Respiration detection of sedentary person using ubiquitous WiFi signals

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***Abstract*—A sedentary lifestyle significantly influences the health of people. Accordingly, to avoid the risks of sudden respiratory illness, a continuous, effective, and inexpensive sensing system is vital. In this paper, we leverage commercial WiFi devices to deploy a respiration detection system for sedentary scenarios. Our results showed a median error, for one and two human subjects' breathing detection, of 0.7 bpm and 1 bpm respectively.**

***Index Terms*—WiFi sensing, vitals detection, channel state information**

I. Introduction

Device-free WiFi sensing is an emerging research trend for nearly a decade, which spanned various kinds of applications including vitals monitoring, daily activity recognition, falling detection, and signs recognition [1]–[3]. In comparison with other equipment of radar-based device-free approaches, the WiFi devices objectively own higher cost-effectiveness which is the better choice for general in-home cases implementation.

Channel state information (CSI) is used to characterize the channel attributes of WiFi links in the physical layer as a sample of the channel frequency response, which can be disturbed by multipath fading and shading. In an indoor environment, the movement of the human body is one of the significant factors that influence the CSI value. Moreover, the CSI values contain person-related information such as daily movement and rhythmic physiological phenomena, for example, respiration and heartbeat. WiFi sensing technique aims to extract and analyze this potential person-related information. The following equation to describe the CSI:

$$H(f,t) = e^{-j2\pi\Delta ft}(H_s(f) + H_a(f,t)) \tag{1}$$

where $e^{-j2\pi\Delta ft}$ is the random phase shift due to the asynchronous transmission and reception processes of the WiFi system; H_s and $H_a(f,t)$ represent the CSI signals from all the static paths (including the signals in line-of-sight (LOS) areas and those reflected off the stationary objects) and active paths (including signals reflected from the dynamic objects) respectively. CSI that is reflected by active paths can be expressed as:

$$H_a(f,t) = \sum_{i=1}^{N_d} a_i(f,t)e^{-j2\pi d_i(t)\lambda} \tag{2}$$

where N_d is the index of the dynamic path, $a_i(f,t)$ represents the complex attenuation factor and the initial phase of the i^{th} path; $e^{-j2\pi d_i(t)\lambda}$ represents the phase change of i^{th} path; $d_i(t)$ and λ are the length of the i^{th} path and the wavelength of the WiFi signal, respectively.

Through coupling Equations (1) and (2), we can discover that person-related information is reflected in the amplitude and phase shift [1]. Compared to CSI amplitude, CSI phase information is more sensitive for the small-scale motion of the human body, especially for respiration detection [4]. Besides, amplitude information can be distorted to an infinite value, which causes loss in the information that cannot be recovered. However, the random phase offset can be recovered through multiple techniques. In this case, phase sanitation is significant for the post-process of WiFi sensing.

To acquire clear and informative respiration signals, the system focuses on the elimination of time-varying phase noise. The main causes of noise signals include sampling frequency offset (SFO) and carrier frequency offset (CFO) caused by the multipath effect and channel fading [1], [3]:

- SFO: The reason is that the clocks are out of sync, causing the sampling frequency of the transmitter and receiver to shift, which will cause the phase of the received signal to be shifted from the transmitted signal.
- CFO: Due to the shallow bandwidth of subcarriers in WiFi modulation protocol, the carrier frequency of transmitter and receiver cannot be completely synchronized.

In our paper, we leverage the commercial WiFi devices with a series of calibration methods and algorithms to achieve the respiration estimation of one and two human subjects in a sedentary status.

II. Methodology

A. Experimental Setup

The system is implemented with a pair of WiFi devices equipped with Intel 5300 wireless network interface controller and the open-source CSI driver [5]. The carrier frequency and sample frequency are set to 5.8 GHz and 200 Hz. We adopt one transmit antenna and two receiving antennas, with a coaxial cable and a splitter to connect two devices. The distance of two receive antennas is set to the half-wavelength of 2.6 cm. In each of the experiments, we asked volunteers to breathe in the fixed rhythm of 0.2 Hz, 0.25 Hz and 0.33 Hz respectively, while collecting data.

B. Calibration of WiFi signals

Although the captured CSI signals are distorted in distinct paths, the main components of noise can be modeled as a whole considering SFO and CFO effects. First, we apply a proposed calibration method of establishing the solid reference link using a coaxial line to connect transmitter and receiver in [1], shown as Fig. 1. The established link is not affected by transmission attenuation in the air. Then calculate the conjugated multiplication of CSI complex signals of reference link and wireless link. Meanwhile, we calculate the inverse fast Fourier transform (IFFT) of raw CSI data to get time of flight (ToF) value. By setting the threshold of ToF and filtering long time-delay components, we can reduce the multipath noise.

Fig. 1: Experiment hardware connection of system

C. Respiration estimation

After the calibration of CSI data, we acquire the de-noised CSI signals which show the lung's periodic movement clearly. Then we calculate the ratio of variance and difference of maximum and minimum value to select a single subcarrier that is the most sensitive to lung movement, which can reduce the static components' influence. The respiration rate estimation is performed for one and two human subjects.

a) Respiration rate estimation for one human subject: Firstly, we adopt the peak detection (PD) method on processed signals. However, in some cases we found the vibration range of lungs during breathing can be different, which led to the inconsistent peak in the respiration signals. To improve the performance, we adopt the auto-correlation function (ACF) to enhance the periodicity of signals.

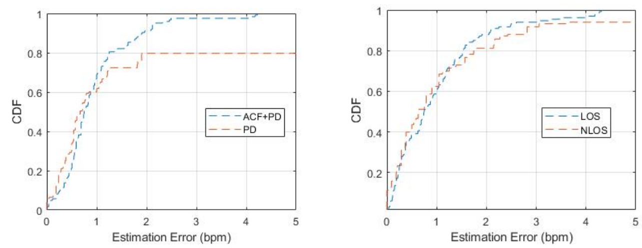
b) Respiration rate estimation for two human subjects: PD cannot work well in the case of the two-person scenario because the components belonging to different identities cannot be separated in the time domain. The accessible solution is to transfer the signal into the frequency domain with Fast Fourier Transformation (FFT).

III. Evaluation

A. Single person respiration rate detection

In the one-person scenario, we firstly discuss the performance of PD and PD with ACF. The CDF shows the performance of our system in Fig. 2a. The overall median error is 0.7 bpm.

Meanwhile, we conduct the experiments under the NLOS environment. NLOS signals usually involve rich reflection, diffraction, and refraction, resulting in significant attenuation of transmission power theoretically. The CDF shows the slightly different performance of estimation in LOS and NLOS scenarios in Fig. 2b. We can find our system can adapt the NLOS scenarios in the sedentary situation.



(a) ACF+PD vs PD (b) LOS vs NLOS

Fig. 2: CDFs of real-time frequency estimation

B. Two-person respiration rate detection

The image of Fig. 3 shows the frequency analysis results in the two-person scenario. The volunteers are asked to breathe in different frequencies (0.2 Hz, 0.25 Hz, and 0.33 Hz). The average error is the account of 1 bpm in total.

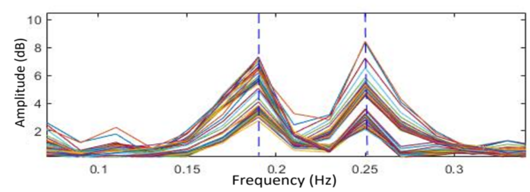


Fig. 3: Frequency analysis of the two-person scenario

IV. Conclusion

This paper leverages commercial WiFi devices to estimate the human respiration rate. We adopt multiple calibration methods to acquire the informative CSI phase and implement PD and ACF algorithms in real-time respiration estimation for one and two human subjects, with an error of 0.7 bpm and 1 bpm, respectively. This method proves the high performance of breathing detection with commercial WiFi devices, which is potential in other kinds of tiny movement sensing, like sedentary activity recognition.

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