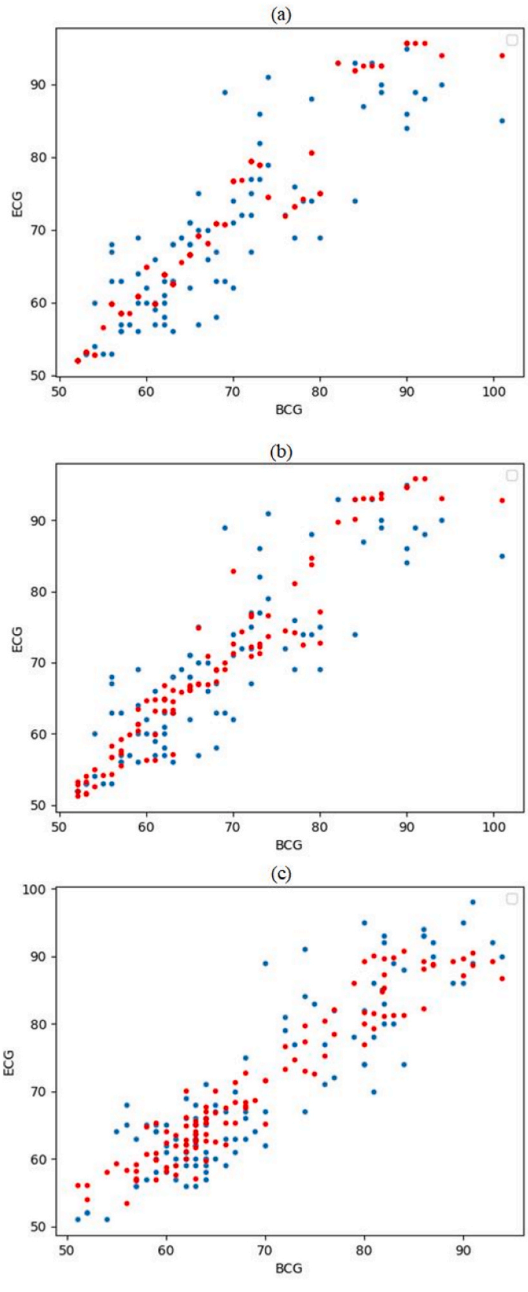


Figure 13. Three experimental data sets used for data regression (a) one independent variable (b) two independent variables (c) three independent variables. The measured BCG heart rate values indicated by shallow blue dots have gradually converged to the ECG heart rate (the near ground truth) values indicated by red dots.

Declarations

Author contribution statement

Chun-Liang Lin: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.
Zhen-Tai Sun: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.
Yang-Yi Chen: Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

No data was used for the research described in the article.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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