Device-Free Human Detection Using WiFi Signals

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***Abstract*—This paper is an initial study of device-free human detection using channel state information (CSI) in WiFi networks. After collecting the CSI data in the target area, the proposed detector contains three steps, preprocess, feature extraction, and making decisions (human presence or absence). Experiments, based on real CSI measurements, proof the concept of human detection. Results show that, using only two features, namely the missing numbers and the average variance among subcarriers, and a simple decision tree, the proposed approach achieves 74.9% detection accuracy (hitting rate), and a general 64.3% accuracy.**

***Keywords*—channel state information, human detection, WiFi application, device-free**

I. Introduction

With the popularity of WiFi, there are more and more applications developed using WiFi signals, such as gesture and activity detection [1], [2], indoor localization [3]–[5], falling detection [6], lips identification, and human detection [1]. These applications are helpful for child and elderly care, home security surveillance, and emergency response. In this study, WiFi signals based on channel state information (CSI) [7] are considered for detecting human. CSI provides the channel response, including the magnitude and phase, for each subcarrier of a trans-receiver pair. Here, the human does not need to take any wearable devices. That is why the problem is generally termed device-free human detection.

The proposed detector contains three steps, preprocess, feature extraction, and making decisions (human presence or absence). First, We reference from [1] to preprocess the CSI data using a bandpass filter to preserve the band around the human breathing frequency. Second, We use two features to predict: one is the missing number (representing as #NaN) over 30 subcarriers; the other is the average variance of 30 subcarriers. Finally, we use a simple two-level tree to make a decision (human presence or absence). In the experiments, we used an AP with two antennas as transmitter and a laptop with a Intel 5300 NIC as receiver and measured in three different test areas. We chose 3 links from same antenna of transmitter, and then aparted them to get 3 times data. Every piece of data has 30 values from 30 different subcarriers. We calculated the variance and missing number for 1 minute data. Results show that the proposed method achieves an 64.3% general accuracy and 74.9% true positive rate (TPR).

II. Detection Design

A. Preprocessing

We follow the same procedure of [1] to preprocess CSI data. We first let CSI data through a bandpass filter in the breathing range to get breathing signals. The range of breathing is between 10 to 40 bpm (breathing times per minutes), that is roughly between 0.15 to 0.7Hz. The range comes from the observation from the chest periodic changes, and in general, an infant breathes 36 bpm, and an adult breathes 14 bpm. After using a bandpass filter to preserve the breathing frequency band, we also remove the mean value to avoid the interference. Figure 1 shows a typical example of subcarrier 2 before and after preprocessing.

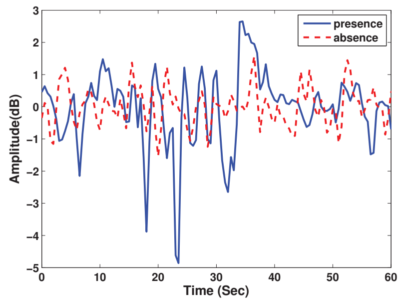

Fig. 1. An example of the preprocessing on subcarrier 2 [1].

B. Feature and Model

After dealing the CSI, we observe the human presence data and human absence data, and then we knew two things: one is presence data sometimes have values which are over or lower than setting range, representing as NaN, but absence always don't have. The other is the average values of presence data calculating from 30 subcarriers' variance are often higher than that variance of absence data. According to this observation, we choose two features. The first feature is the missing number in every piece of data. The second one is the average variance of 30 subcarriers. Then, we use a decision tree to preform the detection, as shown in Fig. 2.

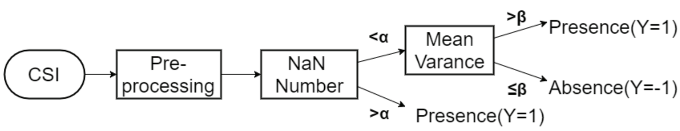

Fig. 2. Empirical parameter setup of the decision tree.

There are two parameters of the two-level decision tree, α and β. In the first level, if the missing number is over α (means the NaN ratio is about $\alpha/30$), the result is presence. Otherwise, it moves to the second level. If the average variance is over β,

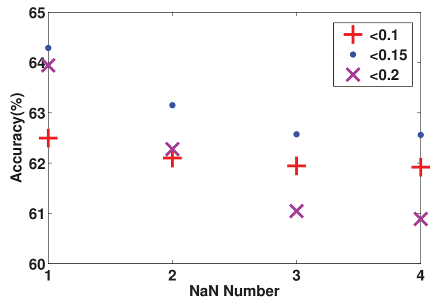

Fig. 3. Prediction results in different thresholds.

the result is presence, otherwise is absence. The formulation can be described as the following equation.

$$Y = \begin{cases} \text{-1} & if \text{ \#NaN} \leq \alpha \; and \text{ variance} \leq \beta \\ 1 & otherwise \end{cases} \quad (1)$$

where α is the threshold of #NaN, β is the threshold of variance using at next step, and Y is the predict label: positive label (+1) for human presence, negative label (-1) for human absence.

III. Experiments and Evaluation

A. Implementation

1) Experimental Equipment: we apply a laptop equipped with a Intel 5300 NIC on Ubuntu 10.04 LTS and a TP-LINK TL-WR841N wireless router with two antennas as a receiver and a transmitter operated at 2.4GHz in IEEE 802.11n [7] with 3 antennas. During the measurements, the receiver keeps receiving packets and recording the CSI from the transmitter.
2) Test Area: we collected data from three different test-beds. The details are shown in Table I. The first testing room is shown in Fig. 4.
3) Parameter Setup: we choose 3 links from same antenna of transmitter, and apart every link data to enhance the quantity. We empirically determine the thresholds in different conditions, as shown in Fig. 3. We select the best parameter from the search range, that is, we choose 1 as α and 0.15 as β.

TABLE I
Data Description

Per link	#human presence	#human absence	Transmitter-receiver/human distance (m)	Room size (m x m)
Person 1	1159	945	2.0/1.2	3.0 x 4.0
Person 2	592	586	3.5/3.0	4.8 x 5.0
Person 3	857	1162	3.0/2.0	3.5 x 3.5

TABLE II
Confusion Matrix

		Predicted: Human Presence	Predicted: Human Absence	Total
Real	Human Presence	36.8%(5860)	12.4%(1964)	74.9%(7824)
	Human Absence	23.4%(3715)	27.4%(4364)	54%(8079)
Total		61.2%(9394)	69%(6509)	64.3%(15903)

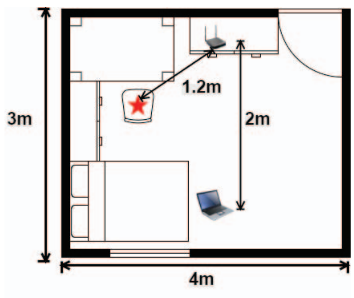

Fig. 4. The layout of the first testing area of person 1, where the star means the location of the human.

B. Evaluation

In this study, we use the confusion matrix as performance metric, as shown in Tab. II. This table shows that the highest general accuracy was roughly 64.3% while the true positive rate (hitting rate) was 74.9%. In Tab. II, we could see that there's only 54% accuracy in human absence. That means many absence data were predicted as presence, making the 46% false alarm rate. Our future study will use advanced signal processing and machine learning to reduce the false alarm rate and enhance the accuracy.

IV. Conclusion

This paper preliminarily investigates how to use two simple features of CSI to detect human presence. Through setting thresholds of #NaN and variance, we got totally 64.3% accuracy and 74.9% detection accuracy. The future work includes the reduction of high false alarm rate.

Acknowledgments

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