Demonstration Abstract: RUBreathing: Non-Contact Real Time Respiratory Rate Monitoring System

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ABSTRACT

The respiration rate of a person provides critical information about their well-being. Conventionally, contact sensing is used for breathing monitoring; however, it is expensive, uncomfortable, and immobile. In-home non-contact breathing monitoring is now possible via Doppler radar and motion capture video sensors, yet these technologies are limited in mobility, among other limitations. When monitoring a patient who is free to move around his or her home, it is difficult to scale current non-contact sensors to cover the large area. Our RUBreathing sensor system uses RF received signal strength (RSS) in a network to estimate breathing rate in real-time with high accuracy over a wide area. In this demonstration, we show the sensor continuously estimating a patient's respiration rate from non-contact RSS measurements between wireless devices.

1. INTRODUCTION

According to the National Academy of Sciences, an estimated 50-70 million adults in the U.S. suffer chronically from a sleep related issue or disorder. There are over 50 sleep disorders classified by the American Academy of Sleep Medicine with the most prevalent disorders being insomnia, obstructive sleep apnea, restless legs syndrome, and narcolepsy. Individuals who suffer from insufficient sleep are also more likely suffer from additional chronic diseases like depression, diabetes, hypertension, obesity and are at a higher risk for cancer [1]. A survey conducted in 2008 from the Behavioral Risk Factor Surveillance System provides relevant data on the negative influence insufficient sleep can cause. According to the data , 35.3% reported receiving less than 7 hours of sleep during a typical 24 hour period, 37.9% reported unintentionally falling asleep during the day at least once in the preceding month, and 4.7% reported nodding off or falling asleep while driving at least once in the preceding month. This data, especially the 4.7%, demonstrates the serious consequences from a lack of sleep. In fact, the National Department of Transportation estimates that drowsy driving is responsible for more than 1,500 fatalities and 40,000 nonfatal injuries in the United States each year [5]. Additionally, there are other sleep related issues that would benefit from in-home sleep monitoring. In 2011, approximately 17,000 deaths were caused by drug overdoses of prescription opioid pain relievers. In fact, prescription drug overdose related deaths have increased by 500% since 1990, and are now the leading cause of unintentional injury deaths in the U.S. [3]. Many patients are safely prescribed opioid pain relievers to effectively treat short-term pain. However, opioids cause respiration depression, a decrease in respiration rate and a shallowing of the volume of air inhaled, thereby decreasing the intake of oxygen and causing moments of apnea. If these moments occur frequently or last too long, the oxygen levels will become dangerously low, and serious injury or death can occur. We propose a robust breathing sensor capable of sending an alarm if the breathing level of the patient falls below a certain safety level to be used to provide caretakers or medical personnel the opportunity to intervene and prevent fatality or irreversible damage to the patient. It is critical that the sensor be able to monitor breathing anywhere in the home, as people who are in pain and on pain medication

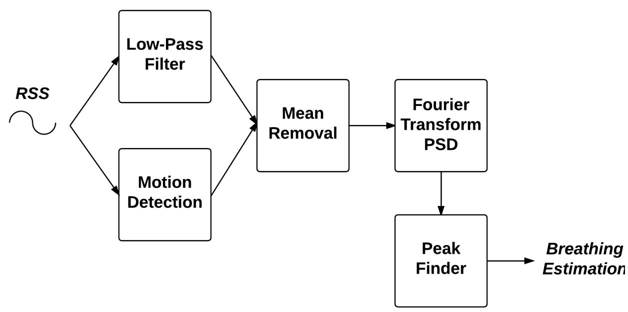

Figure 1: Algorithm overview: The raw RSS data stream is used for motion detection and is low-pass filtered. When no motion is present, the mean is subtracted, and the peak of the averaged power spectral density is used as the breathing rate estimate.

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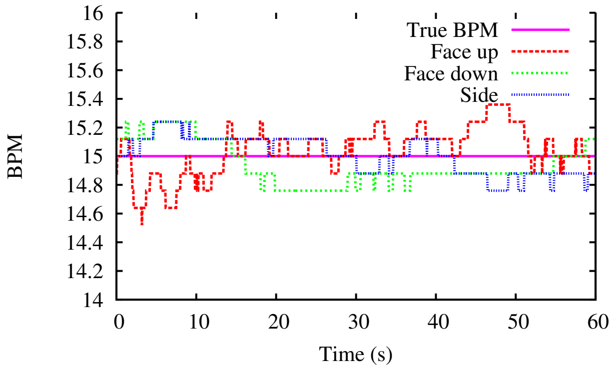

Figure 2: Differences between laying position. In this setup, the subject lies face up, face down, and on his side. The channels are affected the same way and breathing rate estimation remains accurate.

often sleep places other than their bed; for example, it may be more comfortable for a post-surgical patient to sleep in a reclining chair than in a bed.

2. SYSTEM DESIGN

RUBreathing, in this demonstration, utilizes two Texas Instruments CC2530 evaluation modules, each of which contains a system-on-chip, Intel 8051 and Zigbee 2.4GHz radio. This platform is chosen because little computation or memory is required for the RUBreathing sensor, and this platform is low cost and low power.

In order to efficiently sample multiple frequency channels, we use multi-SPIN [2], a time division multiple access (TDMA) protocol in which each node takes a turn broadcasting a packet while the other measures the RSS. Each packet contains the node's latest measured RSS values. After each round of transmission, nodes switch synchronously to the next frequency channel and continue the cycle. A connected sink node overhears all the traffic and records and processes the data.

The RSS is received as a raw stream of data as shown in Figure 1. Pre-filtering is a low-pass filter that removes unwanted frequency components above 0.4 Hz. Following the filter, the mean is subtracted from the signal to remove the unwanted DC component. In parallel, the motion detector identifies any period containing movement. Mean removal and breathing rate estimation is performed only during periods with no motion. The average power spectral density is computed, and its peak becomes the breathing rate estimate [4].

In a simple real-time implementation, the RSS measurement stream is stored in the buffer *rss* which is *buffL* in size. Each new RSS value is pushed onto the *rss* buffer and the oldest value is popped off. At each new sample, the breathing rate is re-estimated.

3. PRELIMINARY RESULTS

In a test, a person lies down on a cot which is 15 cm above the ground. The two sensors are also placed 15 cm off the ground. They are 1.4 m away from the subject's shoulder. The experiments are run in a cluttered room of size 6.1 m by 6.2 m. The subject was alone in this room for the duration of the experiment. In order to create ground truth, the subject is breathing in and out with a metronome at a known fixed rate of 15 breaths per minute (bpm).

People often toss and turn while sleeping. Changes in sleeping orientation can degrade the accuracy of other breathing monitoring methods. In this experiment, we test three different positions including lying face up, lying face down, and lying on the right side. Due to reciprocity, we expect lying on the left side or right side would yield similar results. Figure 2 shows a 60 seconds window of the rate estimates. From the figure, the maximum error is 0.4 bpm. The results show little effect of lying orientation on the accuracy of breathing rate estimation.

4. DEMONSTRATION REQUIREMENTS

We will demonstrate the real-time breathing monitoring algorithm and non-contact sensing system in a small room. We will allow any conference participant to sit, lie down, or move around in the sensor deployment area. When the participant is stationary, the system will display their estimated breathing rate. While they are moving, the system will detect that there is a moving person and not report breathing rate. For this demo, we request a small room. We'd prefer not to be located immediately next to other demos because human motion in proximity to the deployed nodes will cause the sensor to detect motion and be unable to estimate breathing rate.

5. REFERENCES

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