Non-intrusive and non-contact sleep monitoring with seismometer

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Motivation

- Sleep monitoring is extremely important, even a life saver, for people with undiagnosed sleep apnea, which causes respiration and heart failures.
- Traditional harmonic analysis is not suitable for bio-signal processing and analysis, because of the data non-stationary nature.
- Nowadays, as an important tool for non-stationary signal analysis, oscillatory analysis has been widely applied.

Contributions

- A local maxima statistics method is proposed to estimate the heart rate.
- Instantaneous property from oscillatory analysis is used to characterize the respiration rate
- A prototype system is also designed and evaluated with extensive experiments.
- Evaluations demonstrated that bed-mounted seismometer, which is non-intrusive and non-contact, is effective for monitoring sleep status and quality and detecting apnea phenomenon.

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System Workflow

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.

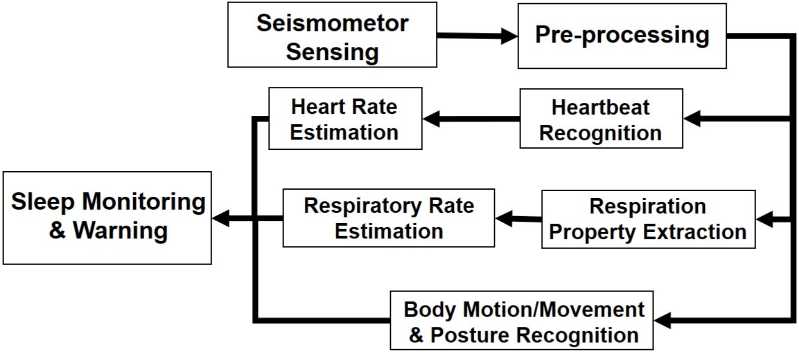

Figure: Sleep monitoring system workflow.

Heart rate estimation

Estimating hearth rate BPM_h directly from the data spectrum is not accurate because the heartbeat waveform is not strictly periodical in reality [1]. To avoid periodicity dependency, we propose a novel local maxima statistics method to address this challenge.

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 (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] We use BPM_h to denote 'beats per minutes' for heart rate and BPM_r to denote 'breaths per minute' for respiratory rate.

Heart rate estimation

To solve instabilities, a novel empirical truncated statistics analysis method is proposed to estimate BPM_h. 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 $(t - \frac{l_h}{2}, t + \frac{l_h}{2})$ is estimated as a truncated average:

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

$$\text{where,} \quad g(x) = f(x) \quad \text{for} \quad F^{-1}(a) < x \leqslant F^{-1}(b);$$

$$g(x) = 0, \quad \text{everywhere else;}$$

$$F^{-1}(p) = \inf\{x : F(x) \geqslant p\}.$$

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.

Respiratory rate estimation

Commodity seismometer is insensitive to lower frequency measurements (usually lower than 0.3 Hz), 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. 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.

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

Respiratory rate estimation

In oscillatory analysis, a non-linear and non-stationary wave-like signal $s(t)$ is defined as a superposition of several oscillatory components:

$$s(t) = \sum_{k=1}^{K} \alpha_k(t) e^{2\pi i N_k \phi_k(t)} + n(t), \tag{2}$$

where, $\alpha_k(t)$ is the instantaneous amplitude, $N_k\phi_k(t)$ is the instantaneous phase, $N_k\phi_k'(t)$ is the instantaneous frequency, and $n(t)$ is the noise contamination. In our study, $\alpha_0(t)$ and $N_0\phi_0'(t)$ correspond to the wanted respiration component.

Respiratory rate estimation

The instantaneous properties (amplitude, frequency and phase) in Eq. 2 are not known and can be are estimated via SSWPT. Suppose $W_s(\xi, t)$ is the wavelet transform of a 1D wave-like component. It was proved that the instantaneous frequency information function $v_s(\xi, t) = \frac{\partial_t W_s(\xi,t)}{2\pi i W_s(\xi,t)}$ is able to approximate $N\phi'(t)$. Hence, we use the SSWPT to obtain a sharpened instantaneous property estimation compared to the traditional methods. When the instantaneous amplitude (IA) of respiration is extracted, the respiratory rate can be easily obtained.

Body motion/movement and posture recognition

In the previous projects, all subjects lay down on their backs. However, the sleep posture influences the recorded data quality and property. Fig. 6 and Fig. **??** show that the body movement generates strong signal (10^7 amplitude) while the respiration and heartbeat show amplitude about 10^5. Thus, based on the dramatic energy change, we can recognize the body movement using a local thresholding method:

$$Tr_m = \begin{cases} 1 & \text{if} \quad s(t) \geqslant \lambda \max(s(z)), z \in (t-\tau, t) \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

where, λ is a threshold coefficient and τ is the time lag.

In addition, the IA of respiration usually changes after the body movement is detected, which probably means the sleep posture has changed. Thus, the posture changes can also be detected by applying Eq. 3 to IA, but with a different λ.

Body motion/movement and posture recognition

Fig. 6 shows three recorded segments: before sleep, normal sleep and body movement, which are extracted from an 8 hour sleep monitoring data set of a human subject.

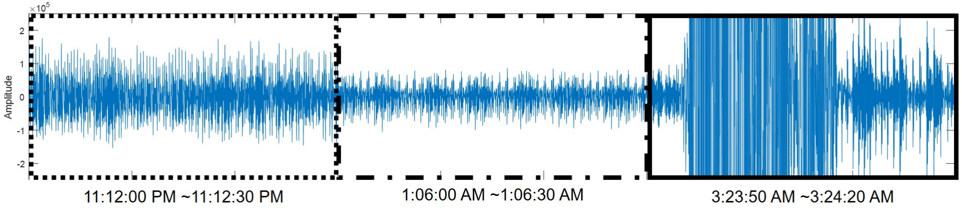

Figure: Sleep monitoring data. The seismometer data are recorded before sleep (11 PM, dashed frame), during sleep (1 AM, dash-dot frame) as well as before and after sleeping posture changes (3 AM, solid frame).

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System Setup

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. 3. A seismometer is naturally a second-order high-pass filter and its general syntonic frequency can be 8 Hz. The vertical channel signal is used in our experiments.

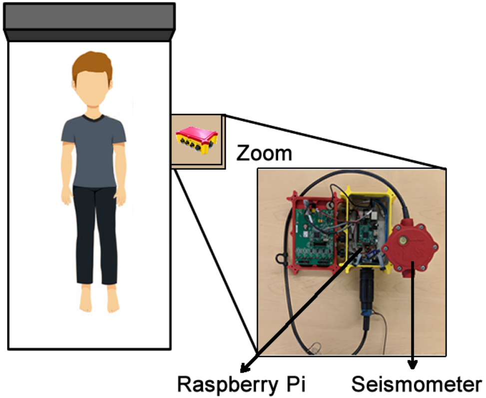


Figure: Prototype system with a seismometer installed on bed side and a Raspberry Pi as the computation unit.

Body parameter monitoring

Using the local maxima search method, the recognized heartbeats are shown. According to the BPM_h estimation, the subject has a 90 BPM_h before sleep (Fig. 4) and a 75 BPM_h during sleep (Fig. 5), which are validated by the smart watch wore. Notice the respiration in Fig. 5 is slower and the IA is weaker than those shown in Fig. 4.

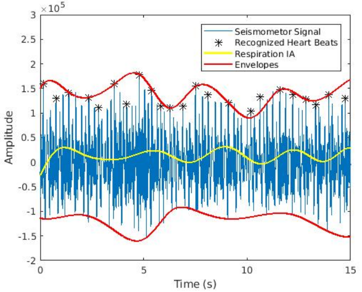


Figure: Before sleep example.

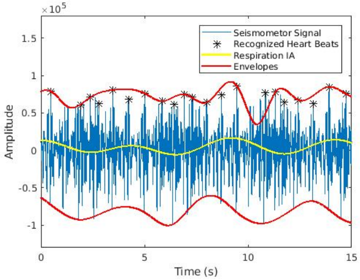
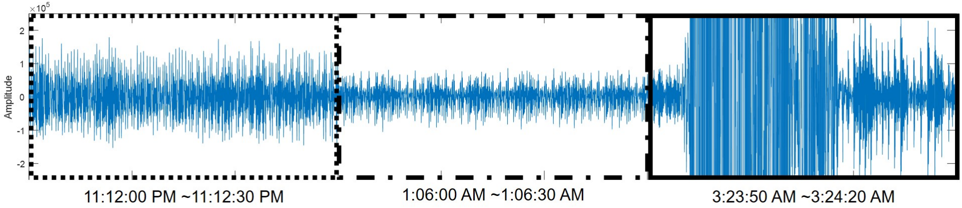


Figure: During sleep example.

Sleep quality and position

Another important potential of our system is to detect the sleep quality and position. If the subject has a lot of movements and motions, it means the sleep quality is not good. A late night data at 3 AM within a solid frame. The signal is too strong (100 times larger) compared with just heartbeats and respiration. Using the amplitude anomalies, the body motions and movements can be recorded and analyzed for sleep quality determination.



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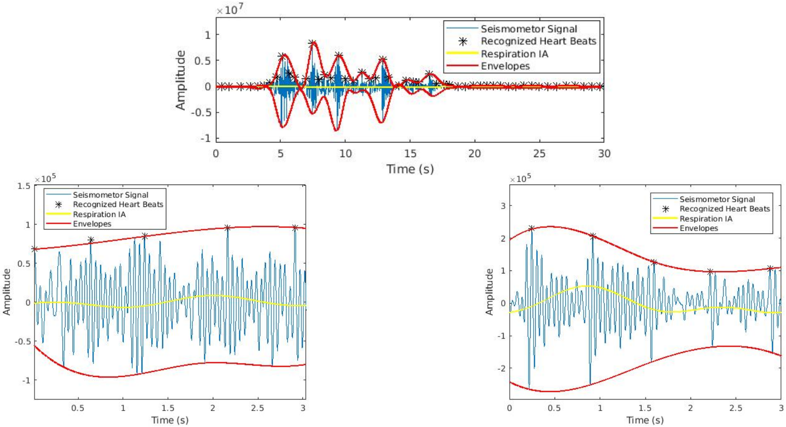
Sleep quality and position



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

Sleep quality and position

The average peak amplitudes are about 1×10^5 before body movement, but after the movement peak amplitudes become around $1.5\sim3\times10^5$, which means the respiration is stronger when the subject changes a posture. So further study will focus on how to fundamentally connect the oscillatory components with the sleep postures. The new information about the sleep status will make a more detailed sleep analysis report possible, which can provide more health advice.

Speaking of the features, we can also notice the latter part of the new posture signal shows double peaks for one heartbeat, which is different with that before the posture change, so a feature learning approach such as machine learning can be used to identify the different postures.

Apnea detection and alert

Apnea or apnoea is suspension of breathing. During apnea, there is no movement of the muscles of inhalation, and the volume of the lungs initially remains unchanged. Depending on how blocked the airways are (patency), there may or may not be a flow of gas between the lungs and the environment. This can be dangerous situation.

A 5s seismometer signal record when a subject lay on a bed holding breath for at least 10 seconds. The recognized heartbeats, envelopes as well as the IA of the respiration are also shown. It is obvious that the respiratory rate is too low. In this situation, we can use the embedded warning module connected with a commercial smart home system to make an emergency call or notify other people.

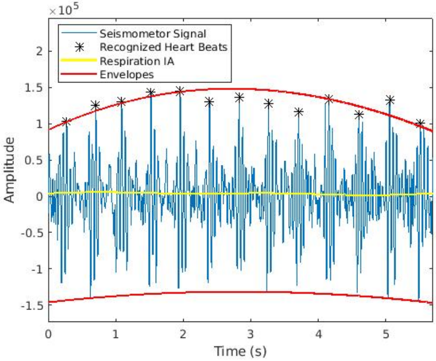


Figure: Apnea example.

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Conclusion

- The bed-mounted seismometer is non-intrusive and non-contact, showing great potentials for sleep quality and status monitoring.
- Oscillatory analysis is promising for time series bio-signal data analysis. The extracted oscillatory components help extract the signal rhythms and useful information on amplitude and frequency for not only heart/respiration rate estimation, but also body movement and position identification.
- Our system is also capable to detect a user's slight activities such as snores during sleep. A more sophisticated sleep monitoring system can be developed to accurately detect a person's sleep stage and evaluate the sleep quality
- More system modules, such as machine learning and deep learning models, will be added implement advanced functions.

Thank you for your attention...

Questions & Comments