Fine-grained Vital Signs Estimation Using Commercial Wi-Fi Devices

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ABSTRACT

Due to the importance of vital signs, breathing rate and heart rate have been widely used in heath care. In the past few years, various systems and approaches have been proposed to detect and monitor breath and heart beat. In this paper, we show that Wi-Fi signals can also be used to recognize and count breath and heart beats with different postures. The intuition is that human activities have different impacts on time-series of Channel State Information (CSI) values, which can be utilized to recognize macro and micro human activities. In this paper, we design a Wi-Fi signal based breath and heart beats recognition system called WiHealth. WiHeath consists of two Commercial Off-The-Shelf (COTS) Wi-Fi devices, a sender (Wi-Fi router) and a receiver (laptop). The sender sends 802.11n packets to the receiver, while the receiver continuously receives these packets and records in real-time CSI value. The receiver analyzes the collected CSI values and determines if the human is alive and the number of heart beats and breaths.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

Human activity recognition, Signal processing

1. INTRODUCTION

The breathing rate and heart rate have been widely used in health care and monitoring. For instance, a low or high heart rate is usually an indicator of a health condition. In addition to health care, such vital signs can also be used in rescue environments. In earthquake rescue, if we detect hearth beat or breath, it usually means someone nearby is alive. The research community has studied various ways to detect life and track human vital signs. Traditional approaches can be classified into two categories: wearable sensor based approaches and life detector based approaches. Wearable sensor based approaches can accurately estimate breathing and heart rate, but they are not convenient because users have to wear these sensors all the time. Life detector based approaches have been widely used in real earthquake rescue scenarios, but they can not provide accurate breathing and heart rate of trapped people.

In today's society, Wi-Fi signals are pervasive in our daily life [4, 5]. Some researchers have found that human activities, even small chest movement, can generate some influences on Wi-Fi signal. Meanwhile, some commercial Wi-Fi devices provide us Channel State Information (CSI) in time-series. Because of the high data rate provided by modern commercial Wi-Fi devices, we can get enough CSI samples within the duration of human chest movement. Since one specific human activity tends to influence the CSI waveform in a specific way, we can analyze CSI waveform to estimate human breathing and heart rate. Several systems like [6] have used this intuition to track human vital signs. Such Wi-Fi based approaches are device-free, low-cost and easy to implement in comparison to wearable sensor based and life detector based approaches. Unfortunately, these solutions only consider scenarios where the user is lying down and remaining still. However, in real rescue situations users may be stuck in different postures, or there could be a wall separating the trapped survivors and the rescue teams.

In this paper, we design a device-free and low-cost Wi-Fi signal based vital signs estimation system called WiHealth. WiHeath consists of two Commercial Off-The-Shelf (COTS) Wi-Fi devices, a sender (Wi-Fi router) and a receiver (laptop). The sender sends 802.11n packets to the receiver, while the receiver continuously receives these packets and records them in real-time CSI value. The receiver analyzes collected CSI values and determines whether of rnot the human is alive, and the number of heart beats and breaths.

Our system only uses one transmitter and one receiver to estimate human vital signs. When the receiver collects time-series CSI value from the Tool [1], it first performs spike removal algorithm and a low-pass filter to remove noise. In order to separately obtain the influences from breathing and heart beat, our system applies two band-pass filters on the CSI waveform. More algorithms are designed to select sensitive subcarriers, analyze spectrum and eliminate similar human activities. Here we define similar human activities as activities that have a similar frequency with breathing ($0Hz \sim 1Hz$), such as waving hands. Extensive experiments are conducted in a typical meeting room environment to evaluate the performance of our system. The experiment demonstrates that our system accurately measures heart and

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breathing rate even if the trapped survivor is in different postures or has similar activities. The results show that our approach provides an accurate and robust solution to estimate human vital signs based on commercial Wi-Fi devices. This allows us the possibility to implement this system into snake-like robots to rescue trapped people in the future.

2. RELATED WORK

Existing wireless signal based human recognition systems can be divided into 2 categories: Received Signal Strength (RSS) basedand CSI based.

2.1 RSS based

The RSS values collected from commercial Wi-Fi chipsets can be used for human activity recognition and human localization. For example, Abdelnasser *et al.* proposed WiGest [2] which uses RSS waveform to detect different gestures over the laptop.However, RSS values collected from commercial Wi-Fi devices only provide coarse-grained channel variation information. Furthermore, they can not utilize multi-path effects of indoor Wi-Fi signals. As a result, most systems only use RSS for macro-movement recognition and distance estimation.

2.2 CSI based

Compared with RSS, CSI provides not only fine-grained channel status information, but information about small scale fading and multi-path effects caused by micro-movement. As a result, most Wi-Fi based human activity recognition systems use CSI as source data. For instance, Ali *et al.* proposed Wikey [3] which can recognize keystrokes of different users in the indoor environment. Wang *et al.* proposed WiHear that can recognize mouth movement and "hear" people talks within the radio range. These systems follow the general structure of machine-learning based systems and have four stages: noise removal, feature extraction, classification, and evaluation.

3. OUR SOLUTION

Preprocessing. The raw CSI waveform we collected from commercial Wi-Fi devices is usually not reliable enough to be used for feature extraction because of the noise from environmental changes and radio signal interference. In our system, we first use median filter to mitigate the samples which have significant different value from other neighboring samples in raw CSI waveform. Next, We apply a low-pass filter to remove high frequency noise that cannot be caused by chest movement, due to the poor performance of the median filter with high frequency noise. Since human chest movement is at low frequency and there is not a significant range of motion, these two filters can still effectively remove noise and keep useful information.

Spectrum Analysis. In order to obtain a robust estimation, we need to combine the results from subcarriers which are sensitive to human activity. As shown in Fig. 1, waveforms of subcarriers (No. 10 $\sim$ No. 15) are more sensitive to human activity.

Both heart beat and breathing will introduce a periodic changing pattern to CSI waveform over the time. However, it is still difficult to identify each heart beat and breathing cycle based on a filtered CSI waveform, especially for heart beat cycle. In order to separately focus on the in-

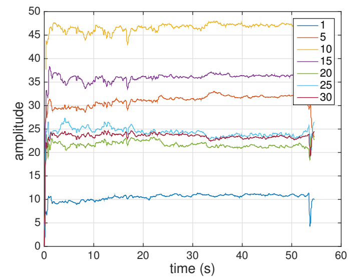
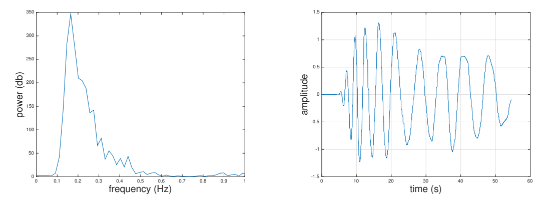


Figure 1: The filtered CSI waveforms of different subcarriers



(a) Spectrum of Breathing (b) CSI waveform after band-pass filter

Figure 2: Spectrum analysis

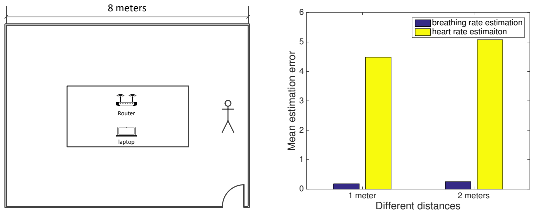
fluences cased by the heart beat and breathing, we apply two band-pass filters on CSI waveform with frequency bands $0Hz \sim 1Hz$(for breathing) and $1Hz \sim 2Hz$(for heart beat). Figure 2(a) shows the spectrum in breathing's frequency band. Each peak in a spectrum means a possible frequency of breathing. If the spectrum has only one significant peak, then we can apply a band-pass filter with a narrower frequency band. For example, in Figure 2(a), we can apply a band filter on the CSI waveform again with a frequency band $0Hz \sim 0.2$ Hz to get a more accurate waveform, and the result is illustrated in Fig. 2(b). We can see from Figure 2(b) that there are 7 peaks in 30 seconds, so the estimated breathing rate is 14 bpm. However, for the spectrum of heart beat, it can be difficult to determine the frequency band of heart beat because there is more than one significant peak. Such extra peaks may be cased by similar human activities.

Eliminating Human Activities with Similar Frequency. In a real rescue environment, there could exist similar activities. We need to eliminate these activities effectively, otherwise these activities may introduce extra peaks in spectrum and cause inaccurate estimation. The key observation is that both the heart beat and breathing will periodically influence CSI waveform,which means the variation of intervals between two peaks should be quite low. We will treat multiple peaks in spectrum as possible frequencies and exploit MSE(Mean squared error) of time intervals in each narrow frequency band.

$$MSE_j = \frac{1}{n}\sum_{i=1}^{n}(\bar{I} - I_i)^2$$

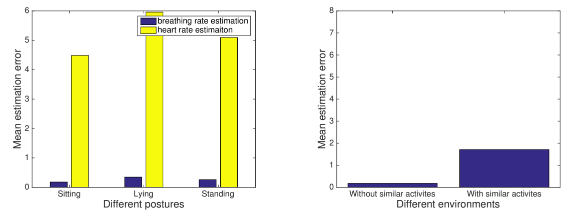
$$1 \leq j \leq m$$

where m is the number of possible frequencies, n is the number of intervals between peaks for a possible frequency, MSE_j is the MSE of j^{th} possible frequency, I_i is the time



(a) Floor plan (b) Estimation Performance under different distanes

Figure 3: Floor plan and estimation performance under different distances



(a) Estimation performance under different postures (b) Breathing rate stimation performance under influence of similar activity

Figure 4: Estimation performance under different postures and influence of similar activity

duration of i^{th} interval, $\bar{I}$ is the average time duration of all n intervals for a possible frequency.

We set two thresholds τ_b and τ_h for MSE. Every possible frequency whose MSE_j is lower than τ_h or τ_b will be recognized as a real heart beat or breathing frequency, respectively. If there exists more than one real heart beat frequency, we argue that there is more than one alive person within the effective range of our system.

Heart Beat and Breath Rate Estimation. Traditional peak finding algorithms determine a sample as a local peak if its value is larger than its two neighboring samples. However, such simple local peak identification method may find some fake peaks. In our system, We are only concerned with the number of real peaks and therefore, adopt a polynomial filter to smooth the CSI waveform in addition to preserving all the real peaks. Then we can apply the traditional peak finding algorithm on CSI waveform to get the count. Considering the human breathing rate are usually at $12 \sim 18$ *bpm*, and human heart beat rate is $60 \sim 120$ *bpm*. We set the minimal peak distances are 3.33 and 0.5 for breath and heart beat, respectively.

We use a time window and set 30 seconds as the window size. Every 30 seconds, we count the number of local peaks b and h for breathing and heart rate respectively. Assume at i^{th} time window, we get b_i and h_i respectively. Then we will average b_i and h_i with b_j and h_j $(1 \leq j < i)$ in previous time windows to get more accurate estimation. So the final estimations for breathing rate and heart rate after i^{th} time window are

$$b_{esitmation} = \frac{1}{i+1} \times b_1 + \frac{1}{i} \times b_2 + \cdots + \frac{1}{2} \times b_i$$

$$h_{esitmation} = \frac{1}{i+1} \times h_1 + \frac{1}{i} \times h_2 + \cdots + \frac{1}{2} \times h_i$$

4. IMPLEMENTATION AND EVALUATION

Hardware Setup. We implement our system using commercial Wi-Fi devices. Specifically, we use a Lenovo X210 laptop with Intel Link 5300 Wi-Fi NIC as receiver which has three linear assigned antennas. The laptop has 2.13 GHz Intel Core$^{\text{TM}}$ I3 processor with 2GB of RAM and Ubuntu 14.04 as its operating system. We use TP-Link TL-WR1043ND Wi-Fi router as transmitter and set the router in AP mode at 2.4 GHz. All the packets are sent under 802.11n protocol. All the CSI samples are collected from Intel 5300 NIC using a modified driver developed by Halperin et al [1]. Both the transmitter and receiver have 3 antennas, so we can get $3 \times 3 \times 30 = 270$ different CSI waveforms for chest movement monitoring in our system.

All experiments are conducted in a typical meeting room. Three different participants are involved over a two-month time period. As shown in Figure 3(a), The environment is a large meeting room with a table in the center. In all environments, the table is used to study the influence of indoor obstacles which are also common in rescue environment. The Wi-Fi transmitter and receiver are placed one each side of the table with distance 1 meter.

Evaluation Results. We study the performance of our system by experimenting with various postures and activities, as well as different distances between the user and our system. Figure 3(b) and 4(a) show the average error of breath and heart rate estimation under different distances and postures. We can observe that our system can estimate breath and heart rate accurately enough with average estimation error under 0.6bpm and 6bpm, respectively. Moreover, we find the estimation is the best when the distance is $1m$, user is sitting and there is no similar activity. Figure 4(b) compares the average error of breathing rate estimation under whether there are or not similar activities. The results illustrate that our system can still get robust breathing rate estimation when there are similar human activities.

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