Can Future Wireless Networks Detect Fires?

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ABSTRACT

Latencies, operating ranges, and false positive rates for existing indoor fire detection systems like smoke detectors and sprinkler systems are far from ideal. This paper explores the use of wireless radio frequency (RF) signals to detect indoor fires with low latency, through walls and other occlusions. We build on past research focused on wireless sensing, and introduce RFire, a system which uses millimeter wave technology and deep learning to extract instances of fire. We perform line-of-sight (LoS) and occluded non-LoS experiments with fire at different distances, and find that RFire achieves a best-result mean latency of 24 seconds when trained and tested in multiple environments. RFire yields at least a 4 times improvement in mean alarm latency over today's alarms.

CCS CONCEPTS

• Computer systems organization → Sensors and actuators; **• Networks → Wireless access networks**; **• Computing methodologies → Machine learning**.

KEYWORDS

mmWave networks; wireless networks; fire detection; deep learning

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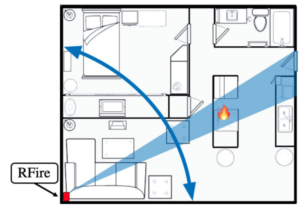

Figure 1: Envisioned deployment of RFire. The device is directional and sweeps its beam in 3-dimensions (3D) to determine the distance and direction to a fire.

1 INTRODUCTION

Each year, structural fires in the United States cause an average of 2,560 civilian deaths, 11,670 civilian injuries, and an estimated $6.5 billion in property damages [18]. Unfortunately, current fire alarms and sprinkler systems have several limitations, including:

High alarm latency: Past studies show that existing alarms do not allow for adequate safe egress time when located more than 6 meters (m) away from a fire [9]. This is because smoke alarms require the smoke to reach the device to be activated.

Nuisance alarms (false positives): Although placing alarms closer to potential fire sources reduces latency, it increases the number of nuisance alarms from non-fire events such as cooking, shown in an extensive study of current alarms [9].

One device per room: Due to range limitations and the potential for closed doors, currently used alarms must be sufficiently close within the same room as a fire. Therefore, multiple alarms must be used for multiple rooms.

In an attempt to solve these limitations, past work has proposed using computer vision and thermal-imaging cameras to detect fires [25]. However, despite their latency advantage, cameras still rely on line-of-sight (LoS) to identify fires and require one camera per room. Moreover, these cameras are costly and raise privacy concerns for the people within the environment [1].

In this paper, we propose using wireless signals to detect indoor fires. Similar to cameras, using wireless signals enables low latency fire detection while overcoming the privacy and LoS issues of cameras. There have been initial studies using wireless signals to detect fire [24], however they have several limitations and fail to address environmental mobility which can perturb the signal similar to fires, and hence do not work in the presence of people.

To address the challenges of past work we build RFire, a prototype fire detector using the millimeter wave (mmWave) wireless spectrum which is used in 5G networks [3], modern 802.11ad WiFi networks [2], and sensing and tracking [13, 21]. In particular, RFire uses directional mmWave signals and a deep learning model to identify and find the location of fires with low latency in LoS and occluded (non-LoS) environments. Additionally, RFire differentiates signal changes caused by fire from other changes from mobility and other heat with a chipset that costs about $30 [12]. As mmWave can monitor through occlusions, and therefore multiple rooms, the cost is further mitigated as an RFire device is not limited to one per room like cameras and fire alarm systems of today. We envision a final deployment of RFire in Figure 1, where a single RFire device monitors multiple rooms within a field of view (FoV) of 170° in 3-dimensions (3D). Our work makes the following contributions:

- We present RFire, the first fire detector prototype using mmWave signals to sense fires in mobile and non-LoS environments.
- We develop a deep learning model to identify fires from changes in wireless signals.

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- We conduct experiments and evaluate RFire for accuracy and alarm latency in LoS and non-LoS environments up to 7 m range.

2 BACKGROUND AND RELATED WORK

Wireless Sensing Systems: Recent research has leveraged wireless signals to develop novel sensing applications, such as object detection [16], human localization [22], and tracking [23]. This work uses Frequency-Modulated Carrier Waves (FMCW) radio technology for localization and detection, to enable the active monitoring of movement through walls and occlusions. FMCW is used in radar systems to measure the time it takes for a signal to travel from a radio's transmitting antenna to an object and back to its receiving antenna, called time-of-flight (ToF) [17]. The range resolution (R) of an FMCW radio is calculated by $R = \frac{C}{2B}$ where C is speed of light and B is bandwidth [19]. At mmWave frequencies there are multi-GHz of unlicensed spectrum available, much more than the bandwidth allocated to lower frequencies. mmWave also enables higher resolution when determining locations and uses small tightly packed antennas to focus the signal in a beam which is steered electronically to scan different directions (see Figure 1).

Fire Sensing Systems: Thermal infrared cameras use the electromagnetic spectrum to detect fires with low latency; however these are limited to LoS, infringe on privacy, and can cost thousands of dollars [1, 25]. Infrared temperature guns are moderately priced, while lasers have also been studied for fire detection [8], but are both limited to LoS, highly directional, and can not determine the distance to objects.

Wireless signals have been proposed to identify fires on trains and for wildland fires in past work [4, 6] Zhong et al. [24] show how fire affects the channel state information of current wireless networks. Although their model has high fire classification accuracy, it is unable to find the location of a fire, does not handle mobility, and only detects fire located between their two devices. They also do not test distances larger than 4 m, define non-LoS as when the fire is only 1 m outside the direct path between devices, and do not test with occlusions. Kempka et al. [15] show that microwaves are affected by fire, although they only study a range of 1 m with no mobility and a single fuel.

3 RFIRE

RFire leverages mmWave and deep learning to identify fires using an array of transmitting (Tx) and receiving antennas (Rx) included in a single device. RFire parses the received signal for each direction and distance into 30-second overlapping *frames* of time, at any location, and the deep learning model performs a binary fire classification on each frame.

The mmWave device captures 10 frames per second and sweeps its 30° beam in two dimensions to cover 170° of the azimuth plane. When contacting an object, some signal reflects back to the sensor and some travel through to other objects before reflecting back to the Rx array. Using the ToF of the signal between transmission and reception, the distance to the reflecting object is calculated with high precision along the direction of the beam. Using a combination of Long Short Term Memory (LSTM), convolutional neural network (CNN), and fully connected deep learning layers, RFire determines if the frame is a fire. The RFire algorithm raises an alarm if the deep learning model classifies three consecutive frames as fire for three adjacent distances within three seconds, a detection method we arrived at empirically.

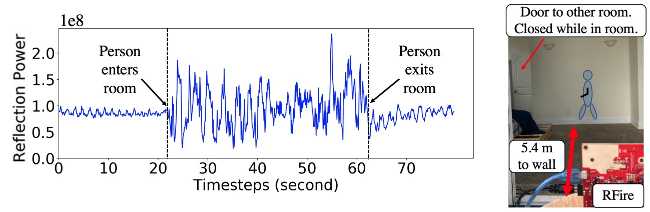

Figure 2: The signal is affected by a person moving behind a wall that is 5.4 m away from the mmWave sensor. We also experimented ranges of 1 to 4 m and observed similar results.

Detection Through Walls: While higher frequency wireless signals enable more accurate localization, they experience higher attenuation through occlusions. In order to realize our vision in Figure 1, it is critical to test if the mmWave signal from RFire can go through walls. We run multiple experiments where RFire is placed 1, 2, 3, 4, and 5.4 m away from a wall. After 20 seconds, a person enters the room behind the wall through a door perpendicular to the sensor and closes the door to eliminate any unobstructed paths between themselves and the sensor. The person then moves around the room for 40 seconds before exiting the room. Figure 2 shows the power of the reflected signal captured by RFire and the setup for the furthest of these experiments, showing the reflected signal power fluctuates when the person enters the other room and continues as they move until they exit the room. This experiment shows that the mmWave signal can sense through walls at least up to 5.4 m of range and in §4 we show RFire has the capability of detecting fires in non-LoS.

The Impact of Fire on mmWave Signals: Transmission loss and attenuation calculations when transmitting mmWave signals for communication include water vapor, mist, oxygen, and other gases [10]. Past work has found that combustion changes the propagation medium, induces carbon scattering, and increases the electron density in plasma by thermal excitation [7, 14, 20]. Changes to the propagation medium affect the air's gas composition, and carbon scattering and electron-rich plasma directly contacts the electromagnetic signal at the particle level.

To study these effects, we conduct experiments with a hotplate and a fire. Figure 3a shows the reflected mmWave signal from a hotplate when the mmWave sensor is located 1 m away. After a one minute baseline the hotplate temperature is increased from 20° to 400° for the duration of the experiment changing the composition of the propagation medium and we observe changes in the signal's amplitude. Figure 3b shows a liquid Methanol fire where the mmWave sensor is 1 m away which causes changes to the propagation medium, As a result, we observe a similar change in the reflected signal but with more signal noise. Our results are consistent with theory and past studies [5] showing the impact of heat and fire on electromagnetic signals while other environmental factors are unchanged.

Robustness to Mobility: Signals in highly controlled environments without human mobility are relatively consistent over short time periods. Realistic environments with mobility may experience fluctuations from movement or ambient environment changes

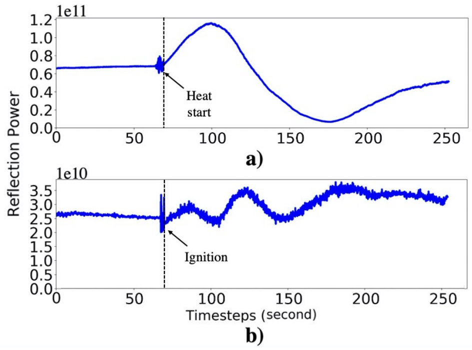

Figure 3: a): Hotplate experiment. b): Methanol fire.

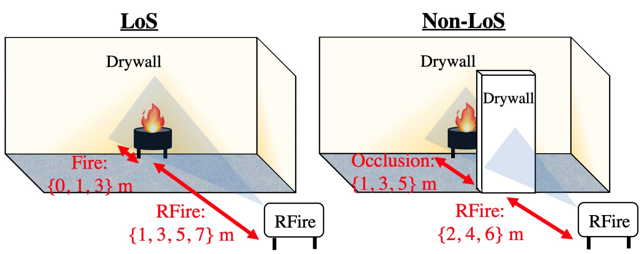

Figure 4: Experiment set-up for LoS and non-LoS fires.

within 30-second frames that appear similar to a fire, making a simple thresholding fire detection technique unreliable. To address these challenges, we design a deep learning model and identification algorithm for RFire to identify signal changes due to fire from other fluctuations. To ensure that the RFire model can train to differentiate fire and non-fire signals which appear similar, it is important to build the training dataset with fire signals and specifically non-fire signals which appear more similar to fire signals. Therefore, we define thresholds to remove frames which do not have characteristics similar to those with fire. We empirically find through observation thresholds on signal variance, Fast Fourier Transform (FFT) variance, and the FFT slope that are consistent with fire in our experiments, though these can also be changed if future fires observe behaviour outside of our threshold distribution. Additionally, by training RFire on a dataset composed by multiple experiments, the pre-trained model becomes robust to different room configurations and works across multiple environments.

Our deep learning model includes two modules: a 1-dimensional (1D) CNN module and a fully connected layer module. The output of the CNN module is passed to an LSTM layer, concatenated with the other module's output, and passed through fully connected layers to a binary output. We build our model using the Keras machine learning library with the Tensorflow backend.

4 EVALUATION

We conduct 23 different fire experiments, each about three minutes long, and also record over two weeks of non-fire experiments to test RFire's accuracy. Our non-fire experiments include other heating sources, different environments, and 16 hours which intentionally does not have human mobility. The general LoS and non-LoS fire experiment configurations are shown in Figure 4, where we list the

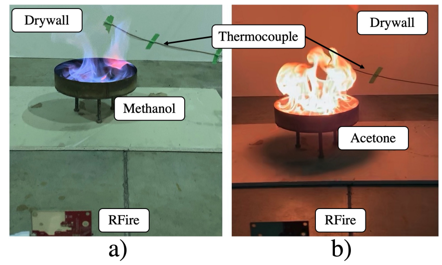

Figure 5: a): 1 m LoS high soot. b): 1 m LoS low soot.

locations of RFire, the occlusions, and the fire. Fire experiments are divided into 18 LoS and 5 non-LoS experiments with RFire ranges from 1 to 7 m in three environments using different rooms (a garage and a living room) and a state-of-the-art fire research lab which is 0°C. Figure 5 shows examples of two LoS 1 m range experiments in the fire lab with liquid fuels containing different levels of soot which produce carbon scattering. The 23 fire experiments are composed of one Heptane (heavy soot), six Acetone (high soot), six Methanol (low soot), two with lighter fluid and drywall, three LoS wood fires, and five non-LoS wood fires. To test RFire for false positive alarms we evaluate our model using data from non-fire environments with and without human mobility. Using the 16 hours of data with no human mobility is consistent with past work [24], whereas our non-fire experiments with mobility include challenging environments such as: lounges, hallways, offices, and kitchens which have different floor plans and as many as 20 people.

RFire is initially trained on a dataset of 30-second frames from 13 LoS fire experiments with Heptane, Methanol, and Acetone fuel and balanced with the same number of non-fire frames, sampled randomly from select non-fire environments. To evaluate RFire for false alarms, we test on all non-fire experiments not included in training, some of which have entirely different floor plans and ambient temperatures to any experiment RFire is trained on. RFire's detection ability is evaluated on the remaining 10 fire experiments, five of which are non-LoS. We employ a "leave-one-out" methodology to evaluate RFire on the 13 fires originally used for training, by removing a training fire and re-training an RFire model on the remaining 12 fires and balanced number of non-fire frames. This creates a new RFire model for each of the 13 fires originally used for training so that we can evaluate RFire on all 23 fire experiments.

RFire is implemented using the TI AWR1642Boost evaluation module [11] (a mmWave radar sensor module operating at 77–81 GHz). The device includes arrays of four Rx and two Tx onboard patched antennas thatprovides distance and angular information that RFire uses to determine the location of fires. This device has a range of about 13 m, a spatial resolution of 4.4 centimeters (cm), and an azimuth FoV of roughly 170°, although we only test to a range of 7 m due to building space limitations.

Results: We evaluate RFire for overall accuracy shown in Figure 6 and alarm latency after ignition in Table 1. Since our fire experiments are about three minutes each and our non-fire experiments are longer, we divide non-fire experiments into three minute intervals to calculate accuracy. We train and evaluate two versions of RFire. First we examine non-fire environments without human mobility (**RFire-static**) and find a mean alarm latency of just 32

Predicted	Actual (RFire-static) Fire	Actual (RFire-static) Non-Fire
Fire	100% 23 / 23	0% 0 / 293
Non-Fire	0% 0 / 23	100% 293 / 293

a)

Predicted	Actual (RFire-mobile) Fire	Actual (RFire-mobile) Non-Fire
Fire	91.3% 21 / 23	0% 1 / 7182
Non-Fire	8.7% 2 / 23	99.9% 7181 / 7182

b)

Figure 6: RFire confusion matrices.

seconds (s) over all 23 fires, including a mean of 7 s for the five non-LoS fires, showing RFire can generalize to new environments and fuels. On 16 hours of data without human mobility, RFire-static achieves 100% alarm accuracy with zero false alarms (see Figure 6a). RFire-static achieves a Matthews Correlation Coefficient (MCC) of 1.0 and a mean location error of 17.6 cm.

Second, we change the hyperparameters of RFire and train **RFire-mobile** to be more resistant to nuisance alarms caused by human movement, while also increasing the difficulty of true fire detection. Figure 6b shows that RFire-mobile detects 21 of 23 fires. It has a mean latency of just 26 s for all fires and takes 16 s for four of the five non-LoS fires. Evaluated with two weeks of data collected in real-world environments RFire-mobile only false alarms once caused by attenuation from human mobility for an MCC of 0.93 and a mean fire location error of 38.4 cm. .

We compare RFire's latency to a study of 10 different fire alarms used at ranges up to 7 m in LoS [9]. We do not compare for accuracy over all experiments because their non-fire experiments are only cooking, whereas ours include sources of heat as well as mobility in real-world environments. With the lowest latency alarm at 7 m being 159 s, the authors conclude that no alarms provide adequate available safe egress time when placed 6+ meters from a fire. The first row of Table 1 shows the average of lowest-latency alarms for multiple experiments with current technology for ranges of 1 m − 3 m and 4 m − 7 m achieving an average alarm time of 109 s and 147 s, and an overall mean of 128 s. For RFire, Table 1 shows the mean latency for all experiments for the specified ranges in LoS and the non-LoS scenarios. RFire-static is 2.7× and RFire-mobile is 2.1× faster than the best alarms tested at 1 m − 3 m distances, and at distances of 4 m − 7 m, RFire-static is 5.7× and RFire-mobile is 6.7× faster.

Technology	1 m - 3 m	4 m - 7 m	non-LoS	Mean
Best Alarm [9]	109 s	147 s	–	128 s
RFire-static	40 s	26 s	7 s	24 s
RFire-mobile	52 s	21 s	16 s	29 s

Table 1: Comparing the best of 10 alarms [9] with RFire latency. We average the best alarms for each range from [9] and average all experiments with RFire in each range.

5 DISCUSSION AND CONCLUSIONS

This paper presents RFire, a system for detecting fire using a deep learning model and a mmWave radar. Our results show that RFire is capable of sensing fires in mobile and non-LoS environments with more than 90% accuracy. Although our current prototype experiences false alarms, we believe we can improve RFire with more training data and/or the use of user feedback in real deployments through active or reinforcement learning. We believe RFire will provide a new, safer way to identify indoor fires with low latency while utilizing the hardware of 5G and 802.11ad wireless networks.

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