NON-INTRUSIVE AND NON-CONTACT SLEEP MONITORING WITH SEISMOMETER

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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. A prototype system is demonstrated, showing great potentials in monitoring a person's sleep status under different conditions.

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

1. INTRODUCTION

Sleep monitoring is extremely important, even a life saver, for people with undiagnosed sleep apnea, which causes respiration and heart failures [1]. The respiration status can be monitored by breathing apparatuses [2], while the heart rate is typically measured by wearable devices [1]. However, those devices need body contact and are intrusive. Many people feel not comfortable to wear or forget to wear before sleep.

Seismometers, including geophones and accelerometers, have been widely used in geophysical and civil engineering applications [3–5]. Recently, new applications for smart environments are explored, such as ambient vibration for building occupancy estimation [6], floor vibration for indoor person localization [7], bed vibration for heart beating and breathing rate monitoring [8–10], etc.

The target sleep measurements are heart and respiratory rates, whose timing and durations are important. However, the traditional harmonic analysis is not suitable for bio-signal processing and analysis, because of the data non-stationary nature [8, 11]. Nowadays, as an important tool for non-stationary signal analysis, oscillatory analysis has been widely applied [12–14]. The hypothesis of oscillatory analysis is that a signal contains a few principle and minor components with different oscillation patterns [11, 12]. For example, Yang et al. [11] extracted both respiratory and cardiac rhythms from PPG (photoplethysmogram) signals using an oscillatory mode decomposition.

In this paper, a local maxima statistics method is proposed to estimate the heart rate, and instantaneous property from oscillatory analysis is used to characterize the respiration rate. Different from [8], the strict periodicity property of the heartbeat is not required thus the proposed algorithm is more robust. And, instead of using the envelope based respiratory rate estimation in [10], the instantaneous property based method is designed for robust and stable estimation. In addition, the algorithms for detecting body movements and sleep posture changes are proposed. A prototype system is also designed and evaluated with extensive experiments. The 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.

2. ALGORITHM DESIGN

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. 1 illustrates the proposed algorithm flows.

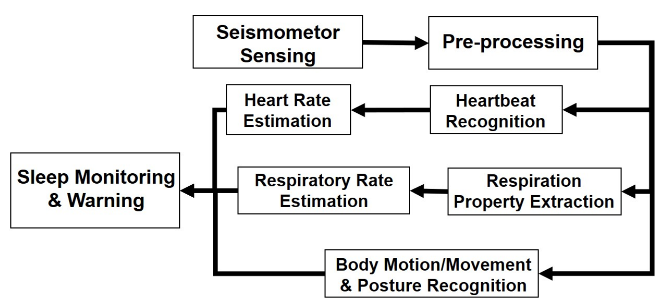

Fig. 1: Sleep monitoring system workflow.

2.1. Heart rate estimation

Estimating hearth rate BPM_h directly from the data spectrum [10] is not accurate because the heartbeat waveform is

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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 [8, 10].

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 $(t - \frac{I_h}{2}, t + \frac{I_h}{2})$ 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.

2.2. Respiratory rate estimation

Commodity seismometer is insensitive to lower frequency measurements (usually lower than 0.3 Hz) [8, 10], 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 [10]. 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) [14] is used to extract the instantaneous properties of the respiration mode. In oscillatory analysis, a non-linear and non-stationary wave-like signal $s(t)$ is defined as a superposition of several oscillatory components [11, 14]:

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

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.

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 $N\phi'(t)$ [15]. Hence, we use the SSWPT to obtain a sharpened instantaneous property estimation compared to the traditional methods [12, 14, 16]. When the instantaneous amplitude (IA) of respiration is extracted, the respiratory rate can be easily obtained.

2.3. Body motion/movement and posture recognition

In the previous projects [8, 10], all the subjects lay down on their backs. However, the sleep posture influences the recorded data quality and property. Fig. 2 and Fig. 6 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.

3. EXPERIMENTS AND VALIDATION

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 [17]. The vertical channel signal is used in our experiments.

[1] In this paper, we use BPM$_h$ to denote 'beats per minutes for heart rate and BPM$_r$ to denote 'breaths per minute for respiratory rate.

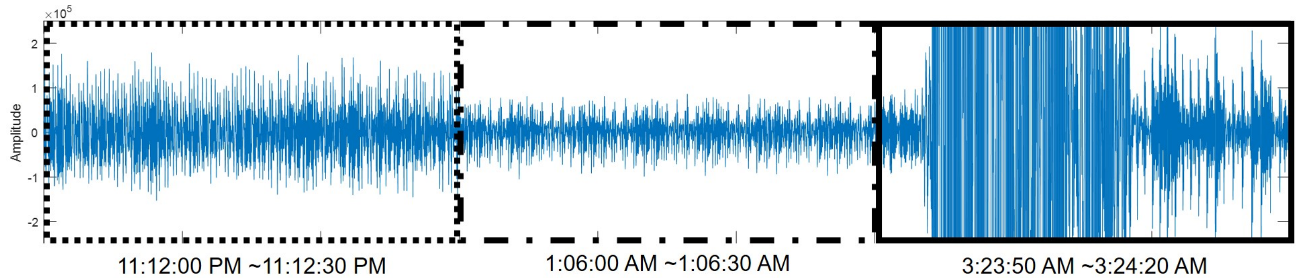

Fig. 2: Sleep monitoring data. The seismometer data are recorded before sleep (11 PM, dashed frame), during sleep (1 AM, dash-dot frame) as well as before and after sleeping posture changes (3 AM, solid frame).

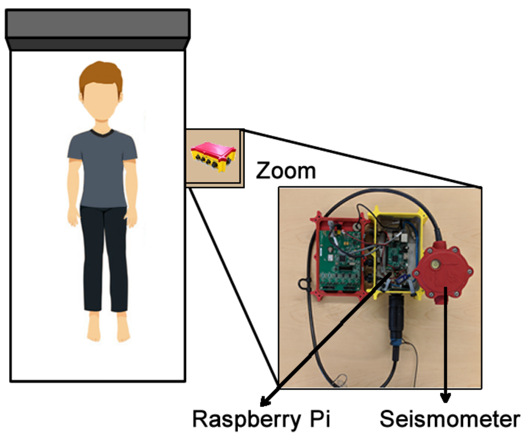

Fig. 3: Prototype system with a seismometer installed on bed side and a Raspberry Pi as the computation unit.

3.1. Body parameter monitoring

Fig. 2 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.

Using the local maxima search method, the recognized heartbeats are shown in Fig. 4, Fig. 5, Fig. 6, and Fig. 7. According to the BPM_h estimation in Eq. 1, 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.

In order to compare with the envelope based method [10], we plot the instantaneous amplitude (IA) of the respiration component $\alpha_0(t)$ and the upper and lower envelopes in Fig. 4. From the envelopes the BPM_r can be estimated [10], however, the upper and lower envelopes do not always have the same periodicity. In addition, the envelope extraction is sensitive to parameters, leading to that the respiration rate estimation have been previously constrained by the predefined parameters. The yellow curve in Fig. 4 is the IA of the extracted respiration component from SSWPT. According to the spectral analysis, the subjects respiratory rate is about 15.6 BPM_r before sleep (Fig. 4), which is very close to the ground truth measured by a stop watch. And the BPM_r during sleep is 12.4 (Fig. 5), which shows an expected decrease.

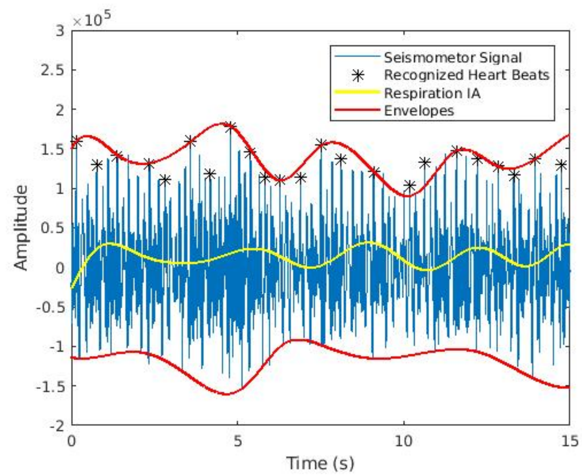

Fig. 4: Before sleep example. Seismometer signal from the dashed frame in Fig. 2, recognized heartbeats, envelopes and respiration IA are plotted.

3.2. Sleep quality and posture

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. Fig. 2 shows a late night data at 3 AM within a solid frame. Fig. 6 shows 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.

In Fig. 2 and Fig. 6, 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.

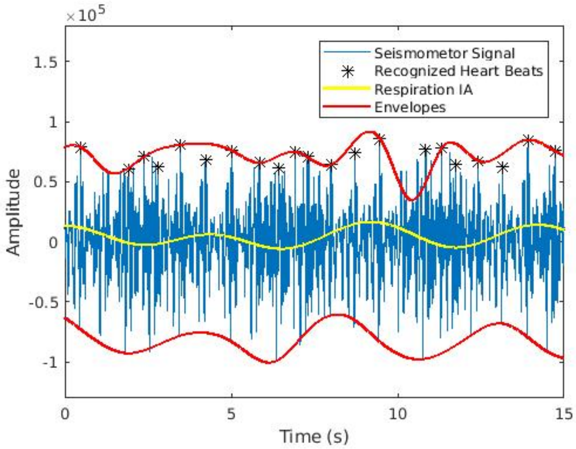

Fig. 5: During sleep example. Seismometer signal from the dash-dot frame in Fig. 2, recognized heartbeats, envelopes and respiration IA are plotted. Notice the respiration is slower and the IA is weaker than those shown in Fig. 4.

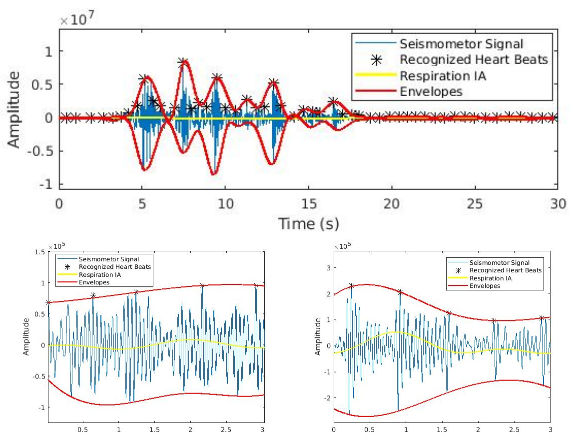

Fig. 6: Body motion and posture recognition example. (Upper) Body movement show strong amplitudes. (Bottom Left) Before and (Bottom Right) after the movement, the IA changes, which indicates there is a sleep posture change.

3.3. 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.

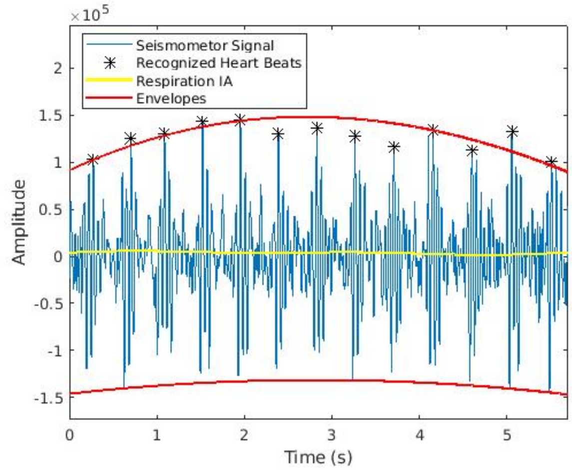

Fig. 7: Apnea example. Seismometer signal, recognized heartbeats, envelopes and respiration instantaneous amplitude (IA) are plotted. Notice the respiration movement is really slow and not obvious in this experiment.

Fig. 7 shows 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.

4. CONCLUSION

The bed-mounted seismometer is non-intrusive and non-contact, showing great potentials for sleep quality and status monitoring. Viewing the respiration and heartbeat are different rhythms of human body, we extract oscillatory components to estimate those body parameters. A novel local maxima statistics method and a SSWPT based instantaneous property analysis approach are designed to estimate heart and respiratory rate. The experiments demonstrate that the 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 posture identification. In addition, we also found 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 persons sleep stage and evaluate the sleep quality. To achieve this objective, we need to add several system modules, such as machine learning and deep learning models, to detect and classify those minor information.

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