2019 IEEE International Conference on Smart Computing (SMARTCOMP)

Demo: Contactless Device for Monitoring On-Bed Activities and Vital Signs

Jose Clemente, Fangyu Li, Maria Valero and WenZhan Song
Center for Cyber-Physical Systems, University of Georgia, USA

Abstract—**Monitoring sleep quality and status is important to learn health condition for improvement and prevent sleep apnea. A bed-mounted seismometer system is proposed to monitor the heart and respiratory rates, and body movement and posture, during the sleep. To effectively monitor sleep status, an innovative local maxima statistics based approach and an instantaneous property based method are developed to estimate heart and respiratory rates, respectively. These methods are more robust and stable compared to previous works. Besides, algorithms for body movement and posture identification are also investigated based on instantaneous properties. We incorporated these algorithms to create a novel contactless sleep monitoring system that can keep track of heart rate, respiration rate, movement patterns and posture changes on events near to the bed. Our technology includes a small, powerful and low-cost smart seismometer, that can be easily installed to a bed frame under the mattress or boxes, and a user-friendly graphic interface, that can be paired with smartphone devices and display results through the APPs notifications. A prototype system is demonstrated, showing great potentials in monitoring a persons sleep status under different conditions.**

Index Terms—**sleep monitoring, heart rate, respiratory rate, seismometer.**

I. Introduction

Currently, in the United States, 47.8 million people are 65 years old and older. From those, nearly 26% live alone at home and 18% in senior healthcare facilities or similar according to U.S Census Bureau. In this target population sector, there is a lack of non-intrusive and low-cost solutions for monitoring sleep activities and vital signs on the bed. Current sophisticated devices for measuring vital signs imply a wearable apparatus/gadget, and those do not detect other important elder health issues like lack of movement on the bed and falls from bed. Other devices require persons actions, like pressing a button when a fall down happen, but those cannot be activated if the person loses the conscience. Senior care facilities and families with elderlies living alone can use this device to trigger alarms if their patients/family-member falls from bed. These life-threatening situations require prompt detection and response, and our user-friendly configurable interface can allow customized real-time notifications. Senior care facilities and hospitals can also adopt this technology as a supplementary device for monitoring the posture and changes in posture during the time that patients are on a bed. This is critical to determine long-periods of lack movement that can lead to health problems like eschars on the body. Furthermore, the product can represent a non-invasive alternative for people with undiagnosed sleep apnea, which causes respiration and heart failures.

Our research is partially support by NSF-CNS-1066391, NSF-CNS-0914371, NSF-CPS-1135814, NSF-CDI-1125165, and Southern Company.

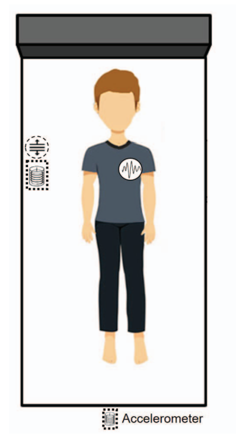

Fig. 1: Prototype system with a seismometer installed on bed side and a Raspberry Pi as the computation unit.

II. System Design

A prototype system is designed to continuously monitor sleep quality and status. The seismometer is attached to bed frame, which is non-intrusive and non-contact to human body. Raspberry Pi 3 is connected with seismometer for real-time data processing. The setup is illustrated in Fig. 1. A seismometer is naturally a second-order high-pass filter and its general syntonic frequency can be 8 Hz [17]. The vertical channel signal is used in our experiments.

III. Algorithm

For sleep monitoring, heart and respiratory rates, as well as body movement and sleep posture are important parameters. In this section, we present several novel algorithms for those parameter estimation and monitoring. Fig. 2 illustrates the proposed algorithm flows.

A. Heart rate estimation

Since a heartbeat generates one peak on the recored seismometer data $s(t)$, the point $(t, s(t))$ is defined as the local maximum within an interval I_h if $s(t) \geqslant s(z)$ for every $z \in (t - \frac{I_h}{2}, t + \frac{I_h}{2})$, where I_h is initialized according to the heartbeat frequency range. In addition, the heartbeat strength

978-1-7281-1689-1/19/$31.00 ©2019 IEEE
DOI 10.1109/SMARTCOMP.2019.00091

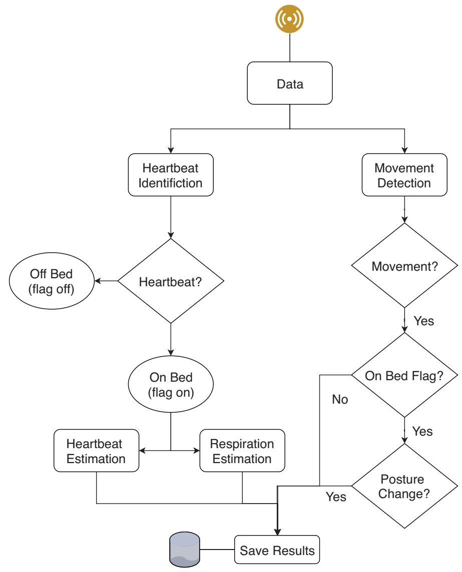

Fig. 2: Sleep monitoring system workflow.

(amplitude) can also be a constraint during the local maxima search. However, even with filtering and autocorrelation operations, the heartbeat recognition results are not stable and can be influenced by interferences [1], [2].

To solve instabilities, a novel empirical truncated statistics analysis method is proposed to estimate BPM$_h$ [3]. When local maxima are obtained, there are falsely picked peaks and some missing peaks. Those falsely picked peaks result in smaller period estimation, while the missed peaks lead to larger estimation results. Here, X is the interval between two sequential picked peaks. The heartbeat period within $(t-\frac{I_h}{2}, t+\frac{I_h}{2})$ is estimated as a truncated average:

$$E(X|F^{-1}(a) < X \leqslant F^{-1}(b)) = \frac{\int_a^b xg(x)dx}{F(b)-F(a)}, \tag{1}$$

$$\begin{aligned} \text{where,} \quad & g(x) = f(x) \quad \text{for} \quad F^{-1}(a) < x \leqslant F^{-1}(b); \\ & g(x) = 0, \quad \text{everywhere else;} \\ & F^{-1}(p) = \inf\{x : F(x) \geqslant p\}. \end{aligned}$$

The lower and upper bounds (a and b) are determined based on the local maxima detection performance. In our applications, 0.1 and 0.9 are chosen, respectively. Results are shown on Fig. 3.

B. Respiratory rate estimation

Commodity seismometer is insensitive to lower frequency measurements (usually lower than 0.3 Hz) [1], thus the respiratory rate BPM$_r$ can not be directly observed from seismic data. Previously, an amplitude-modulation approach is proposed to use the envelope to estimate carrier frequency [2]. However, the amplitude modulation of the recorded seismometer signal is not stable. According to our experiments, the lower and upper envelopes usually show different behavior, so it is difficult to use the amplitude modulation methods for reliable estimation.

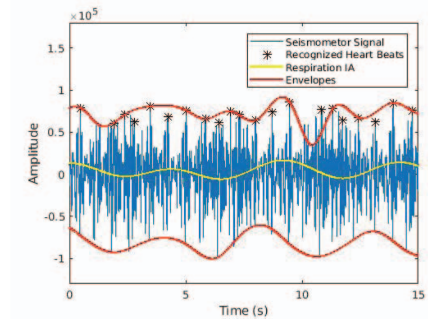

Fig. 3: During sleep example. Seismometer data signal, recognized heartbeats, envelopes and respiration IA are plotted.

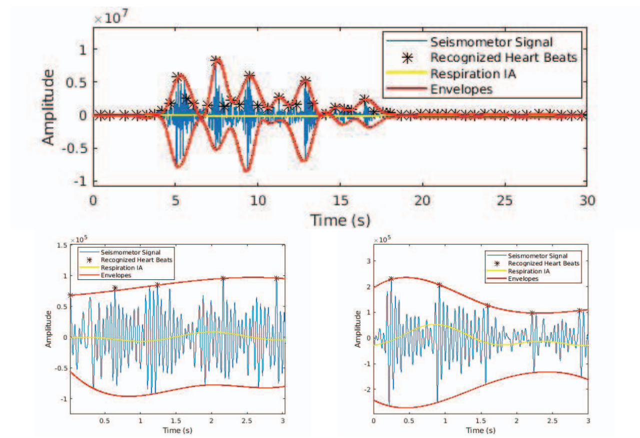

Fig. 4: Body motion and posture recognition example. (Upper) Body movement show strong amplitudes. (Bottom Left) Before and (Bottom Right) after the movement, the IA changes, which indicates there is a sleep posture change.

We propose a novel signal configuration model to formulate the relation among seismic data, heartbeat and respiration components [3]. Then, oscillatory analysis technique synchrosqueezed wavelet packet transform (SSWPT) [4] is used to extract the instantaneous properties of the respiration mode. Results are shown on Fig. 3.

C. Movement and Sleep Posture Monitoring

Another important potential of our system is to detect the sleep quality and posture. If the subject has a lot of movements and motions, it means the sleep quality is not good. Using the amplitude anomalies, the body motions and movements can be recorded and analyzed for sleep quality determination. In order to determine the movements, we measure events with high amplitudes. These magnitudes are just sensed when a person moves on the bed. The posture change is estimated using 15 seconds of the data before and after the events as is shown on Fig. 4. Some features in time and frequency domain are used to determine is the person changed the posture after the movement.

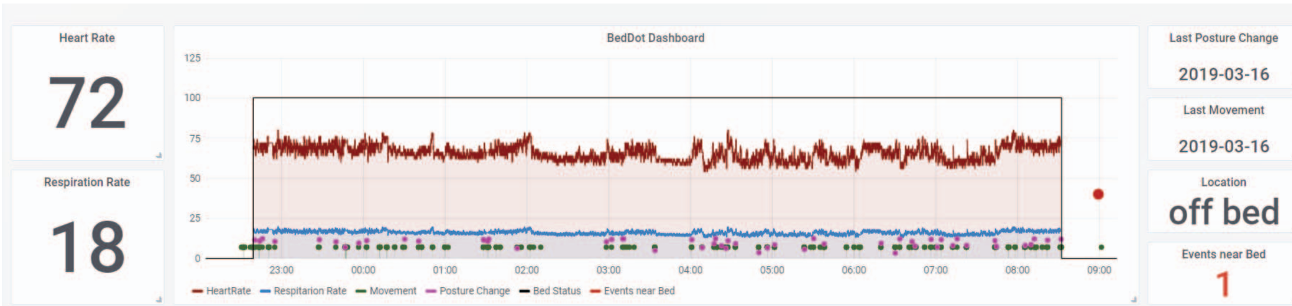

Fig. 5: Monitoring Dashboard.

D. Events near to the bed

Our sensor is sensitive enough to detect movements that occur near to the bed. Because the sensor is attached to the bed and not to the ground, the events that occur in it do not have high magnitude comparing with events generated on the bed. When we detect a event when analyze the features and classify it as a movement or event near to the bed. We use a SVM in order to classify the event as a fall down, jumping, dropping object, closing door, closing drawer, and hitting a table.

IV. Demonstration

We will demo the real-time system for monitoring on-bed activities and vital signs. First, we will show the real time raw data collected for our device (on site). Where we are going to generate some events and show the differences between them. We will show the signals from (i) heartbeat, (ii) respiration, (iii) on bed movements and floor and (iv) floor movements. Second, we are going to show the dashboard with the results on real-time as is shown in Fig. 5. Normally, to detect on/off bed the system needs 5 seconds to get stable results. To calculate heart rate and respiration rate we need 30 second of data. Movements and events near to bed need one second. Third, we plan to show some historical data collected during our tests. Finally, we plan to show the real-time system with two devices installed in our house than run 24/7. Finally, we plan to show a little video demonstration of our system.

References

[1] Z. Jia, M. Alaziz, X. Chi, R. E. Howard, Y. Zhang, P. Zhang, W. Trappe, A. Sivasubramaniam, and N. An, “HB-phone: a bed-mounted geophone-based heartbeat monitoring system,” in *Information Processing in Sensor Networks (IPSN), 2016 15th ACM/IEEE International Conference on*. IEEE, 2016, pp. 1–12.

[2] Z. Jia, A. Bonde, S. Li, C. Xu, J. Wang, Y. Zhang, R. E. Howard, and P. Zhang, “Monitoring a Person’s Heart Rate and Respiratory Rate on a Shared Bed Using Geophones,” 2017.

[3] F. Li, J. Clemente, and W. Song, “Non-intrusive and Non-contact Sleep Monitoring with Seismometer,” in *2018 IEEE GlobalSIP*, 2018. [Online]. Available: http://sensorweb.engr.uga.edu/wp-content/uploads/2018/09/Dropbox_li2018intrusive.pdf

[4] H. Yang, “Synchrosqueezed wave packet transforms and diffeomorphism based spectral analysis for 1D general mode decompositions,” *Applied and Computational Harmonic Analysis*, vol. 39, no. 1, pp. 33–66, 2015.