NotiFi: Non-Invasive Abnormal Activity Detection Using Fine-grained WiFi Signals

Dali Zhu*, Na Pang†*, Gang Li‡, Shaowu Liu§
* Institute of Information Engineering, Chinese Academy of Sciences, Beijing, China
† University of Chinese Academy of Sciences, Beijing, China
Email: {zhudali, pangna}@iie.ac.cn
‡School of Information Technology, Deakin University, Geelong, Australia
Email: gang.li@deakin.edu.au
§Advanced Analytics Institute, University of Technology Sydney, Sydney, Australia
Email: shaowu.liu@uts.edu.au

***Abstract*—Abnormal activity detection has increasingly attracted significant research attention due to its potential applications in numerous scenarios, such as patient monitoring, health care of children and elderly, military surveillance, etc. Pioneer systems usually rely on computer vision or wearable sensors which pose unacceptable privacy risks, or wireless signals which require the priori learning of wireless signals to recognize a set of predefined activities. In this paper, we take the first attempt to achieve non-invasive abnormal activity detection with only *commodity off-the-shelf* (COTS) WiFi devices, namely *NotiFi*, that can accurately detect the abnormal activities. The intuition of *NotiFi* is that whenever the human body occludes the wireless signal transmitting from the access point to the receiver, the phase and the amplitude information of *Channel State Information* (CSI) will experience a sensitive variation. By creating a multiple hierarchical Dirichlet processes, *NotiFi* automatically learn the number of human body activity categories for abnormal detection. Extensive experiments in typical real-world environments indicate that *NotiFi* can achieve satisfactory performance in abnormal activity detection.**

I. Introduction

Abnormal activity detection, the ability of finding "rare and different" activities that do not conform to expected pattern, has achieved a significant growth in recent years. It has become a task of high interest in many potential applications, such as patient monitoring in hospitals, health care of children and elderly at home, military surveillance for enemy activities etc. [1]. For example, the abnormal activities of patients with depression, dementia or psychosis could be detected for preventing undesirable consequences. The soldiers' activities might be useful to send immediate alerts in case of emergency or injury in tactical scenarios.

Traditional sound/motion wearable sensor based systems combine inputs from multiple sensors, including accelerometer, gyroscope, compass, etc., to perform abnormal activity detection. However, they require additional sensors to be worn or installed which is difficult for the elderly to comply with. Computer vision-based systems, such as the *Xbox Kinect* [2], equip with several high resolution cameras to capture a sequence of image frames. However, their requirements of *line-of-sight* (LoS) scenario and the involved privacy disclosure are still practical concerns. Besides, there are many blind spots such as the stairwells and toilets in which the camera is not convenient or even illegal to install.

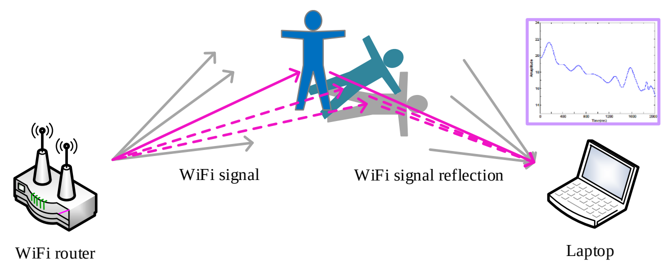


Fig. 1: Device-free abnormal activity detection.

As the popular deployment of wireless networks, WiFi signal has recently been considered as promising in addressing those concerns. However, conventional military radar techniques have the limitation of multiple GHz level of sampling rate for high-resolution, which is not available on the *commodity off-the-shelf* (COTS) WiFi infrastructure. *Received Signal Strength Indicator* (RSSI) based techniques suffer from the performance degradation in indoor environments due to interference or multipath fading. More recently, researchers have resorted to *Channel State Information* (CSI), which reflects channel frequency response in IEEE 802.11 a/g/n, to recognize some simple activities such as falling down [3], smoking [4], human identification [5]. However, the performance of existing CSI solutions is usually with too high false alarm rates or too low detection recall rate [6]. Moreover, they require a priori learning of the wireless signals for predetermined activities.

In this work, we firstly attempt to fill the void by proposing the *NotiFi* (Notification of WiFi) system and show that non-invasive device-free abnormal activity detection is possible, using *Channel State Information* (CSI) provided by *commercial off-the-shelf* (COTS) WiFi products. An overview of the device-free abnormal activity detection system is shown in Figure 1. The key intuition behind *NotiFi* is that variances of the phase and the amplitude of CSI are good indicators for abnormal activity of moving people. *NotiFi* works under both *line-of-sight* (LoS) and *non-line-of-sight* (NLoS) conditions, without any dedicated sensor or additional WiFi infrastructure, and does not require a priori learning of wireless signals for pre-determined activities. Furthermore, unlike cameras, *NotiFi* does not require lighting and works in dark just as well as in light. This unsupervised framework without human intervention will save a lot of human power. There are several technical challenges, however, that need to be addressed:

- The first challenge is to extract valuable human body features under the circumstance of CSI values fluctuate. The CSI values contain noises from various sources such as interference coming from nearby devices, transmission power adaptation at the sender, and imperfect clock synchronization. To address this challenge, *principal component analysis* (PCA) based denoising method is used to correlate the signal fluctuations caused by human body movements.
- The second challenge is how to model the abnormal activities, especially for 180 groups of CSI values in one packet extracted at the receiver. To address this challenge, we model an activity as a series of CSI states trajectory which including amplitude and phase information. Given a group of trajectories between two CSI states, the task of abnormal activity detection can be transformed into the task of finding those trajectories that are significantly rare and different from the others.
- The third challenge is how to automatically learn the number of human body activity categories especially in large-scale datasets. The patterns of abnormal activities are with different characteristics. They can not or should not be simply categorized into a set of predetermined activities. To address this challenge, hierarchical Dirichlet processes are used for abnormal activity detection. The samples with low likelihoods are more likely to be abnormal activities.

We implemented *NotiFi* on COTS WiFi devices and evaluated the system's performance in realistic scenarios. *NotiFi* can detect abnormal activity with an average accuracy of 89.2% in LoS, 85.6% in NLoS, and 75.3% in through-one-wall scenarios. This accuracy in LoS can be increased to 92.4% when the device hears multiple APs, and it is robust to signal interference such as obstacles. In summary, we make the following main contributions:

- By exploiting physical layer *Channel State Information* (CSI), we are first to validate the feasibility of using WiFi for non-invasive abnormal activity detection.
- Our proposed framework uses a nonparametric hierarchical Bayesian method for non-invasive abnormal activity detection. The number of human body activity categories can be learn from CSI data automatically instead of being set manually.
- We implement *NotiFi* on *commercial off-the-shelf* (COTS) WiFi devices, and extensive evaluations demonstrate the effectiveness of *NotiFi*.

The remainder of the paper is organized as follows. In Section II, we summarize the related works. In Section III, we present the proposed abnormal activity detection system *NotiFi*. In Section IV, we present the implementation and extensive evaluation. We conclude this paper in Section V.

TABLE I: Capabilities of Different Methods.

Type	Approach	Privacy	Device-free	Accurate	Comprehensive
Camera	Camera	×	×	√	√
Sensor	Sound	√	×	×	×
	Motion	√	×	√	×
Wireless	Radar	√	×	√	×
	RSSI	√	√	×	×
	CSI	√	√	√	×
Wireless	***NotiFi***	√	√	√	√

II. Related Work

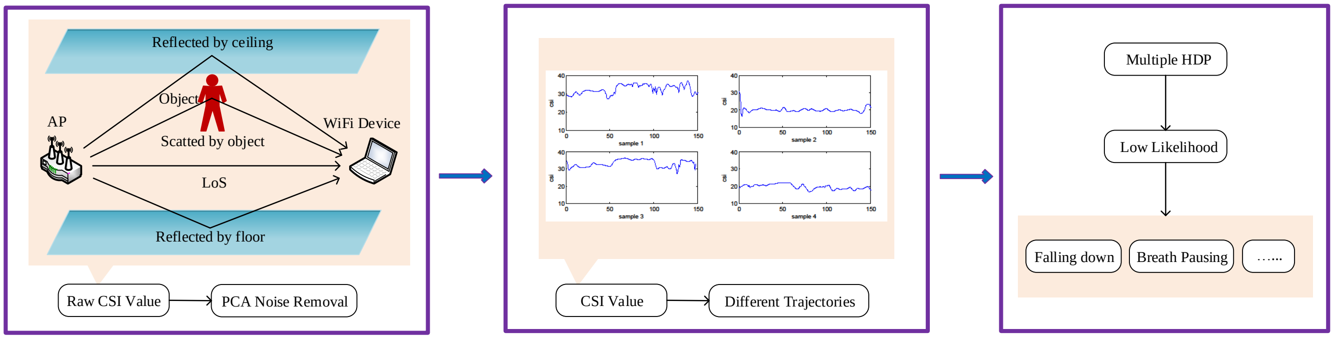
A. Vision/Sensor based Activity Detection

Computer vision based systems such as *Xbox Kinect* [2], HON4D [7], RGBD-HuDaAct [8], and DSTIP [9], equip with several high resolution cameras to record the object with a sequence of image frames. Both sound/motion based inertial sensors and on-body sensors systems combine inputs from multiple sensors, including gyroscopes, accelerometers, barometers, compass, magnetic, etc. [10]. Kim et al. [11] uses wrist-worn sensor to recognize hand pose. While promising, these systems either require human to wear additional sensors which is inconvenient, or demand *line-of-sight* (LoS) between the device and the concerned target. Besides, they pose privacy concerns.

B. Wireless based Activity Detection

Typically, existing systems can be classified into three groups: Radar based, RSSI based and CSI based systems.

1) **Radar based systems:** Human body daily activities, such as eating, drinking, bending, breathing, can cause obvious Doppler shifts in the reflected wireless signals. The Doppler shifts can be discerned from a radar. WiSee leverages the USRP to measure minute Doppler patterns from OFDM transmission to recognize nine whole-body gestures. WiTrack [12] implements a *Frequency Modulated Carrier Wave* (FMCW) gesture tracking system. WiVi [13] leverages the ubiquity of Wi-Fi chipsets to track gestures and walking, and uses the *Inverse Synthetic Aperture Radar* (ISAR) to improve spatial resolution. WiHear [14] focuses on analyzing radio reflections of human speech by extracting the micro-movements of mouth movements. However, they require dedicated hardware.
2) **RSSI based systems:** RSSI measurements, which capture the propagation attenuation of wireless signals, have been adopted for device-free activity recognition by mapping RSSI to the closest fingerprint. Patwari et al. [15] proposed the MODEL that applies the RSSI variance of small-scale fading effects to detect and localize a moving target. Kosba et al. [16] adopted a



(a) CSI Processing (b) Activity Modeling (c) Abnormal Activity Detection

Fig. 2: *NotiFi* workflow.

nonparametric technique and analyzed the RSSI features to further improve the accuracy of human detection in different environment. However, due to multipath fading, these systems can only recognize those coarse-grained activities with reasonable accuracy but high susceptibility to noise.

3) **CSI based systems:** Recently, *Channel State Information* (CSI) based scheme attracts more attention since it discriminates multipath characteristics. It can be extracted from commodity wireless *Network Interface Card* (NIC). Han et al. [3] proposed to exploit the special diversity of CSI to recognize human fall. Zeng et al. [5] presented WiWho that exploits CSI-based gait to identify a person. Wang et al. [17] presented location-oriented activity recognition system to recognize bathing and washing dishes. Wang et al. [18] proposed CARM that correlates CSI dynamics and human activities. Some pioneer CSI-based systems have demonstrated high accuracy, however, they require a priori learning of wireless signals for pre-determined activities [19], and they can not be used for abnormal activity detection.

C. Summary

Table I compares the features of existing solutions. We can see that no existing system simultaneously satisfies the privacy protection, device-free, accurate, and comprehensive capability. In this paper, we attempt to build an non-invasive abnormal activity detection system on *commodity off-the-shelf* (COTS) WiFi device. It should be without any dedicated sensor or firmware modification, and does not require a priori learning of wireless signals on pre-trained activities. It should automatically learn the number of human body activity categories for detecting abnormal activities.

III. *NotiFi* System

NotiFi leverages *Channel State Information* (CSI), the fine-grained channel frequency response of OFDM subcarriers, to detect abnormal activity. The work flow of *NotiFi* is shown in Figure 2, and it contains three main phases: *CSI Processing*, *Activity Modeling* and *Abnormal Activity Detection* phase.

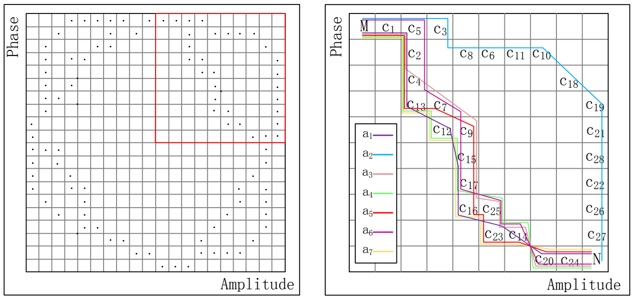
1) **CSI Processing**: *NotiFi* takes the time-series *Channel State Information* from the *commodity off-the-shelf* hardware as input. *Principal Component Analysis* (PCA) denoising scheme is to improve the reliability of the time-series of CSI.
2) **Activity Modeling**: Variance of CSI phase and amplitude over a certain time interval forms different trajectories, which can indicate different activities. The task of abnormal activity detection can be transformed into the task of finding those trajectories that are significantly rare and different from the others.
3) **Abnormal Activity Detection**: *NotiFi* uses a nonparametric Bayesian model, Dynamic Hierarchical Dirichlet Process, for unsupervised activity analysis. The number of human body activity categories can be learnt from CSI values automatically instead of being set manually. The samples with low likelihoods are more likely to be abnormal activities.

A. CSI Processing

Multipath channel response extracted at the receiver can be estimated as *Channel State Information* (CSI), which depicts both the phase and the amplitude information of each OFDM subcarrier. *NotiFi* collects CSI values from 30 OFDM subcarriers used by 802.11n. Eq. (1) represents the CSI channel matrix $H_{i,j}$ reported by Intel 5300 *Network Interface Card* (NIC) for 6 streams (3×2 *Multiple Input Multiple Output* (MIMO) system) and 30 subcarriers in each stream. Specifically, each packet can extract 180 groups ($3 \times 2 \times 30$) of CSI values.

$$H_{i,j} = \begin{bmatrix} h_{1,1} & h_{1,2} & h_{1,3} & \cdots & h_{1,30} \\ h_{2,1} & h_{2,2} & h_{2,3} & \cdots & h_{2,30} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{6,1} & h_{6,2} & h_{6,3} & \cdots & h_{6,30} \end{bmatrix}, \tag{1}$$

where $h_{i,j}$ is the CSI value the for i^{th} stream and the j^{th} subcarrier.



(a) CSI distribution (b) Certain activities

Fig. 3: Activity modeling of *NotiFi*.

However, the CSI values extracted from commercial WiFi cards contain noises from various sources such as frequent changes of CSI reference levels, transmission rates, or even the environment change such as temperature. We use *Principal Component Analysis* (PCA) denoising scheme to correlate the CSI fluctuations caused by human body activity on the filtered subcarriers. We extract the first twenty PCA components from the 180 CSI streams and discard the rest, which are mostly noisy components. This optimal number of PCA components is determined by experiments shown in the experimental results section.

B. Activity Modeling

We define a state m_i of CSI value as a triple, which includes time stamp ts, amplitude a, and phase p as $m_i = (ts, a, p)$. A trajectory t is a series of states as $t = (m_1, m_2, ..., m_n)$. On a two dimensional plane, we split the CSI space into a grid of equal sized cells with two axises representing the amplitude and the phase respectively. Then we project all the calibrated CSI data into the cells as shown in Figure 3a. Figure 3b shows part of CSI cells in Figure 3a, which is the collected time series of CSI data containing the phase and the amplitude information. Variance the phase and the amplitude over a certain time interval forms different trajectories, which can indicate different activities. Given a group of trajectories $T = \{t_1, t_2, ..., t_n\}$ between M and N, the task of abnormal activity detection can be transformed into the task of finding those trajectories in T that are significantly rare and different from the others. Using *Hierarchical Dirichlet Processes* (HDP), the number of activities can be learnt from CSI data automatically and the samples with low likelihoods are likely to be abnormal activities.

C. Abnormal Activity Detection

1) Multiple Hierarchical Dirichlet Process: Dirichlet process (DP) [20] is a measure on a measure G, $G \sim DP(\alpha_0, H)$, in which α_0 is a positive concentration parameter, and H is a base measure. Sethuraman [21] defined a stick-breaking process to obtain an explicit form of G:

$$G = \sum_{k=1}^{\infty} \pi_k \delta_{\theta_k^*} \qquad \pi_k = \tilde{\pi_k} \prod_{i=1}^{k-1} (1 - \tilde{\pi_k}) \tag{2}$$

where θ_k^* is independent random variable distributed according to H, and $\delta_{\theta_k^*}$ is an atom at θ_k^*, π_k is a weight scalar, $\sum_{k=1}^{\infty} \pi_k = 1$, and each $\tilde{\pi_k}$ is drawn in an independent identically distributed manner from $Beta(1, \alpha_0)$.

Nonparametric *Hierarchical Dirichlet Process* (HDP) model links these Dirichlet process mixture models, and can be processed as the prior distribution across multiple data sets [22]. The global measure G_0 is generated from a Dirichlet process:

$$G_0 | \gamma, H \sim DP(\gamma, H). \tag{3}$$

Each CSI trajectory t is a distribution G_j which is conditionally independent given G_0:

$$G_t | \alpha_0, G_0 \sim DP(\alpha_0, G_0). \tag{4}$$

For each CSI state m_i on trajectory t, a hot path model θ_{ti} is drawn from G_t. The CSI state value x_{ti} is drawn from the hot path, $x_{ti} \sim Discrete(\theta_{ti})$. Under this hierarchical structure, different CSI states across different trajectories share parameters as a consequence of the discrete form of G_0. Different CSI state m_i on trajectories can be clustered into hot paths.

Unfortunately, HDP can not cluster human body activities. We use multiple hierarchical Dirichlet process to cluster CSI state and activities. Figure 4 shows the graphical model. All the CSI activities in cluster s are in the same prior distribution over hot paths, $\widetilde{G}_s = \sum_{k=1}^{\infty} \widetilde{\pi}_{sk} \delta_{\widetilde{\theta}^*_{sk}}$, which is an infinite mixture of CSI states as we don't define the number of activity clusters in advance. Following [23], *Dependent Dirichlet Process* (DDP) proposed in [24] is used to cluster activities.

$$Q = \sum_{s=1}^{\infty} \epsilon_s \delta_{\widetilde{G}_s} \quad \epsilon_s = \epsilon_s^{'} \prod_{l=1}^{c-1} (1 - \epsilon_l^{'}) \quad \widetilde{G}_s \sim DP(\rho, G_0). \tag{5}$$

G_0 is the prior probability distribution over the whole CSI values, $G_0 \sim DP(\gamma, H)$. Q is from *Dependent Dirichlet Process* $DDP(\mu, \rho, G_0)$, where $\epsilon_c^{'}$ is drawn from $Beta(1, \mu)$. The prior of each CSI trajectory t samples a probability measure $\widetilde{G}_{s_t}$. Different CSI trajectories have a certain probability to be in the same prior $\widetilde{G}_s$, resulting in forming one cluster s. The CSI trajectory t draws its own probability measure $G_t \sim DP(\alpha, \widetilde{G}_{s_t})$, in which the same measure is provided by cluster c_t as HDP did. The concentration parameter γ is sampled from gamma priors. Each CSI state m_i samples a hot path θ_{ti} from G_t and samples its CSI state value w_{ti} from *Discrete*(θ_{ti}).

2) Gibbs Sampling under multiple HDP: Gibbs sampling is a *Markov chain Monte Carlo* (MCMC) algorithm, where variables are conditioned on the current values of all other variables and successively sampled from their distributions. We describe inference using Gibbs sampling in the following three steps:

- When the cluser assignment $\{s_t\}$ of CSI trajectories is given, it can sample the CSI state assignment $\{z_{ti}\}$, hot path $\{\pi_{0k}\}$ and $\{\widetilde{\pi}_{sk}\}$. When $\{s_t\}$ is given, we can use the sampling method presented by Teh et al. [22].

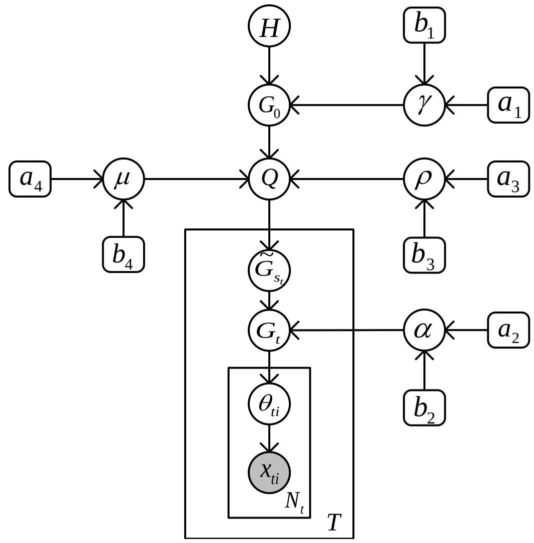


Fig. 4: The graphical model of multiple HDP.

- When $\{z_{ti}\}$, $\{\pi_{0k}\}$ and $\{\widetilde{\pi}_{sk}\}$ are given, the activity cluster assignment s_t can be sampled. It can be assigned to a new cluster or one of the existing clusters. Chinese restaurant franchise is used for sampling.
- When other variables are given, we use the sampling scheme presented in [22] to sample the concentration parameters.

We calculate the likelihood of trajectory t when other trajectories is given, for abnormal activity detection, $p(\mathbf{w}_t|\mathbf{w}^{-t})$, in which $\mathbf{w}_t = \{w_{ti}\}_{i=1}^{N_t}$ is the CSI state in trajectory t and $\mathbf{w}^{-t}$ is the remaining trajectories exclusing t. During the Gibbs sampling procedure, there are N samples $\{\mathbf{z}^{-t(n)}, \{\epsilon_s^{(n)}\}, \{\widetilde{\pi}_s^{(n)}\}, \pi_0^{(n)}, \alpha^{(n)}\}_{n=1}^{N}$ drawn from distribution $p(\mathbf{z}^{-t}, \{\epsilon_s\}, \{\widetilde{\pi}_s\}, \{\pi_0, \alpha, |\mathbf{w})$ which is very close to $p(\mathbf{z}^{-t}, \{\epsilon_s\}, \{\widetilde{\pi}_s\}, \{\pi_0, \alpha, |\mathbf{x}^{-t}\})$. $p(\mathbf{w}_t|\mathbf{w}^{-t})$ is approximated as

$$\begin{aligned} p(\mathbf{w}_t|\mathbf{w}^{-t}) = & \frac{1}{N}\sum_n \sum_{s_t} \int_{\pi_t} \sum_{z_t} \sum_i \epsilon_{s_t}^{(n)} p(\pi_t|\alpha^{(n)} \cdot \widetilde{\pi}_{s_t}^{(n)}) \\ & p(z_t|\pi_t) p(w_{ti}|z_{ti}, \mathbf{z}^{-t(n)}, \mathbf{w}^{-t}) d\pi_t \end{aligned} . \quad (6)$$

In Eq. (6), $p(\pi_t|\alpha^{(n)} \cdot \widetilde{\pi}_{s_t}^{(n)})$ is Dirichlet distribution. If $H = Dirichlet(\cdot; (u_1, ..., u_T))$, where T is the size of the codebook,

$$p(w_{ti}|z_{ti}, \mathbf{z}^{-j(n)}, \mathbf{w}^{-t}) = \frac{u_{w_{ti}} + n_{w_{ti}, z_{ti}}}{\sum_{c=1}^{T}(u_c + n_{c, z_{ti}})}, \quad (7)$$

is a multinomial distribution, where $n_{c,z_{ti}}$ is the number of CSI states in $\widetilde{\pi}^{-t}$ with value c and being assigned to hot path z_{ti}. The calculation of

$$\int_{\pi_t} \sum_{z_t} p(\pi_t|\alpha^{(n)} \cdot \widetilde{\pi}_{s_t}^{(n)}) p(z_t|\pi_t) p(w_{ti}|z_{ti}, \mathbf{z}^{-t(n)}, \mathbf{w}^{-t})$$

is complicated, but it could be approximated of a variational method following [25].

$\{\pi_{0k}\}$, $\{\theta_k^*\}$, and $\{\widetilde{\pi}_{sk}\}$ could be esimated when Gibbs sampling on the CSI values converges. A newly arrived activity outside the training set can be regarded as abnormal or not by calculating the likelihood. It can be also classified as the pre-learned activities by calculating the posteriors $p(s_t|\mathbf{w}_t, \{\theta_k^*\}, \{\pi_{0k}\}, \{\widetilde{\pi}_{sk}\})$.

IV. Experimentation Evaluation

A. Implementation

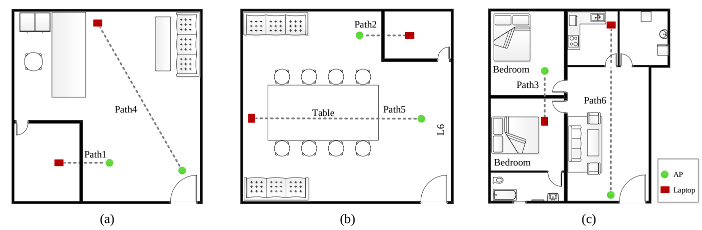


Fig. 5: Office (a), Laboratory (b), Apartment (c).

We conducted *NotiFi* on Think-pad X200 and a wireless router TP-LINK TL-WDR4300. The laptop is with Intel 5300 *network interface card* (NIC) running Ubuntu 10.04 with a sampling rate of 50 Hz as a receiver, and the access point runs in the 5 GHz frequency band with bandwidth channels of 20 MHz as the transmitter. The laptop has two antennas while the access point has three antennas. We extract CSI values from IEEE 802.11 data frames by modifying the driver as described in [26]. The CSI matrix consists of 30 readable groups of subcarriers that evenly distributes in the 56 subcarriers with 20 MHz channel. The packet transmission rate is set to 100 *pkts/s*. We implemented *NotiFi* abnormal activity detection algorithm using MATLAB platform in this prototype.

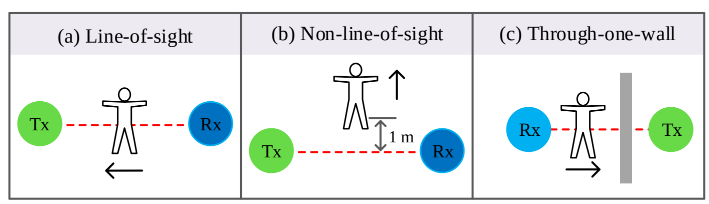


Fig. 6: Three test scenarios.

B. Experimental Setup

We then evaluate the performance of *NotiFi* in three indoor environments as shown in Figure 5: (a) an office covering an area of around 9×9 m^2 with one sofa and two tables; (b) a laboratory covering a 9×10 m^2 area with dozens of chairs, a long meeting table and two groups of sofas; (c) an apartment covering about 8×9 m^2 area with one living room, two bedrooms and a group of sofas. The thickness of the door is 40 mm while the wall is 180 mm.

In addition to evaluating *NotiFi* in three different test environments, we extensively evaluate *NotiFi*'s performance under

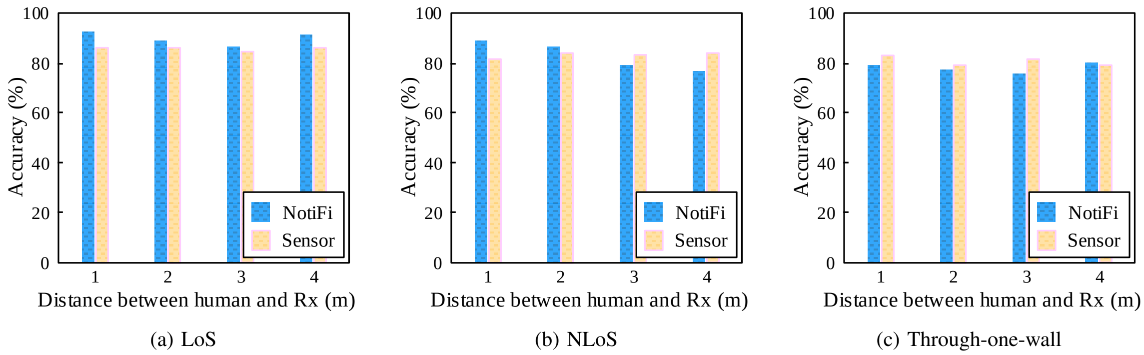


Fig. 7: Abnormal activity detection accuracy in different scenarios.

three typical scenarios as shown in Figure 6. Tx represents transmitter AP while Rx represents the receiver laptop.

- **Line-of-sight (LoS).** The human is on the range of line of sight between Tx and Rx.
- **Non-line-of-sight (NLoS).** The human is within the range between Tx and Rx, but not on the line of sight. The projected distance from human body to the line links the antenna and the receiver is 1 m.
- **Through-one-wall.** The Rx and Tx are in adjacent rooms.

C. Evaluation Metrics

We focus on TPR and FPR to quantify the performance of *NotiFi*:

- **True Positive Rate (TPR)**: the proportion of cases that *NotiFi* detects the abnormal activities correctly among all the activities.
- **False Positive Rate (FPR)**: the proportion of cases that *NotiFi* generates false alarm mistakenly when there is actually no abnormal activity.

The transmitter AP and the receiver laptop are placed at location "Path1",...,"Path6" as shown in Figure 5. The distance between transmitter and receiver is $l1$,...,$l6$ corresponding to different location "Path1", ... ,"Path6", and it satisfies that $l1 = l2 = l3$, and $l4 = l5 = l6$. This test lasts for 4 hours. It the first two hours, 7 volunteers observed the activities of three users via video in the 3 scenarios. Then in the second two hours they labeled the new arriving activity as normal or abnormal every two minutes. We consider it as normal activity when over 3 volunteers support. At the same time *NotiFi* executes the non-invasive abnormal activity detection to determine it as normal or abnormal activity and puts the previous activity into historical records. Obviously, the high true positive rate and low false positive rate mean a good performance of detection system. We then evaluate the robustness of *NotiFi* by calculating the accuracy of detecting abnormal activities in three scenarios of three environments, and we evaluate the performance of *NotiFi* under different number of PCA components. Then we conduct experiments in scenarios with one up to five APs in LoS to estimate the impact of multiple APs. Finally, we vary the number of humans occurring concurrently from one to three.

TABLE II: Top five abnormal activities.

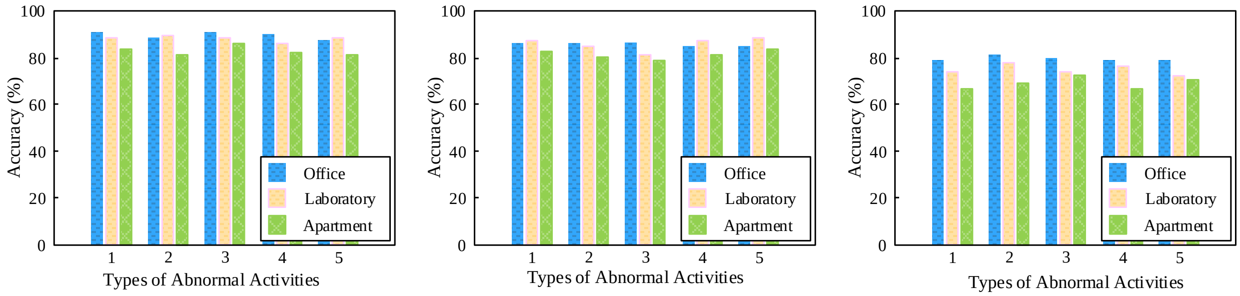
	Abnormal Activity	Time
1	Slipping on the ground	9:16 AM
2	Falling down backwards	9:58 AM
3	Falling down forwards	9:06 AM
4	Running	10:40 AM
5	Breath pausing	10:23 AM

D. Experimental Results

1) Feasibility of Abnormal Activity Detection: We firstly evaluate the *NotiFi*'s abnormal activity detection accuracy by asking the human to vary activities and location according to the direction in three scenarios as shown in Figure 6. We use the same setting of sensor based method in [27] and compare *NotiFi* with it in three scenarios. Figure 7 shows the accuracy of *NotiFi* in LoS and NLoS is much higher than the accuracy of sensor based method in average. As for *NotiFi*, the accuracy reduces as the distance increases in Figure 7b. This is because the received CSI strength through signal reflecting reduces. In Figure 7a and Figure 7c, the accuracy does not reduce obviously. This is because as while user is away from the Rx, he is more closer to the Tx. The transmitted signals increase while the signal reflections reduce.

In Table II, based on the normalized log-likelihoods $p(\mathbf{w}_t|\mathbf{w}^{-t})$, we display the top 5 abnormal activities *NotiFi* detected. The possible reasons in terms of the nonparametric probability distribution is: (1) The activity can not fit any major hot path. (2) The activity fits more than one hot paths, but the combination of hot paths is strange. That's to say, the activity is either rare or different from others.

2) Robustness Validation: Figure 8 shows the abnormal activity detection accuracy in different scenarios. In each scenario, the distance between the transmitter and the receiver is the same. The results show that overall *NotiFi* has an average accuracy of 89.2% in LoS, 85.6% in NLoS, and



(a) LoS

(b) NLoS

(c) Through-one-wall

Fig. 8: Robustness evaluation of *NotiFi*.

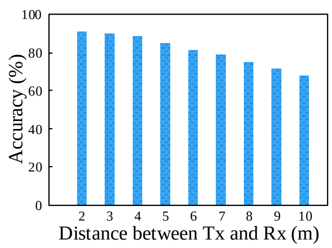


Fig. 9: Performance under different distances between Tx and Rx.

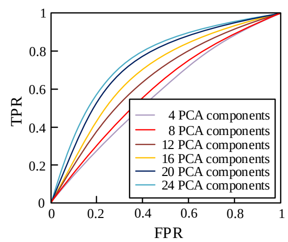


Fig. 10: Tradeoff between TPR and FPR.

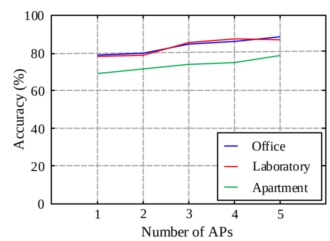


Fig. 11: Impact of multiple APs.

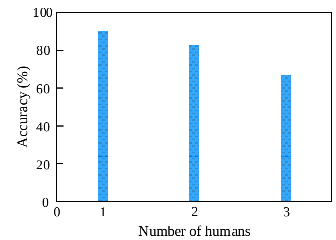


Fig. 12: Impact of multiple humans.

75.3% in through-one-wall scenario. The accuracy of abnormal activities detection in office has a higher average accuracy of 91.8% in LoS, 86.7% in NLoS, and 79.2% in through-one-wall scenario. The accuracy of abnormal activities detection at laboratory has an average accuracy of 91.3% in LoS, 87.6% in NLoS, and 76.4% in through-one-wall scenario, while the accuracy of abnormal activities detection at apartment has an average accuracy of 84.7% in LoS, 82.5% in NLoS, and 70.3% in through-one-wall scenario. The office and the laboratory scenarios have higher accuracy than the apartment scenario. This is primarily because that even though we adopt PCA to denoise the channel state information, it still has more complex electromagnetic interference for apartment environment than the office or laboratory in which has less furniture. The results show that *NotiFi* is robust in detecting abnormal activities in different environments.

The laboratory environment is chosen to evaluate the performance of abnormal activity detection under different distances between the transmitter and the receiver. The transmitter and the receiver are placed at opposite sides of the table with distances from 2 to 10 meters. Figure 9 presents the accuracy under different distances when there is a single person performs activity. The accuracy is over 86% when the distance is shorter than 5 meters. Overall, we observe that shorter distance between the AP and the laptop results in higher accuracy. This is because the received WiFi signals are stronger with shorter communication distances, providing more reliable extraction of CSI to capture the human body movements.

3) Different Size of PCA Components: Figure 10 gives the performance of *NotiFi* under different number of PCA components. Using 20 PCA components is enough, since adding more components do not further improve the performance of *NotiFi*.

4) Impact of Multiple APs: We then analyze the impact of different AP densities through increasing the number of APs up to five. We deploy AP at the corner of office, laboratory, and apartment, where the receiver laptop is on the center of the scenarios. The Figure 11 shows that the system accuracy increases to 86.2% on average when the number of APs increases to three, and reaches 92.4% on average when the device hears five APs at office and laboratory scenarios. This is because we will have more strong direct path measurements as the increasing of the number of APs. When the environment deploys dense WiFi APs, *NotiFi* can achieve robust performance.

5) Impact of Multiple Humans: In this experiment, we set the the distance to 3.5 m between the laptop and AP. It has up to three users in one room at random locations performing random actions. Figure 12 shows the overall abnormal detection accuracy reduces when we increase the number of users and activities. We note, however, that increasing the number of interfering users within a small area, e.g. a conference scenario, may affect the system accuracy. This needs to be further investigated.

V. Conclusion

Abnormal activity detection has been an important component in various applications ranging from well-being monitoring, health care, and building surveillance. Non-invasive abnormal activity detection system based purely on physical channel information with COTS WiFi infrastructures is a challenging issue. This current implementation of *NotiFi*, however, has the following limitations:

1) Presence of multiple humans: When there are multiple humans moving at the same time, the CSI variance patterns captured by *NotiFi* are complex mixtures of multiple activities. For future work, we may address this issue by separating concurrent activities in isolated spaces and then track them respectively [12].
2) Requiring walking: The second limitation is that *NotiFi* analyzes the variances of the phase and the amplitude of *Channel State Information* (CSI) to perform abnormal detection. Hence, the continuous static target and pieces of furniture cannot be distinguished. *NotiFi* may need a training period to be aware of the setting of the environment [28].

In this paper, we presented *NotiFi*, a non-invasive device-free abnormal activity detection system on the *commodity off-the-shelf* (COTS) WiFi devices. *NotiFi* does not have the requirement of additional hardware or dedicated wearable sensors, and can work under both *line-of-sight* (LoS) and *non-line-of-sight* (NLoS) conditions. The number of abnormal activity categories is automatically learn from *Channel State Information* (CSI) value instead of being set manually so that it does not need a priori learning of wireless signals.

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