Sleep Monitoring Using WiFi Signal

Xuyu Wang, Chao Yang and Shiwen Mao

Abstract Sleeping monitoring is to detect and analyze the activities of a subject during sleep, such as respiration rate, heart rate, and posture, to provide important information for the subject's health conditions. Effective techniques are needed to enable contact-free and long-term sleep monitoring. In this article, sleep monitoring using WiFi signals is reviewed. The preliminaries of WiFi signals is first introduced, followed by a detailed discussion of existing techniques on vital sign monitoring using WiFi signals.

Key words: Sleep monitoring, received signal strength indicator (RSSI), channel state information (CSI), WiFi.

1 Introduction

Sleeping monitoring is to detect and analyze the activities of a subject during sleep, such as respiration rate, heart rate, and posture, to provide important information for the subject's health conditions Pantelopoulos and Bourbakis [2010], Chen et al. [2013], Wang et al. [2018a,b]. In addition, sleeping quality can also be monitored by analyzing such vital signs. For example, monitoring the breathing signal while sleeping can help to detect sleep disorders, as well as sudden infant death syndrome

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(SIDS) Hunt and Hauck [2006] and apnea Nandakumar et al. [2015]. However, most traditional sensors are intrusive, such as a capnometer Mogue and Rantala [1988] or a pulse oximeter Shariati and Zahedi [2005]. A patient can hardly sleep comfortably with these sensors attached to the body. Because of the restrictions of traditional sensors, effective and comfortable sensors are in a great demand for long-term and contact-free vital sign monitoring.

Recently, sleep monitoring are implemented using different techniques, including RF radar, RFID, motion sensors, and acoustic based sensors. Vital-Radio is an RF radar based technique, which uses a frequency modulated continuous wave (FMCW) radar to monitor breathing and heart rates Adib et al. [2015]. It requires a customized hardware using a large bandwidth from 5.46 GHz to 7.25 GHz. Moreover, other radar based vital sign monitoring techniques are proposed, including ultra-wideband radar Salmi and Molisch [2011] and Doppler radar Droitcour et al. [2009], Nguyen et al. [2016], which all require customized hardware with a high cost and operates at high frequency. RFID tags are used for vital sign monitoring too. For example, Tagbreathe estimates breathing rates with phase information by grouping the signals with the same channel index Hou et al. [2017]. In fact, the system does not work very well in the US, where the RFID frequency range is from 902.5 MHz to 927.5 MHz with 50 channels; the channel hopping among the 50 different frequencies leads to a large latency. Zephyr is a motion sensor based monitoring techniques, which can monitor breathing rates by fusing the data from the accelerometer and gyroscope available in many smartphones Aly and Youssef [2016]. In addition, HeartSense can even achieve a 1.03 bpm median absolute error for heart rate estimation using different gyroscope axes with a probabilistic model Mohamed and Youssef [2017]. The SleepMonitor system uses the built-in accelerometer to estimate breathing rate and body position with a smartwatch Sun et al. [2017]. For acoustic signal based sensors monitoring, the Apnea system employs an active FMCW sonar built in a smartphone to monitor the breathing signal Nandakumar et al. [2015], while SonarBeat considers sonar phase information for breathing rate estimation with a continuous-wave (CW) radar Wang et al. [2017a].

Although different techniques have been proposed for sleeping monitoring, contact-free and long-term vital signs monitoring at low cost are still of high interest. Currently, WiFi based systems have become an effective solution for sleep monitoring, as shown in Fig. 1, because of the wide availability and the low hardware requirements of WiFi. Received signal strength (RSS) in WiFi networks has been used for vital sign monitoring in Abdelnasser et al. [2015]. Moreover, by slightly modifying the device driver, channel state information (CSI) can be extracted from off-the-shelf WiFi network interface cards (NIC) Halperin. et al. [2010], which reflects fine-grained channel information. CSI amplitude Liu et al. [2015] and phase difference Wang et al. [2017b,c] have been leveraged for sleep monitoring. WiFi based techniques for sleep monitoring will be reviewed in detail in the remainder of this article.

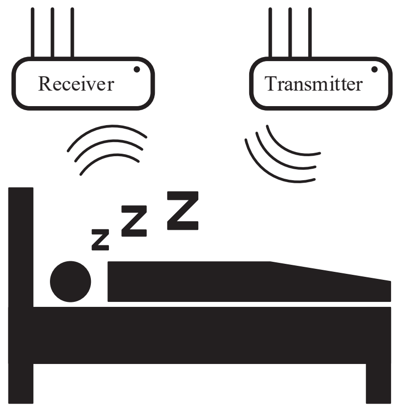

Fig. 1 Sleeping monitoring using WiFi signals.

2 Preliminaries of WiFi Signals

WiFi standards, such as IEEE 802.111a/g/a/ac, all use the Orthogonal Frequency Division Multiplexing (OFDM) technique in Physical Layer (PHY), which can effectively overcome frequency selective fading in indoor environments. With OFDM, the total spectrum is divided into multiple orthogonal subcarriers, while data is encoded and mapped to these subcarriers to be transmitted using the same modulation and coding scheme (MCS) Wang et al. [2016a, 2017d]. At the receiver, the wireless signal is down-converted to the baseband. Using the serial-to-parallel (S/P) transform and Fast Fourier Transform (IFFT), the subcarriers can be converted from the time domain to the frequency domain as in Fig. 2. For some commodity NICs, such as the Atheros AR9390 chipset Xie et al. [2015] and Intel 5300 NIC Halperin. et al. [2010], there are open-source device drivers that allow reading the CSI of subcarriers, which represents fine-grained PHY channel measurements, containing rich information on channel features such as shadowing, power distortion and multipath effect.

Let H_i be the CSI value of subcarrier i, which is a complex value, as

$$\mathrm{H}_i = |\mathrm{H}_i| \exp\left(j \angle \mathrm{H}_i\right). \tag{1}$$

where $|\mathrm{H}_i|$ and $\angle \mathrm{H}_i$ are the amplitude response and phase response of subcarrier i, respectively. The measured phase of subcarrier i, $\angle \widehat{\mathrm{H}}_i$, is Wang et al. [2017b,c]

$$\angle \widehat{\mathrm{H}}_i = \angle \mathrm{H}_i + (\lambda_p + \lambda_s) m_i + \lambda_c + \beta + Z, \tag{2}$$

where m_i is the subcarrier index of subcarrier i, β is the initial phase offset at the phase-locked loop (PLL), Z is the measurement environment noise, and λ_p, λ_s and λ_c are the phase errors from the packet boundary detection (PBD), the sampling frequency offset (SFO), and the central frequency offset (CFO), respectively.

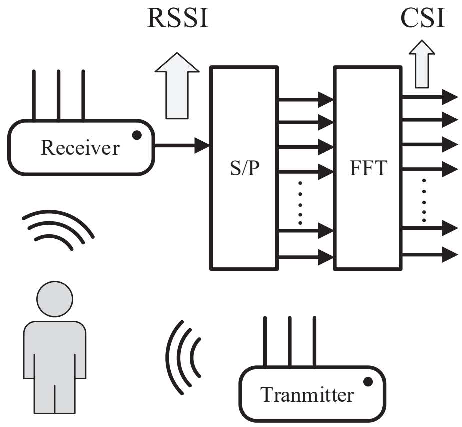

Fig. 2 CSI and RSSI in OFDM based WiFi system.

The measured CSI phase data is not stable because of the randomness in the RF chain, but the measured *phase difference* (i.e., the difference of phases from different antennas) can be exploited for vital sign monitoring, which is given by

$$\Delta\angle\widehat{H}_i = \Delta\angle \mathrm{H}_i + \Delta\beta + \Delta Z, \tag{3}$$

where $\Delta\angle \mathrm{H}_i$ is the true phase difference of subcarrier i, $\Delta\beta$ is the unknown difference in phase offsets, which is a constant, and ΔZ is the noise difference. Obviously, $\Delta\angle\widehat{H}_i$ is a stable signal, because the randomness from PBD, SFO, and CFO are all canceled.

On the other hand, RSSI can be described as a function of sender-receiver distance d with a path-loss model, as Wang et al. [2014]

$$\mathrm{RSSI} = P_0 - 10n\log_{10}(d) + w, \tag{4}$$

where P_0 is the RSS value at a reference distance d_0, n is the path loss exponent, which is different from 2 in free space to 4 (or a higher value) in indoor environments), w is a zero mean Gaussian noise. Measurements show that RSSI not only fluctuates over distance, but also varies over time. Thus, a small change of the propagation environment will cause large changes in RSSI, which can also be exploited for vital sign monitoring.

3 Existing Techniques of Vital Sign Monitoring with WiFi Signals

3.1 RSS based Vital Sign Monitoring

UbiBreathe is a WiFi RSS based technique, which can capture the human respiration signal with RSS values obtained from off-the-shelf WiFi devices Abdelnasser et al. [2015]. In particular, the system uses a cellphone as receiver, and a laptop as transmitter. To extract the respiration signal, raw RSS values are firstly filtered by a bandpass filter with cutoff frequency from 0.1 Hz to 0.5 Hz. Then, noise is further removed by a Discrete Wavelet Transform (DWT) and outlier removal. Breathing rate can be then estimated using FFT. The system also detects abnormal breathing symptoms such apnea using a threshold method, while the subject is sleeping. Experimental results show that the estimation error of breathing rate of UbiBreathe is less than 1 beats per minute (bpm). However, the system has special location requirements for the user and two devices. The system can only detect human breathing signal when the receiver is on the user's chest or the user is in the LOS path of the transmitter and receiver.

However, RSS values collected from 2.4GHz and 5GHz WiFi devices can hardly capture the human heart rate because of the low resolution of RSS values. In addition, the received RSS values can be easily corrupted by other persons nearly, because of the omnidirectional propagation of WiFi signals. To address this issue, the mmVital system employs 60 GHz WiFi devices to measure both breathing rate and heart rate Yang et al. [2016]. Since the 60 GHz WiFi signal is transmitted in a highly directional beam, the subject can be easily separated from other unrelated objects/people in the environment. In fact, it is necessary for the system to first identify the location of the user, before monitoring vital signs. To deal with this challenge, the authors develop a novel human finding technique to differentiate the reflections from the user and other surrounding objects. With this technique, the system can locate two users and monitor their vital signs simultaneously. The evaluation of the system shows that the accuracy of human finding subsystem is up to 98.4%, and the mean errors of breathing rate and heart rate estimations are 0.43 bpm and 2.15 bpm, respectively. The accuracy of the system is high, but there are still some deficiencies for the system. For example, the user has to stay in the LOS or the reflection path of the transmitter and receiver, and the special 60 GHz hardware is required for this technique.

3.2 CSI based Vital Sign Monitoring

CSI can provide much more information of the wireless channel than RSS. Several CSI based systems have been proposed for more accurate vital sign monitoring. The amplitude of CSI is firstly used to detect breathing rate. The WiFi-sleep system monitors the human respiration and different sleeping postures by analyzing the amplitude of CSI Liu et al. [2014]. To denoise the CSI amplitude and remove outliers, the raw received signals from all subcarriers are firstly filtered by DWT. Because the sensitivities of CSI values over subcarriers are different, some of the signals may not be useful. The system only chooses the most sensitive signal to estimate the human breathing rate. Furthermore, the system also analyze the effect of human sleeping postures on breathing estimation. To reduce the impact of different sleeping postures, the system will automatically choose the best antenna pair to obtain the most appropriate CSI signal.

In addition to breath monitoring, another work can also estimate heart rate from CSI amplitude Liu et al. [2015]. Different from the breathing signal, which can be obviously observed in CSI, the heart signal is very weak and cannot be easily detected from raw CSI measurements. To focus on heart rate monitoring, the received signal is filtered by a bandpass filter with the cutoff frequency from 1 Hz to 1.33 Hz. The experiment results with this technique show that the mean estimation errors of heart rate and breathing rate is 2 bpm and 0.3 bpm, respectively.

Compared with CSI amplitude, CSI phase is more robust for monitoring vital signs at different distances and orientations. However, due to the asynchronous options of the transmitter and receiver, the measured phase information cannot be directly used. To this end, the Phasebeat system leverages the phase difference between two receiving antennas to monitor vital signs Wang et al. [2017b]. With phase difference data, the robustness of respiration rate estimation is greatly increased. In addition, Phasebeat can detect the breathing signal at longer distances, e.g., when the transmitter is 11 meters away from the receiver. The median error of breathing rate estimation is about 0.25 bpm. PhaseBeat can also detect heart rate with a 1 bpm median error.

Although distance has less impact on phase difference, the sensitivities of CSI phase difference and amplitude can be affected by the reflection from surroundings or the posture of the user Wang et al. [2016b]. Fig. 3 shows a colormap for breathing signals using CSI phase difference and amplitude, which illustrates the independence of the sensitivities of CSI phase difference and amplitude. To enhance the robustness of CSI based systems, the bimodal data system ResBeat leverages not only phase difference but also amplitude Wang et al. [2017e]. Resbeat implements an adaptive signal selection algorithm to ensure that only the most sensitive amplitude and phase difference be used for extracting respiration signal. The final estimation result is calculated with the combination of both amplitude and phase difference data. The system is shown to remain robust, even though the location or the posture of the user is changed. The success rate of human respiration rate estimation is higher than 90% in the experiments.

The TensorBeat system is proposed to handle the case of multiple persons with tensor decomposition Wang et al. [2017c]. First, TensorBeat system uses CSI phase difference data between pairs of antennas to create CSI tensors, and then Canonical Polyadic (CP) decomposition is used to decompose the tensor. In addition, a stable signal matching algorithm is utilized for obtaining the decomposed signal pairs for each person. Finally, a peak detection method is exploited to estimate the breathing

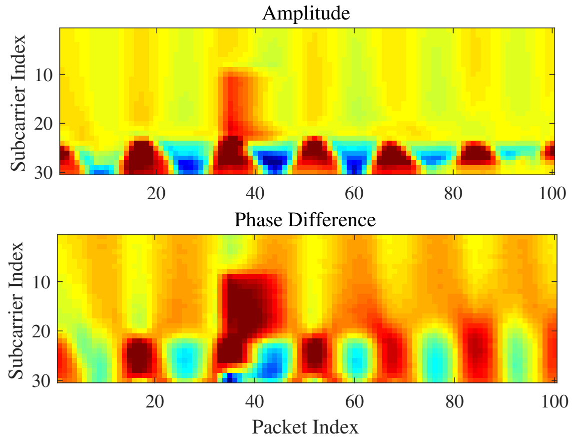

Fig. 3 Colormap for breathing signals using CSI phase difference and amplitude.

Table 1 Comparison of Different Systems for Vital Sign Monitoring

	Breathing rate	*Heart rate*	*Multiple users*	*Special hardware*	*LOS path requirement*
UbiBreathe Abdelnasser et al. [2015]	√	×	√	×	√
mmVital Yang et al. [2016]	√	√	√	√	√
Wi-sleep Liu et al. [2014]	√	×	×	×	×
Amplitude based method Liu et al. [2015]	√	√	√	×	×
Phasebeat Wang et al. [2017b]	√	√	√	×	×
Resbeat Wang et al. [2017e]	√	×	×	×	×
Tensorbeat Wang et al. [2017c]	√	×	√	×	×
TR-BREATH Chen et al. [2018]	√	×	√	×	×

rates for multiple persons. Experimental results show that TensorBeat can achieve high accuracy under different environments for multi-person breathing rate monitoring. In addition, TR-BREATH system is also proposed for monitoring breathing rates for multiple persons Chen et al. [2018]. CSI values is used for obtaining time reversal resonating strength (TRRS) features, which can be thus analyzed by root-MUSIC and affinity propagation algorithms to estimate multiple persons breathing rates. The difference between Tensorbeat and TR-BREATH is that TensorBeat can obtain different breathing signals for different persons while TR-BREATH system only estimates the breathing rates. In fact, both systems cannot tell which breathing rate belongs to a specific person.

Table 1 provides a comparison of different systems for vital sign monitoring in detail.

4 Conclusions

We addressed the problem of sleep monitoring using WiFi signals in this article. The preliminaries of WiFi signals is first introduced, where RSSI and CSI amplitude and phase difference information are presented. Then, an overview of existing techniques of vital sign monitoring using WiFi signals is provided, where RSS and CSI based techniques are discussed.

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