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Smart Sleep Monitoring System via Passively Sensing Human Vibration Signals

Fangyu Li, Maria Valero, Jose Clemente, Zion Tse, and WenZhan Song

Abstract—In this paper, a bed-mounted vibration sensor-based system is proposed to monitor vital parameters during sleep, including heartbeat rate (HR) and respiratory rate (RR), body movements and sleep postures. Our system enables smart healthcare that monitors daily sleep in a ubiquitous and non-invasive manner. Besides, the system is contact-free, as no external wearable devices and physical contacts are required. Furthermore, the vibration-based approach also avoids the privacy violation caused by the usage of surveillance cameras. To effectively monitor sleep status, a robust stable signal mode decomposition based HR and RR estimation method is developed for the complicated and noisy vibration signals. Besides, algorithms for body movement and sleep posture identification are also proposed based on vibration signal features. A prototype system is demonstrated with system details, showing great potentials in monitoring sleep status in a real-time user-friendly manner. Experimental results of short term and long term experiments with different participants and beds show that our system achieves satisfying accuracy compared with dedicated commercial devices.

Index Terms—bed vibration, heart rate, respiratory rate, sleep monitoring, sleep posture identification.

I. INTRODUCTION

Sleep monitoring helps track human health status, which is an important human activity monitoring [1]–[3]. The respiration status can be monitored by breathing apparatuses [4], which is uncomfortable; while the heartbeat rate (HR) is typically measured by wearable devices [5], such as chest and wrist sensors, like Apple Watch [6], which need body contact and are intrusive [7]. Many people feel uncomfortable or forget to wear before sleep. In addition, the surveillance camera could cause privacy violation issues [8].

Biomedical vibration signals, such as seismocardiogram (SCG), which measures micro-vibrations produced by the heart movement [9], are analyzed for human health assessment and monitoring. The chest vibration was used to implement user authentication on mobile phones, where SCG features in response to heartbeat were extracted, but the respiration rate (RR) was not considered [10]. Seismometers, including geophones and accelerometers, have been widely used in geophysical and civil engineering applications [11]–[13] as well as indoor smart home applications [14], [15], and can be used to characterize the vital parameters. In addition, vibration sensing is “contact-free”, which means no external device needed to wear, so it is suitable for a sleep monitoring system.

Signal mode decomposition has been widely used to characterize biomedical signal properties [16]. However, because of the frequency mixing issue, empirical mode decomposition (EMD) fails to detect RR or HR when the respiratory or cardiac frequency is not constant [17]. Ensemble EMD (EEMD) was proposed to solve the frequency mixing problem [18], which can stably extract the respiratory and cardiac information. To identify the sleep postures, a machine learning-based approach should be employed [14], which maximizes the distances between different clusters. To implement the sleep posture recognition, we should extract effective and adequate features of heartbeat and respiratory caused body vibrations.

In this paper, we propose a contact-free sleep monitoring solution. The proposed system continuously monitors sleep status. An embedded system collects real-time data from a vibration sensor attached to the bed frame. A robust HR and RR estimation method is proposed to obtain stable vital parameters. Furthermore, sleep posture identification is also important to track and analyze sleep status, which is implemented based on a machine learning model. There has been a posture identification work [19], but it was based on three wearable sensors, which is not as contact-free as our solution. The data collection, computation, storage, visualization are all carried out by the “smart” sensor, which is the future of
healthcare. Extensive real sleep experiments are carried out for the system evaluation. The contributions of our work are:

1) We propose an innovative and comprehensive human vibration-based sleep monitoring system, which includes not only vital parameter estimation but also sleep posture identification. This is the first attempt to use a human body vibration sensor to identify sleep postures. Advanced vibration features are extracted and utilized.

2) The proposed HR/RR estimation method shows better performances compared with the previous time domain, envelope, and frequency domain based methods in terms of accuracy and robustness.

The remainder of this paper is organized as follows. We introduce related sleep monitoring work in Section II. In Section III, we describe the method details. Meanwhile, the prototype system is demonstrated in Section IV. In Section V, we quantitatively test and validate our proposed system using multiple people’s sleep data under different conditions. Finally, conclusions are drawn in Section VI.

II. RELATED WORK

Typically, sleep sensing approaches are based on the assessment of body behaviors during sleep by instrumenting sensors either on the mattress or bed frame [20]. An ultrasound-based system required to install an ultrasound transmitter and receiver pair to characterize the mattress movements [21]. Force sensors installed on bed legs could classify body movements, but the minor heartbeat and respiration were not considered [22]. Load cells placed at bed corners were used to detect body movements, which is based on short-term analysis of the mean-square differences of the load cell signals, and not applicable for detecting specific sleep postures [23]. A multi-channel infrared sensor-array was adopted to analyze both body vibration and respiratory activities [24]. Conductive fiber sensors were also adopted to detect body position, respiration, and heart rate, but costly and not applicable for home use [25]. Pressure sensors in the mattress [26] and piezoelectric sensor in an intensive care unit (ICU) [27] were also used to detect body movements. These previous solutions are not applicable for sleep monitoring for home use in a non-intrusive way.

Vibration-based sleep monitoring is promising as it is contact-free [16], [28]. Based on a bed-mounted geophone, HR was monitored during sleep [29]. More recently, both HR and RR can be estimated from a vertical vibration sensor [30]. Speaking of vibration, ballistocardiogram (BCG) and SCG are two typical measurements. BCG indicates the cardiac ejection of blood into the vasculature, while SCG represents the local vibrations of the chest wall caused by the heartbeat [31]. So, SCG signal reflects the physiological events of heart movements, whereas, BCG waveform represents the combined mechanical pulse response of the vasculature and body to the cardiac ejection of blood [32]. Wang et al. [33] detect the detailed fiducial point of the SCG signals with the aid of photoplethysmogram (PPG), whereas, our system solely relies on the vibration sensor to extract detailed heart movement pattern without other sensors. In [34], sleep monitoring was carried out by a tri-axial accelerometer and a pressure sensor, but vital parameters were mainly estimated by the pressure sensor, while our solution is only based on a vibration sensor.

III. METHODOLOGY

Fig. 1 demonstrates the flow chart of the proposed system. The main functions include, on/off bed detection, HR estimation, RR estimation, and sleep posture detection. Streaming bed vibration data are collected and analyzed. Our system generates real-time instantaneous sleep monitoring results, which requires the computation of efficient algorithms. Our continuous monitoring system measures changes in HR/RR at a segment of 30 seconds and therefore, the proposed system is more sensitive to subtle abnormal changes.

A. Pre-processing

For HR/RR estimation, because the typical HR is between 40 bpm (beat per minute) and 150 bpm and RR is between 12 rpm (respiration per minute) and 25 rpm, which means the target HR/RR should include 0.2 Hz to 2.5 Hz, only a small frequency range is needed. Thus, we apply a bandpass filter to extract target vibration signals. As shown in Fig. 2, a bandpass filter with 0.1 Hz low-cut frequency and 8 Hz high-cut frequency is applied to the sleep vibration signal. It is clear that, after the filtering, the signal mean has changed to zero as the DC bias has been removed. In addition, the filtered waveform retains the vibration signatures.

![Fig. 2: Raw and filtered vibration data during sleep.](image-url)
Preprocessing
EEMD
IMF Selection
RR
HR
1st PC of HR
1st PC of RR
Spectrum Analysis
RR = 20 rpm
HR = 59 bpm

Fig. 3: Overview of the proposed HR/RR estimation method. The first step is to remove the high-frequency noises. Then, we apply EEMD to decompose the bed vibration signal. Based on the intrinsic mode functions (IMF) selection criterion, the artifacts are removed. IMFs having frequencies 0.1 to 0.75 Hz and 0.75 to 2.5 Hz are grouped to RR and HR groups, respectively. Principal component analysis (PCA) is applied to each group to generate the first PC, where spectrum analysis is applied to extract HR and RR, respectively. For this example, the measured HR is 59 beats/min and the RR is 20 breaths/min, which are both accurate.

B. On/Off-Bed Detection

We analyze the bed status using an autocorrelation function (ACF) [30] after applying appropriate pre-processing filters. We characterize the time lag properties. Generally speaking, a lag $k$ autocorrelation $\text{Corr}(y_t, y_{t-k}), k = 1, 2, ..., $ where $\text{Corr}(\cdot)$ denotes the correlation coefficient, is the correlation between values that are $k$ time periods apart, so ACF denotes the signal periodic features. If someone is on the bed, because of the human body vibration caused by heartbeat and chest wall movement, the intrinsic bed vibration patterns will be different from the random background noise situation. More specifically, if there shows more periodic features according to ACF, on-bed status will be flagged.

C. HR/RR Estimation

Fig. 3 shows an example of the whole proposed HR/RR estimation process. And the key steps are summarized below:

1) EEMD: Because of the well-known limitation of EMD - frequency-mixing issue, intrinsic mode functions (IMFs) generated by EMD sometimes fail to demonstrate clear physical meanings. EEMD was applied to the PPG signal to obtain stable IMFs [35]. In our study, the bed vibration signal is more complicated and has more non-stationary properties. Thus, EEMD is also suitable to eliminate the frequency mixing issue in our applications [36]. Then, the intrinsic features of the target signals are extracted.

2) IMF Selection and principal component analysis (PCA): Once obtained, the IMFs with dominant frequencies out of the target range are rejected based on spectrum analysis. The normal ranges of RR and HR for 2 to 18 years old children and young adults are typically 8 to 45 breaths/min and 45 to 145 beats/min, respectively [37], which means 0.13 to 0.75 Hz and 0.75 to 2.4 Hz. Through a simple spectrum analysis, dominant frequencies of IMFs are measured, IMFs having dominating frequency less than 0.1 Hz and greater than 2.5 Hz were considered as interference. IMFs with dominating frequency within the range of 0.1 to 2.5 Hz are selected for further processing. As shown in Fig. 3, IMF5 to IMF10 (total 6 IMFs) were selected from 11 IMFs, because they have the
dominating frequencies within the range of 0.1 to 2.5 Hz. IMFs having dominating frequencies within the range of 0.75-2.5 Hz were then selected for HR estimation, where IMF 5 and 6 were selected; while IMFs having dominating frequencies within the range of 0.1-0.75 Hz were selected for RR estimation, where IMF7 to IMF10 (total 4 IMFs) were included. To extract the intrinsic cardiac and respiratory information from IMFs, we apply PCA to the HR and RR groups. The 1st principal components (PCs) present the intrinsic frequencies of cardiac and respiratory activities, because they retain most of the variation presented in the selected IMFs.

3) HR and RR Extraction: The first PCs of HR and RR groups represent the intrinsic heartbeat and respiratory activities. We calculate the dominant frequencies from the Fourier spectrum. Once the heartbeat frequency \(f_{HR}\) and respiratory frequency \(f_{RR}\) are extracted, they are converted to HR and RR following: \(HR = f_{HR} \times 60, RR = f_{RR} \times 60\).

D. Sleep Posture Identification

Sleep posture information reflects the sleep status. For example, frequent posture changes usually denote a shallow ineffective sleep. In addition, certain posture, for instance, sleep on the front, is not good for the chest movement, which should be avoided, especially for baby and young children. If the sleep postures can be identified and recorded effectively, we can track the human movements during sleep. Fig. 4 shows the four typical sleep postures we study. The contact areas between human body and the bed are determined by the sleep postures. So different postures generate different vibration patterns. In previous studies, such as [29], [30], all subjects lay down on their backs. So, body movement analysis was ignored. In our study, because the sleep posture can be identified, we can make more detailed and valuable sleep analysis.

1) Bed Vibration Features: Heartbeat motion features have been extracted for user authorization [10]. Similarly, in our study, the bed vibrations caused by heartbeat and respiration can be used to get physical human vibration features to differentiate the sleep postures on the bed. Features related to sleep postures are extracted as follows:

Automatic Segmentation: We separate the vibration signal into individual events in an automatic manner. As Fig. 5 shows, we first extract a heartbeat template by stacking a certain period of heartbeat signal. Then we implement the cross-correlation between the bed vibration signal and the template of the reference heartbeat motion cycle. The correlation coefficient is calculated, and a threshold of 0.90 is established to identify the starting point of the events. The result of the correlation is shown in Fig. 5(c). Next, the event is segmented based on the starting point and the template length.

Features Selection: Once the event is isolated, we locate the local maximum points by their amplitudes. A heartbeat motion cycle recorded by SCG has seven stages [10], atrial contraction (ATC); mitral valve closing (MC); aortic valve opening (AO); point of maximal acceleration in the aorta (MA); aortic valve closure (AC); mitral valve opening (MO); rapid filling of left ventricle (RF), which are denoted on Fig. 5(d). We use these stages to construct three features for the classification model. The first and the second features are rate magnitude on time domain between AO:RF and AL:RF. Also, we realize that there are some delays in the arrival time of RF depending on the lying position. Therefore, we use as the third feature the time difference between ATC (the first stage) and RF. Finally, we incorporate the event standard deviation as a feature to increase the accuracy of our posture classification model.

2) Sleep Posture Identification: Support Vector Machine (SVM) and its derivatives have been widely used in the biomedical engineering [10], [14], because it is efficient and easy to implement on embedded devices. We adopt a one-against-all strategy in the MC-SVM (multi-class SVM) classification model [38]. More specifically, the inputs of the MC-SVM are the four features mentioned above, and the detailed evaluations can be found in Section V-A.3.

IV. PROPOSED SLEEP MONITORING SYSTEM

A. Hardware and Software Setup

The installed prototype system is shown in Fig. 6, which is installed along the bed. The dimensions are 11.9 cm × 9.8 cm × 4.2 cm. The prototype unit is easy to deploy in a common bed without any special alterations.

We use a sensitive seismometer to collect human vibration data during sleep. A single board computation unit–Raspberry Pi, receives data from the ADC (Analog to Digital Converters) which is connected to the seismometer and saves raw data to a local database. A prototype device is illustrated in Fig. 7.
A Raspberry Pi 3 collects, stores, and processes data in a real-time manner. The online data collection is 24/7 continuous. Recently, a vertical geophone with 2.5 kHz sampling frequency was used in [30], whereas, our sampling frequency is 100 Hz much lower than the previous work, which is relatively cheap and does not bring heavy computation burdens.

B. Visualization

To visualize the sleep status, we develop a graphical user interface (GUI), as shown in Fig. 8, which is based on Grafana [39]. The instantaneous HR and RR results are shown in the left panel. In the right panel, historic HR/RR, body movements and posture changes, as well as bed status, are shown. Note that the bed status indicates the device installation condition, which is important to the system performance analysis. Note that because all the information is processed locally, there will be no chance for the privacy violation.

To sum up, the sleep monitoring system has been built on top of the layered architecture. The “Data Access Layer” is composed by the bed vibration sensing phase. The streaming data are stored locally in the Raspberry Pi. A database named InfluxDB [40] is used to save new upcoming data; however, to allow real-timing of the results, we employ a data buffer that sends data segments to the next layer for pre-processing. The buffer size can be configured in the system. In the “Data Pre-processing Layer”, background noises and machine noises are suppressed. Next layer is the “Computation Layer” which has inner layers. The first one is the on/off bed detection, then two separated modules, HR/RR estimation and posture identifications are followed. The “Interface Layer” is in charge of showing sleep monitoring results in real-time.

V. Experiments and Evaluations

A. Short-term Controlled Experiments:

In the first phase of evaluation, we conducted controlled experiments in an environment using the same bed and similar background noise. For every participant, we collected 48 posture changes. For the whole HR, RR, posture experiment, 20 minutes of data are recorded and analyzed, which were distributed as follows (i) 3 minutes on and off the bed (ii) 5 minutes for HR, (iii) 5 minutes for RR, (iv) 2 minutes for movements and (v) 5 minutes for posture change. Our evaluation in this phase involved 16 participants (10 males and 6 females) and collected over 320 minutes of vibration signals. For HR estimation, we use a commercial Food and Drug Administration (FDA) approved fingertip pulse oximeter as the reference. For RR estimation, we did experiments using a metronome, which is a generally accepted approach to collect ground truth breathing data in the research community [41]. Subjects are asked to breathe artificially following the metronome. For posture identification, we organized the participants to change postures randomly to avoid the bias in certain posture transitions.

In a quantitative evaluation, we employ statistical metrics, which are defined based on the indexes in the confusion matrix [42]: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Recall ($Re = TP / (TP + FN)$), precision ($Pr = TP / (TP + FP)$), accuracy ($Acc = (TP + TN) / (TP + FP + FN + TN)$), and $F_1$ score ($F_1 = 2(Pr \cdot Re) / (Pr + Re)$) are listed in Tables I and II.

1) On/off-Bed Detection: The on/off bed experiment duration was set for 3 minutes per participant. We collected 36 bed status from each participant, 12 for each type (on-bed, off-bed, sitting). The participants change the status every 5 seconds according to our directions. For this experiment, the system was set up to detect bed status every 3 seconds.

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>On Bed</td>
<td></td>
</tr>
<tr>
<td>Sitting</td>
<td></td>
</tr>
<tr>
<td>Off Bed</td>
<td></td>
</tr>
<tr>
<td>Ac</td>
<td>0.98</td>
</tr>
<tr>
<td>Pr</td>
<td>0.93</td>
</tr>
<tr>
<td>Re</td>
<td>1.00</td>
</tr>
<tr>
<td>$F_1$</td>
<td>0.96</td>
</tr>
<tr>
<td>Average</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 6: Prototype system is installed on bed side.

Fig. 7: Proposed system uses a seismometer to collect vibration data, a Raspberry Pi as the computation unit, and an ADC board to convert collected raw data.

Fig. 8: Sleep monitoring GUI, from which HR/RR, body movement and posture change features are visualized.
Table I shows the results of the bed status test. The method used to calculate the bed status proved to be robust and reliable due to the low error level. The method got a perfect score detecting off bed. On the other hand, the method was able to detect correctly all on bed status when the participants were lying in bed. In addition, after carefully analyzing these specific cases we detected that when a person sits in a distance less than 30 centimeters from the sensor, it can detect a faint heartbeat signal that has high auto-correlation levels. We improved the accuracy analyzing the variability between HR peaks where high variability implies sitting. In some cases, the system can estimate the HR if the person is next to the sensor. After getting an accuracy greater than 98%, we determined that the method was ready for testing in different environments.

2) HR/RR Estimation: HR error is 1.604 bpm with a standard deviation of 1.735 bpm. While the RR error is 0.3 bpm with a standard deviation of 1.033 bpm. It is clear that our method achieves promising accuracy in the HR/RR estimation. For RR estimation, participants were asked to breath 20 rpm following the metronome, while the measured average RR is 19.77 rpm with a standard deviation of 1.678 rpm.

3) Sleep Posture Identification: We employ a MC-SVM model to recognize the sleep postures. Note that proportions of four postures are equal, and we adopt a 10 fold cross-validation strategy with a ratio 6:2:2 of training, testing and validation data. It is clear that our proposed method works well for sleep posture identification, as listed in Table II.

TABLE II: Sleep posture classification metrics.

<table>
<thead>
<tr>
<th></th>
<th>Recall</th>
<th>Precision</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left</td>
<td>0.71</td>
<td>0.9218</td>
<td>0.8550</td>
</tr>
<tr>
<td>Right</td>
<td>0.92</td>
<td>0.9109</td>
<td>0.9524</td>
</tr>
<tr>
<td>Chest</td>
<td>0.86</td>
<td>0.7478</td>
<td>0.8877</td>
</tr>
<tr>
<td>Back</td>
<td>0.91</td>
<td>0.8053</td>
<td>0.9164</td>
</tr>
<tr>
<td>Average</td>
<td>0.85</td>
<td>0.8465</td>
<td>0.9029</td>
</tr>
</tbody>
</table>

B. Long-term Experiments:

We carry out extensive long-term experiments, which lasted for two weeks and used 10 different beds with 10 different subjects. There are 5 males and 5 females, who are in the age range of 24–45. Mattresses were different in term of height (in a range of 8 to 12 inches), size (twin, full, queen, and king), and material (foam and innerspring). We carry out the long-term experiments using mattresses with different properties to validate the proposed sleep monitoring system. Table III summarizes the subjects’ information. In total, we conducted experiments for 140 days (3360 hours).

1) HR Estimation: We used and FDA class 2 device, Apple Watch series 4, to validate the accuracy of our HR method. Based on PPG sensors, Apple Watch provides a relatively accurate HR estimate, and can be used as an accuracy reference.

Fig. 9 shows the comparisons of two participants S1 and S2 between Apple Watch and the proposed system. Apple Watch provides HR continuous reading in a range between 3 to 10 seconds, which is easy to wear, and it does not cause much discomfort at bedtime. One of the limitations is the battery life since it only allows collecting around 5 hours of continuous HR. It is clear that the Apple Watch results have a lot of spikes, which has been discussed by some customers already1. The spikes can be caused by various reasons, such as the bad contact between the sensor and skin, human movement and so on. However, it is not reasonable to have so many spikes during sleep for healthy people. On the contrary, our method generates “smoother” results, which follow the same trend.

2) Sleep Posture Detection: Besides the HR estimation evaluation, we also conducted a sleep posture detection experiment. Using a surveillance camera, the view of an entire

1Some discussions related to abnormal spikes can be found: https://discussions.apple.com/thread/8560282.
VI. CONCLUSION

A comprehensive sleep monitoring system based on a bed-mounter vibration sensor is proposed in this paper. The approach is non-intrusive and contact-free with no need for wearable devices/gadgets nor cameras or other privacy-intrusive methods. One key contribution is the novel estimation of HR and RR only based on vibrations excited by the person while sleep. The proposed method outperforms conventional approaches for calculating HR and RR like time/frequency domain analysis and envelope estimations. On the other hand, a first attempt to use human body vibration to identify sleep postures is introduced. A deep signal analysis allows the identification of different postures of the body in bed, and a machine learning technique is used to estimate the sleep posture. The proposed system can accurately measure HR and RR, and it can identify the sleep posture changes with a low error, which leads to a promising sleep monitoring system.

REFERENCES


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