Wi-Fire: Device-free Fire Detection using WiFi Networks

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***Abstract*—Conflagration is one of the major disasters that threatens human life and property. If the proper action is not taken in detecting the symptom of conflagration events ahead of time, the number of such disasters will keep increasing. An effective solution in this context will alleviate many fire-related global problems to a great extent. Although fire detectors are not available in many places, WiFi networks are increasingly prevalent nowadays. Motivated by the previous works that used WiFi signals for the purpose of environment monitoring and activity recognition, we make an attempt to use WiFi signals to detect fire. Through several experiments, we find that fire influences the transmission of wireless signals uniquely, and consequently it affects the amplitude and phase of the resultant Channel State Information (CSI). Based on this observation, in this paper, we propose a device-free fire detection system, namely Wi-Fire, using commercial WiFi devices. To the best of our knowledge, this is the first work that leverages CSI of radio frequency (RF) signal to detect fire events using existing wireless infrastructure without requiring any additional device. We implement our proposed system on desktop computers equipped with commercial 802.11n network interface cards (NICs). Comprehensive experiments have been conducted for different scenarios in different environments to verify the effectiveness of our proposed system. The results verify that the fire detection accuracy of this training-based system is up to 96.67% on average.**

I. Introduction

Conflagration is one of the most destructive disasters, and can damage human life and wealth at the worst possible level. Around $4,000,000$ fire events occur every year on earth. The death toll of these disasters is as high as $40,000$ people and the economic losses account for 3.2% of gross national product (GNP). With the gradual sociological development, the aforementioned statistics even show a rising trend.

Many recent memorable aggravated such disasters remind us that an efficient and flexible fire detection method is urgently required. There are some existing fire detection methods based on different technologies. However, they all have their own limitations. For example, sensor-based fire detection method [1] uses different types of sensors to detect fire. It requires dedicated extra devices, and hence it cannot be used extensively due to its high cost. Ultrasound-based fire detection method [2] utilizes the ultrasonic wave to monitor the influence of fire on the air flow. It has high false negative rate (FNR). The last one is based on Received Signal Strength Indicator (RSSI) [3] of radio frequency (RF) signal, which detects the influence of fire on wireless channels. It has high FPR because of using the coarse-grained technology.

There are some existing works that use WiFi signal to detect falls, gestures and respiration [5, 6, 8]. Motivated by these works, we want to detect fire using WiFi signal. To achieve this, the key idea is that hot enough flame may become ionized to produce plasma, which responds strongly to electromagnetic fields. However, to implement an unobtrusive fire alarm system, there are still many challenges. First, it is hard to distinguish whether the affected CSI [9] is caused by fire or environmental disturbance. Moreover, the influence caused by fire is not very obvious, and cannot be captured directly with raw data. We conduct extensive experiments for several different scenarios, and finally we conclude that fire can influence WiFi signal uniquely.

In this paper, we study wireless radio propagation in a domestic environment under fire both theoretically and experimentally. Through a number of experiments and the corresponding analyzed data, we find that if there is symptom of fire in some environment, the resultant flame influences the transmission of WiFi signal, which leads to scattering effects on the signal. This observation is nicely illustrated in Fig. 1. As a result, the amplitude and phase of received signals change because of multipath effects. Based on the outcome of our study, we design a commodity WiFi-based device-free indoor fire alarm system, namely Wi-Fire. The proposed system does not require any dedicated device, and hence it incurs lower cost and higher applicability. Moreover, it utilizes fine-grained CSI of WiFi signal, which ensures high accuracy and reliability. In our experiments, we have collected data in different environments, such as home, laboratory and roof of a house. Followed by the collection of CSI data, Wi-Fire passes through feature extraction and training-based classification phases. In the feature extraction phase, Discrete Wavelet Transform (DWT), Power Spectral Density (PSD) and phase differences are applied to extract the amplitude and phase information of CSI, and finally an activity classifier using Random Forest learning algorithm is applied to detect fire event. The main contributions of this paper are summarized as follows.

- We exploit the feasibility of using fine-grained CSI of RF signal in developing a device-free fire detection system. To the best of our knowledge, this is the first work that leverages CSI of WiFi signal to detect fire.
- We reconstruct the radio propagation model that takes

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fire in an indoor environment into full consideration. Followed by data processing and feature extraction phases, we apply training-based Random Forest classifier to detect fire events.
- We conduct extensive experiments for both line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios in two typical indoor environments, i.e., laboratory and home.

The rest of the paper is organized as follows. First, we review the existing works related to this paper in Section 2. In Section 3, we introduce some preliminary concepts related to the proposed system. Followed by the description of components and fire profiling, in Section 4, we describe the mechanism of the system in detail. We evaluate the performance of our proposed system in Section 5. Finally, Section 6 concludes the paper.

II. Related work

In this section, we review the existing works from two perspectives, i.e., fire detection and WiFi CSI-based activity recognition.

A. Work on Fire Detection

Sensor-based fire detector detects the variances of environment with sensors. *Temperature-sensing-based fire detector* [1] detects the velocity of temperature rise and the temperature difference between fire-erupted and fire-free environments. *Smoke-sensing-based fire detector* [4] detects the liquid or solid smoke particles released in a fire-event. *Light-sensing-based fire detector* [1] (also named as *flame detector*) detects the infrared, ultraviolet or visible light. *Mixed fire detectors* are equipped with the features of multiple aforementioned fire detectors. All these commercial fire detectors need dedicated devices. Some of them may have the advantages in terms of accuracy. However, these may also suffer from some disadvantages, such as high cost and high sensitivity, etc.

Ultrasound-based fire detector [2] utilizes ultrasonic wave to monitor the influence of fire on air flow. This method is novel and has received some attention from the academia. However, this method has high FPR, and consequently it needs the help from other sensors.

RSSI-based fire detector [3] uses RSSI to measure the influence of fire on wireless signals. Typically, this method exploits wireless signals of WiFi devices. However, RSSI is a coarse-grained information of wireless signals, which means that it only can provide aggregated information about the wireless channel. Therefore, the use of RSSI in detecting fire may cause high FPR/FNR.

Unlike the aforementioned approaches, our CSI-based fire detection technique utilizes subcarrier-based technology to extract fine-grained information from wireless channels. Consequently, it is possible to detect fire incidents more accurately using this technique. Moreover, our technique does not require any extra dedicated device and can report the real-time environment information instantly with minimal delay to the fire alarm system.

B. Work on WiFi CSI-based Activity Recognition

Previously, researchers utilized the CSI trace of commercial WiFi devices for monitoring environments and activity recognition. For example, WiFall [5] and RT-Fall [6] use WiFi signals to detect the fall of certain objects. Ali et al. [7] exploit the CSI to extract keystroke recognition information in a controlled setting. Wag et al. [8] employ CSI of WiFi signals to detect human respiration events.

III. Preface

In this section, we first introduce the basic concept of CSI in commodity Wi-Fi devices, and then we portray our observation in this context via extensive experiments.

A. Elaboration of CSI

In domestic environments, signals are easily affected by multiple paths, such as ceiling, floor, walls and furniture. CSI of wireless signals can present the corresponding environments [6] accurately. In a narrowband flat-fading channel, the channel is modeled as

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{n}, \tag{1}$$

where $\mathbf{y}$ and $\mathbf{x}$ represent the receive and transmit signal vectors, respectively; $\mathbf{n}$ denotes the channel noise vector; and $\mathbf{H}$ is the CSI matrix. As noise is often modeled by circular symmetric complex normal distribution with the parameter $\mathbf{n} \sim \mathrm{cN}(0, \xi)$, $\mathbf{H}$ can be estimated as $\hat{\boldsymbol{H}} = \frac{\mathbf{y}}{\mathbf{x}}$.

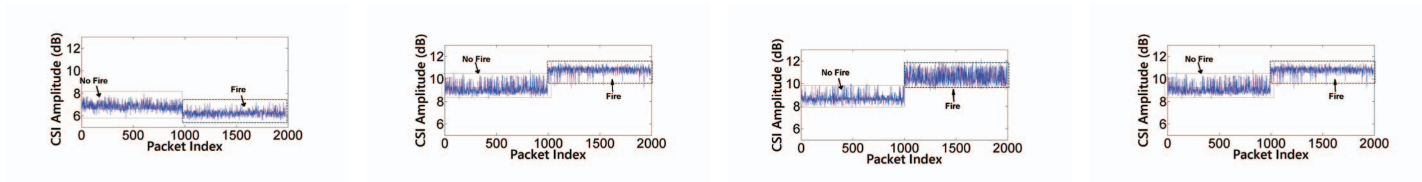
Current WiFi standards use orthogonal frequency division multiplexing (OFDM) technique in their physical layer to split its spectrum band (20MHz/40MHz) into multiple subbands, namely subcarriers. Moreover, these standards specify to transmit data over multiple subcarriers simultaneously, which improves efficiency and accuracy of the system greatly. The wireless signal carried by each subcarrier has amplitude and phase, and it is given by $h = |h|e^{j \sin \theta}$. Here, $|h|$ and θ are the amplitude and phase, respectively.

B. Our Experimental Observation

Fire is the rapid oxidation of a material in the exothermic chemical process. If hot enough, the flame may become ionized and produces plasma, which responds strongly to electromagnetic fields. Through several experiments, we find out that if fire takes place, the resultant flame influences the transmission of WiFi signals. Hence, the received signals can characterize fire events as additional signaling paths introduced due to scattering. As shown in Fig. 1, we see that the amplitude of wireless signals change in a fire-erupted environment. Fig. 2 shows that fire event also changes the phases of wireless signals.

IV. System Framework

In this section, we first introduce the structure of our device-free fire detection system. We also describe the algorithms for extracting the features of CSI trace, and the classifier to distinguish fire events from the no-fire one.



(a) LOS Distance = 2m (b) LOS Distance = 4m (c) NLOS Distance = 2m (d) NLOS Distance = 4m

Fig. 1: Sample raw data of WiFi signal from fire-free to fire-erupted scenario.

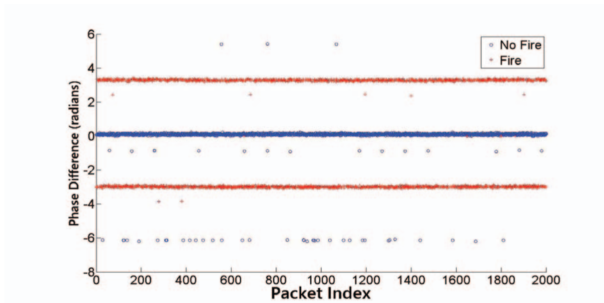


Fig. 2: A sample phase difference of WiFi signal from fire-free to fire-erupted scenario.

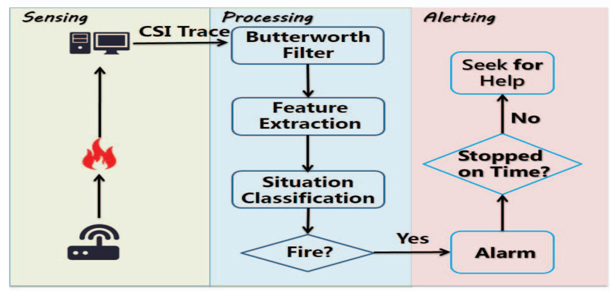


Fig. 3: System overview.

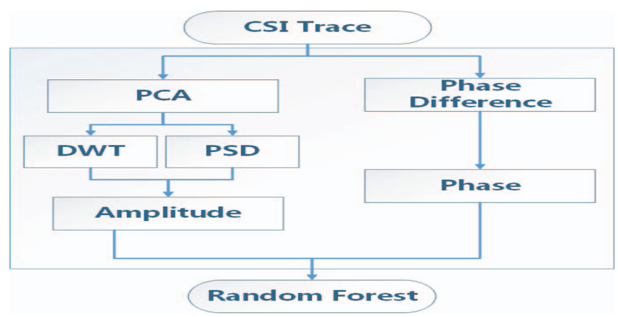


Fig. 4: Feature extraction procedure.

A. System Overview

Wi-Fire works in a situation when there is no one in the fire-erupted area. Now, the question is that how we do know that the change of signal is caused by fire? First, the variances of CSI caused by fire is entirely different from that caused by human activities as human activities lead to drastic changes of waveforms in subcarrier level. Second, dropping of objects from a high place or blowing of curtains due to wind influence CSI. However, these events are temporal and inconsistent, and these lead to sharp and dynamic changes of CSI over a short period of time. For the fire event, the change of wireless signal on each subcarrier is relatively small and stable, and it does not change the shape of entire waveform. In Wi-Fire, we can set threshold to distinguish aforementioned two events.

Wi-Fire enables commodity WiFi devices to detect fire using CSI. Fig. 3 illustrates the framework of Wi-Fire. It consists of a transmitter and a receiver. Typically, AP equipped with one antenna is considered as transmitter, and a mobile device (e.g., laptop) equipped with three antennas is considered as receiver. Wi-Fire consists of three main functional modules, i.e., sensing, data processing and alert modules.

Sensing module is responsible to monitor the change of environments. It basically collects CSI traces from subcarriers, and pass them to the next module. The most important part of the system is data processing module which is used to extract features from CSI traces, and then determine whether a fire event is about to take place. There are three main steps in the data processing module, as shown in Fig. 4, namely data filtering, feature extraction, classification and feedback modules. At the first step, data filtering techniques are required as CSI data collected by commodity WiFi NICs is easily affected by the subtle changes in the environment. Since we have $M_{T_x} \times M_{T_r}$ (M_{T_x} and M_{T_r} are the number of transmit and receive antennas, respectively) links and each link is associated with 30 subcarriers, direct usage of CSI trace collected from all subcarriers of all links is computationally intensive. Therefore, we choose Principal Component Analysis (PCA) to compress data and extract the main components. Subsequently, we apply DWT to separate high and low frequency information, and PSD to transform CSI trace collected over a period of time into its power density. Phase difference implies the variance of signal between a pair of antennas, and it is also sensitive to the change of environment [6]. Consequently, we also extract phase difference of signal waveforms to characterize the influence of fire on the corresponding signal. Finally, Random Forest is adopted to classify data based on aforementioned features. The last one, feedback module, cooperates with the alert module and provides feedback to refine the detection and decision-making algorithms.

When the data processing module ensures that there is fire, the alarm module is triggered. If the alarm is turned off by

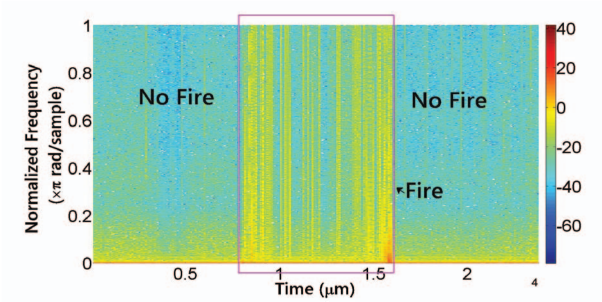


Fig. 5: A sample spectrogram for both fire and no fire scenarios.

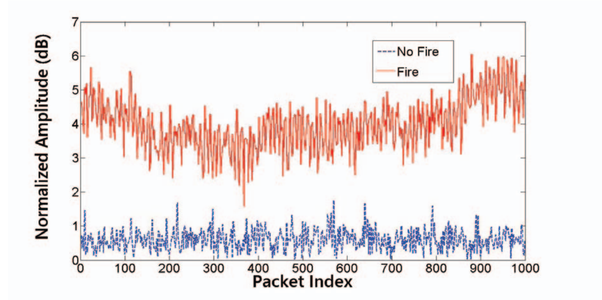


Fig. 6: A sample outcome of DWT technique.

some person, it might be a false alarm and he/she does not need any help. Otherwise, a message is delivered automatically to the Internet for help.

B. Fire Profiling

The objectives of the fire profiling stage are three-fold, which are 1) filtering out signal noise; 2) extracting both amplitude and phase features; 3) classifying extracted information to detect fire. These objectives are achieved by applying PCA, Butterworth Filter, DWT, PSD, phase difference and Random Forest techniques/algorithms.

1) De-Noising: The CSI is collected over 30 subcarriers for 3 data streams. The collected information reflects the signal diversity in frequency and space domains. Since CSI is slightly influenced by environmental noise, this information must be processed with butterworth filter and PCA before applying the feature extraction techniques on these.

- **Butterworth Filter:** As shown in Fig. 5, we observe that the frequency variation caused by fire over a period of time is about 50Hz. In this case, Butterworth low-pass filter is a good choice and can preserve better phase information of the signal and has the maximal flat amplitude response in the passband. Since we collect CSI data at 1000 samples per second rate, the cut-off frequency is set to $W_c = \frac{2\times\pi\times\mathrm{f}}{F_s} \approx 0.03$rad/s.
- **PCA:** Empirically, we find out that the impact of fire event on each subcarrier is relatively small, and therefore we decide to apply PCA [12] to enlarge the influence. PCA is mainly used to reduce the dimension space of data while keeping the characteristics of data intact. In our experiments, in order to reduce computational cost, we apply PCA on each instance of data at first to obtain p principal components. As a result, we obtain a matrix with dimension $p \times N$, where N is the number of instances of the collected data set per second. Empirically, a few upper-level principal components contain significant and stable variations in CSI values caused by fire, and hence we set $p = 4$. The detailed breakdown of this process is given as follows.
  1) Preprocessing: Among the data set, for the sake of convenience, the CSI of collected data over every 1 second interval is captured in matrix $\mathbf{H}$. This formatting of data brings convenience to the latter processing stage. At the first step, we subtract the constant offsets from CSI of each subcarrier in order to remove the static components, which is the average value of CSI amplitude over a period of time.
  2) Calculate correlation matrix: We calculate the mean of each column, and then observe the deviation between individual and mean values. Finally, we compute $\frac{1}{N}\mathbf{H} \times \mathbf{H}^T$ correlation matrix.
  3) Calculate eigenvectors: From the correlation matrix, we calculate eigen vectors $\mathbf{q}_i, i = 1, \cdots$ via eigen decomposition.
  4) Reconstructing signal: We construct a new signal matrix using correlation matrix and eigen vectors, which is $\mathbf{h}_i = \mathbf{q}_i \times \mathbf{H}$, where $\mathbf{q}_i$ is the ith eigen vector and $\mathbf{h}_i$ is the ith principal components, respectively.

2) Features Extraction: The changes of signals due to fire events are so tiny that it is easy to have false alarm, and hence we adopt several algorithms to extract amplitude and phase features, which can bring more accuracy in detecting fire and make the system robust.

- DWT: We apply DWT to compress the main components, which eventually facilitates signal-level analysis in both time and frequency domains. DWT helps us to extract tiny difference from original signals.We apply this method for some possible wavelets, such as Daubechies, Symlets and Coiflets [14]. Based on their performance, we select the Daubechies D1 wavelet and use approximation coefficients to represent the shape features of waveforms. As shown in Fig. 6, by applying DWT, we can figure out the tiny difference of signal due to fire.
- PSD: We apply PSD to transform the CSI data collected over a period of time into its power intensity in the frequency domain via Fast Fourier Transform (FFT). The power spectrum describes the distribution of power in terms of frequency components [8]. As shown in Fig. 7, we clearly find out that fire mainly influences the signal in low frequency domain.
- Phase Difference: Phases provided by commercial NICs are randomly distributed and the analysis of its feature is hard. As mentioned in [6], phases can be calibrated

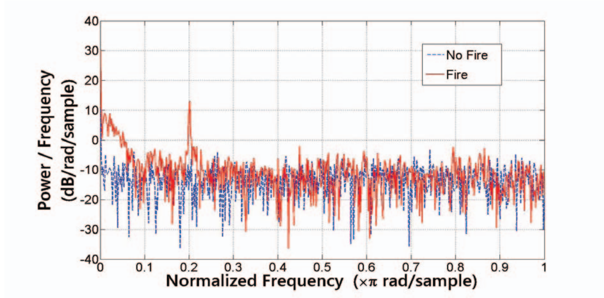


Fig. 7: A sample outcome of PSD technique.

through phase difference value over a pair of antennas. Moreover, from [15], we know that phase difference is sensitive to the environment as it is the sum of individual variance across two antennas. Fig. 8 compares some sample phase differences for both fire and no-fire cases.

3) Classification: Random Forest is adopted to classify the processed data. We randomly sample data from the training data while considering the replacement, and then construct a number of Decision Trees with the sampled data. Decision Trees finally vote for the classification of test data. The training procedure of this algorithm is as follows.

Step 1: We calculate the Gini coefficient of the sampled data, which is as follows

$$\text{Gini}(S) = 1 - \sum_{i=1}^{m} {P_i}^2, \tag{2}$$

where P_i is the frequency of samples in feature class i, m is the number of feature classes, and S is the sampled data.

Step 2: We split the nodes in data set S, and compute Gini coefficient of the split data set as follows

$$\text{Gini}_{\text{split}}(S) = \frac{|S_1|}{|S|}\text{Gini}(S_1) + \frac{|S_2|}{|S|}\text{Gini}(S_2). \tag{3}$$

Step 3: We continue spliting the nodes in set S via the minimum Gini index. Over the split data set, we continue applying *Step 1* and *Step 2* until all nodes become leaves of a tree.

The classification procedure of this algorithm is as follows.

Step 1: Given test data X and the number of decision trees k, we have

$$R(X) = \max \sum_{i=1}^{k} I(r_i(X) = y), \tag{4}$$

where $R(X)$ is the classification result of Random Forest algorithm, $r_i(X)$ is the classification result of decision tree i, y represents the goal of the classification and $I(.)$ symbolizes the Characteristic Function.

Step 2: The last step is to calculate the proportion of $R(X)$ according to voting.

(a) Roof of a house with LOS scenario. (b) Lab environment with LOS scenario. (c) Lab environment with NLOS scenario.

Fig. 9: Different experiment environments and scenarios.

4) False Alarm and False Positive: While analyzing data, we found that two antennas in the AP are close to each other. Consequently, both antennas receive data from two separate links and it might lead to false alarm. Therefore, we remodel the AP in order to make sure that only one antenna works at a time.

V. Experiments and Performance Evaluation

In this section, we first describe the details of the experimental settings and the implementation of our system, WiFire. Then, to justify the effectiveness of WiFire, we show the results of our experimentation.

A. Experimental Setup

We use HP desktop with Intel Link 5300 WiFi NIC as a receiver, which has 3.2GHz Intel(R) Pentium 4 CPU, 4GB RAM, and Ubuntu 14.04 operating system. TP-Link DWR 7500 WiFi router is a transmitter that operates in 802.11n AP mode in 5GHz band. In detail, the transmitter has 1 antenna, and the receiver has 3 antennas. As shown in Fig. 10, we conduct our experiments in lab and home environments. The area of the first test environment is about 8×5 square meter and it has two sofas and one desk. The area of the second test environment is about 3×4 square meter, and this does not have any other furniture. We place the transmitter and the receiver at 2m and 4m distance for both LOS and NLOS scenarios. In the LOS case, the fire source is placed in the middle of the transmitter and the receiver. We send ICMP ping packets from the WiFi router to the desktop at 1000 packets/s rate.

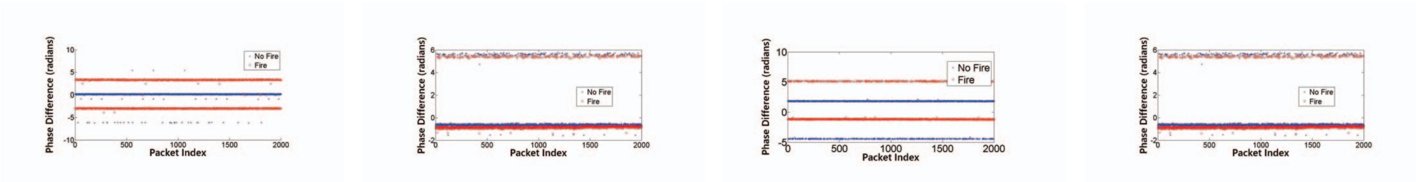
B. Data Collection

We collect data mainly for three different scenarios, i.e., before, on, and after the fire event. We send ICMP ping packets continuously in order to understand the variance of wireless signals intuitively for these different scenarios.

C. Experimental Results

1) Classification Accuracy:

- Accuracy of LOS-based experiments: We select 10 samples for each scenario to train the classifier randomly, and the rest of the samples are used for testing. As shown in Fig. 9, in this case, we achieve at least 96.67% accuracy regardless of the experiment sites (e.g., home, lab or roof of a house).
- Accuracy of NLOS-based experiments: Similar to LOS-based experiments, we select 10 samples for the training purpose, and the rest of the samples for the testing



(a) LOS Distance = 2m (b) LOS Distance = 4m (c) NLOS Distance = 2m (d) NLOS Distance = 4m

Fig. 8: A sample outcome of phase difference.

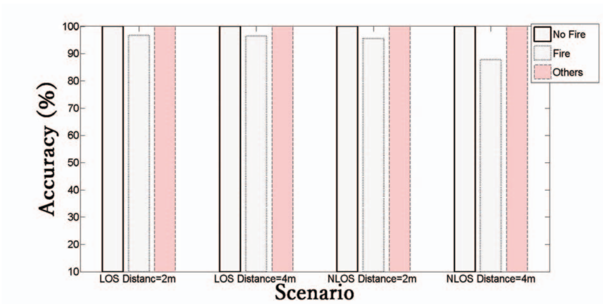


Fig. 10: Average fire detection accuracy in different experiment environments and scenarios.

purpose. For this case, we achieve 95.5% and 87.96% fire detection accuracy at $26.5°$ and $45°$ NLOS angles, respectively, as shown in Fig. 10.

- Accuracy for other scenarios: To verify the robustness of the system, we also simulate the case when there is no one at home. When someone walks around, the alarm module of our system is not triggered as the variance of CSI caused by walking around is totally different from that caused by fire.

2) Resistance to Environmental Dynamics: Given the fact that CSI is sensitive to environments, our goal is to propose a fire detection system which is resilient to environmental dynamics. We conduct experiments in different locations, such as home, laboratory rooms and roof of a house, and have proved its robustness.

VI. Conclusion

In this paper, we proposed a WiFi signal-based fire detection, which takes the advantages of wireless physical layer information CSI in commercial NICs. Unlike the previously proposed fire detection methods, the proposed system does not incur additional cost as WiFi networks are widespread nowadays. As per the mechanism of the system, we collected CSI trace from different channels of WiFi networks. Then, we proposed several methods to extract the features from the collected CSI trace. Finally, we applied a supervised learning model, Random Forest, to detect the fire event if it really takes place. In order to verify the effectiveness of the system, we designed several experimental scenarios in typical indoor environments. The results show that the accuracy of the fire detection system can be up to 96.67% and 95.5% for LOS and NLOS scenarios, respectively.

Acknowledgment

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