WarnFi: Non-Invasive WiFi-based Abnormal Activity Sensing Using Non-parametric Model

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***Abstract*—Abnormal activity sensing has attracted increasing research attention in military surveillance, patient monitoring, and health care of children and elderly, etc. Researchers have exploited the characteristics of wireless signals to sense "keystrokes" and "human talks", relieving the privacy invasion concern caused by mounting the surveillance cameras or wearing the smart devices. However, existing technologies usually require some specialized hardware, and can only sense a fixed set of pre-defined activities through a supervised learning from those wireless signals patterns. In this paper, we propose *WarnFi*, a non-invasive abnormal activity sensing system with only two *commodity off-the-shelf* (COTS) WiFi devices. The intuition of *WarnFi* is that whenever the human body occludes the wireless signal transmitting from the access point to the receiver, the time-series of *Channel State Information* (CSI) will experience a unique variation. By using a non-parametric model, *WarnFi* can dynamically cluster the human body activities for abnormal sensing. Extensive experiments in various scenarios demonstrate the satisfactory performance of *WarnFi*.**

I. Introduction

Abnormal activity sensing, the ability of finding "rare and different" activities that do not conform to expected patterns, has become an important task in many applications, such as military surveillance, health care, patient monitoring, etc. [1]. For example, if soldiers' abnormal activity can be sensed automatically, immediate alerts would be possible in case of emergency or injury. Traditional vision based systems, such as *Xbox Kinect* [2] and *HON4D* [3], require the *line-of-sight* (LOS) with adequate lighting, and bring the new concern in privacy disclosure. Wearable sensor based systems cause inconvenience in occasions such as *bathing*, let alone the extra cost [4].

Recently, wireless signal has been exploited to alleviate above issues. *Received Signal Strength* (RSS) based solutions leverage the changes in the signal strength to sense human activity. *Radio Frequency* (RF) based solutions, such as *Frequency Modulated Continuous Wave* (FMCW) radar and *Doppler* radar, can reflect the unique patterns of activities [5]. The implementation of the RSS or RF based methods usually involves two practical issues: one is how to overcome performance degradation due to multi-path fading; the other one is how to relax the dependence on specialized hardware.

Recent advances in wireless communication technology, especially the physical layer channel information extraction, has provided alternative approach to human activity sensing method using WiFi signals. In particular, the exposed physical layer *Channel State Information* (CSI) have been used for activity sensing such as *falling down* [9], *smoking* [10], *breathing beats* [11], *motion direction inferring* [12], [13], *hand counting* [14]. and *hand-free drawing* [15]. These systems are based on the observation that CSI is highly sensitive to different human body activities. However, these systems can only recognize a pre-defined set of activities through a supervised learning from observed wireless signals patterns. For more practical cases, these systems do not work as expected. More specifically, an activity might be sensed as abnormal when it appears in the first time, however, it may be considered as normal when more and more instances are observed. Existing abnormal activity sensing methods can not support this, because not all abnormal activity can be pre-defined, and also the abnormal is a concept that depends on the observation frequency [16].

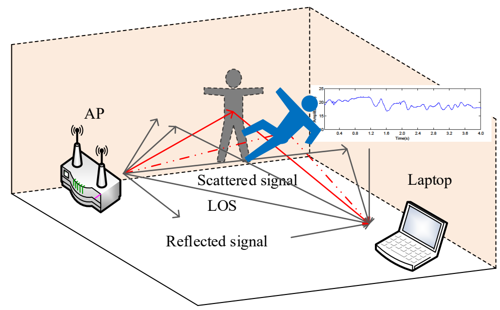


Fig. 1: Human activity affects the WiFi signal propagation.

In this paper, we show the potential to non-invasive abnormal activity sensing by using *commodity off-the-shelf* (COTS) IEEE 802.11 devices. The key insight is that the time series of CSI values can reflect the unique characteristics of activities in both time and frequency domains. To translate the above ideas into a working system entails several technical challenges: (1) How to extract effective human body features under the subtle signal changes? (2) How to model the abnormal activities, especially for 180 groups of CSI values embedded in one packet extracted from the receiver? (3) The abnormal activities are with different patterns which can not and should not be

TABLE I: Capabilities of different methods.

Type	Typical System	Approach	Non-invasive	Device-free	Accurate	Easy for installation	Comprehensive
Computer Vision	Xbox Kinect [2]	Camera	×	×	√	×	√
Wearable Sensor	BodyScope [4]	Acoustic	×	×	√	×	×
	TEXIVE [6]	Motion	√	×	√	×	×
Wireless Signal	WiTrack [7]	RF	√	×	√	×	×
	WiGest [8]	RSS	√	√	×	√	×
	RT-Fall [9]	CSI	√	√	√	√	×
Wireless Signal	***WarnFi***	**CSI**	✔	✔	✔	✔	✔

simply pre-defined, but how to automatically cluster the human body activities especially in large-scale datasets?

We addressed the above challenges and demonstrated the feasibility of WiFi-based abnormal activity sensing system called *WarnFi* (Warn of WiFi). As shown in Figure 1, *WarnFi* consists of a receiver such as a laptop, and a transmitter such as a router. After clustering the wireless signal patterns using non-parametric model, *WarnFi* senses the abnormal activities under both *line-of-sight* (LOS) and *non-line-of-sight* (NLOS) situations. Unlike cameras, *WarnFi* does not require lighting and works in dark just as well as in light. It requires no dedicated sensor, nor the supervised learning of WiFi signals for pre-defined activities. This unsupervised framework will save the human interventions needed.

Experiment results in different scenarios including *apartment*, *meeting room* and *bathroom* demonstrate that *WarnFi* can achieve great performance. More specifically, *WarnFi* accurately senses abnormal activity with an average accuracy of 88.6%, and the accuracy in LOS situations reaches 90.2% in which the WiFi device can hear multiple APs. We highlight our main contributions as follows

- We propose and validate the feasibility of *Channel State Information* (CSI) based abnormal activity sensing method.
- We present a CSI grouping algorithm to reduce the overall computation cost, and utilize a density-based mean-shift clustering method to automatically cluster the human body activities.
- We implement *WarnFi* using commercial WiFi device and extensive evaluations in different scenarios show that *WarnFi* is robust to the change of environment.

The rest of this paper is organized as follows. Section II discusses the related work. In Section III we present the system design. Section IV presents the design details of *WarnFi*. We report the empirical evaluation in Section V. Finally, we conclude our paper in Section VI.

II. Related Work

A. Computer Vision based Activity Sensing

Vision based systems use camera to estimate a sequence of abnormal activity [2], [17]. Zhu *et al.* combined skeleton joint and spatiotemporal features to achieve 3D activity recognition [18]. Chen *et al.* improved the activity recognition accuracy by combining inertial body sensor and depth camera [19]. However, the sensitivity to lighting conditions and the introduced privacy disclosure remain practical concerns. Besides, for the blind areas such as the bathroom and stairwells, mounting the camera is inconvenient or even illegal.

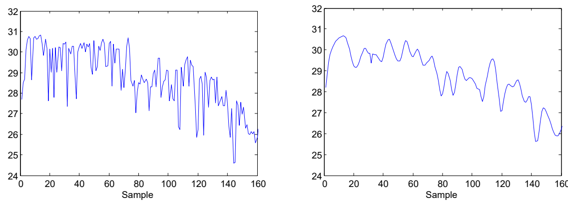
B. Wearable Sensor based Activity Sensing

TAHAR [20] achieved a real-time activity classification with a data collection of inertial sensors such as gyroscopes and accelerometers. *TEXIVE* [6] leverages smartphone sensors to sense texting operations and driving simultaneously. *BodyScope* [4] records the sounds to classify activities, such as speaking and laughing. However, additional sensors need to be installed or worn, which is difficult for many people to comply with.

C. Wireless Signal based Activity Sensing

According to the source of wireless signals, it can be classified in three types: *Radio Frequency (RF) based Sensing Systems*, *RSS based Sensing Systems*, and *CSI based Sensing Systems*. RF based methods require specialized high cost devices. RSS based methods are not enough accurate to provide fine-grained sensing. *Channel State Information* (CSI) discriminates multi-path characteristics. *WiFinger* [14] shows the potential to detect and recognize finger gestures available on COTS devices. *WiDance* [13] leverages *Channel State Information* (CSI) to extract activity-induced Doppler shifts for inferring motion direction. *WifiU* [21] extracts the spectrogram signatures to describe the detailed gait patterns for person identification. *WiKey* [22] exploits the micro-movements of fingers while typing to extract the individual keystrokes. *PreFi* [23] leverages CSI to analyze customer's product preference. However, they need the supervised learning of WiFi signals for pre-defined activities.

Table I shows the capabilities of different methods. No existing system simultaneously satisfies *non-invasive*, *device-free*, *accurate*, *easy for installation*, and *comprehensive*. The abnormal activity should be dynamic, rather than static so that a frequently observe activity can not be abnormal. More specifically, an activity might be sensed as abnormal when it appears in the first time, however, it may be considered as normal when more and more instances are observed. Existing abnormal activity sensing methods can not support this, because not all abnormal activity can be pre-defined, and also the abnormal is a concept that dependents on the observation frequency.



(a) Original CSI

(b) Denoised CSI

Fig. 2: CSI variance of a single subcarrier.

III. System Design

A. Channel State Information

In a wireless communication system, *channel state information* (CSI) portrays how the wireless signal propagates between transmit-receiver antenna pairs. For each subcarrier, CSI exposes the wireless fading phenomenon in the form of amplitude and phase. The channel matrix $\mathbf{H}$ for each subcarrier is modeled as

$$\mathbf{H}_i = \mid \mathbf{H}_i \mid e^{j\sin(\angle \mathbf{H}_i)},$$

in which $\mid \mathbf{H}_i \mid$ is the amplitude, and $\angle \mathbf{H}_i$ is the phase information. The received signal $\mathbf{R}(t)$ at time t can be expressed as

$$\mathbf{R}(t) = \mathbf{H}(t)\mathbf{T}(t) + \mathbf{N}(t),$$

where $\mathbf{T}(t)$ is transmitted vector and $\mathbf{N}(t)$ is the noise vector. For each transmit-receiver antenna pair, we can collect *channel state information* (CSI) for 30 OFDM subcarriers from the driver of Intel 5300 WiFi NIC as described in [24]. Figure 2 shows the original and denoised CSI.

B. System Overview

WarnFi is a WiFi-based non-invasive abnormal activity sensing system on COTS WiFi devices. Figure 3 gives the framework of *WarnFi*, which can be divided into 3 parts: CSI sampling, abnormal activity sensing, and alerting part.

1) **CSI Sampling**
The wireless signal continuously propagates between transmit-receiver antenna pairs. The time-series CSI data is sampled from COTS WiFi devices and processed on the computer. Then filtering method is adopted to smooth out noisy data for improving the robustness of environmental change.
2) **Abnormal Activity Sensing**
WarnFi reduces the overall computation cost and distinguishes those abnormal activities by leveraging data calibration. We employ a non-parametric clustering model and weighted hierarchical majority voting method to automatically cluster the human body activities for abnormal sensing.
3) **Alerting**
Based on the clustering model, the next component of our design is decision making, which identifies the "rare and different" activities such as *falling down*, *slipping to the ground*, *breath pausing*, etc.

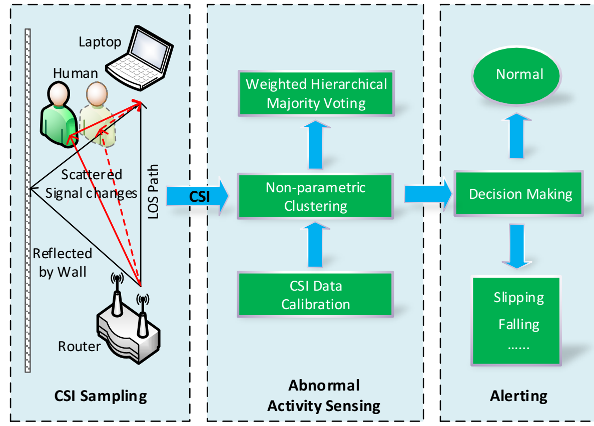


Fig. 3: Framework of *WarnFi*.

IV. Abnormal Activity Sensing

WarnFi leverages physical layer information CSI to sense the abnormal activities. It consists of three main components, including CSI data calibration, non-parametric clustering and weighted hierarchical majority voting.

A. Data Calibration

The goal of data calibration is to avoid the overall computation for decision making and distinguish those abnormal activities. Specifically, our data calibration strategy involves three steps: CSI grouping, feature extraction, feature normalization.

- **CSI Grouping**
CSI grouping process groups the whole CSI values into n groups, and the group i is formed by the CSI values at sampling i, $n+i$, $2n+i$, $\cdots$ etc. It can reduce the overall computation cost.
- **Feature Extraction**
In each group, we collect CSI features and transfer them into a uniform format for characterizing the activity. *Principal Component Analysis* (PCA) is adopted to discover the correlations between CSI streams. Eq. (1) is the CSI feature matrix $\mathbf{F}_{i,j}$ for n groups and 30 subcarriers.

$$\mathbf{F}_{i,j} = \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,30} \\ f_{2,1} & f_{2,2} & f_{2,3} & \cdots & f_{2,30} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{n,1} & f_{n,2} & f_{n,3} & \cdots & f_{n,30} \end{bmatrix}, \quad (1)$$

where $f_{i,j}$ is the CSI feature value for the i^{th} group of the j^{th} subcarrier.
- **Feature Normalization**
As the collected data have different scales, the matrix $\mathbf{F}_{i,j}$ is normalized into the range of 0.0 and 1.0.

B. Non-parametric Clustering

We utilize a density-based mean-shift clustering method that requires no supervised information as input parameters. The bandwidth of searching window, which does not need to be pre-defined, is calculated by:

$$l_i = \parallel x_i - x_{i,n/2} \parallel_1,$$

where $x_{i,n/2}$ is the $m/2$ nearest neighbor of CSI feature $x_i (i = 1, \cdots, m)$. The clustering method is conducted in the following steps:

1) The new center of the CSI feature in the window is calculated by:

$$\tilde{x_i} = \frac{\sum_{j=1}^{m} x_{i,j} g(\parallel \frac{x_i - x_{i,j}}{l_i} \parallel^2)}{\sum_{j=1}^{m} g(\parallel \frac{x_i - x_{i,j}}{l_i} \parallel^2)},$$

in which $x_{i,j}$ is a CSI feature in the x_i search window and $g(x) = q'(x)$, in which $q(x) (0 \leqslant x \leqslant 1)$ is the kernel for estimating the density of CSI feature x_i.

2) Starting from $\tilde{x_i}$, step 1 is repeated until a convergence.

C. Weighted Hierarchical Majority Voting

Based on the above non-parametric clustering, the goal of our design is to sense the abnormal CSI features in each group.

1) In the first level, a CSI feature is labeled with Ma (Majority) if $p_1 \geq \xi_1$, where p_1 is the probability x_i belongs to the majority of the group and ξ_1 is a threshold. A CSI feature is labeled with Mi (Minority) if $p_1 < \xi_1$.

2) In the second level, only the CSI features labeled with Ma are selected to vote. x_i is labeled with N (Normal) if $p_2 \geq \xi_2$, where p_2 is the probability x_i belongs to the majority of Ma in first level; otherwise the CSI feature will be labeled with An (Abnormal).

The probability that the CSI feature is regarded as abnormal is $p = 1 - p_1 \cdot p_2$. The probability of a normal CSI feature being regarded as Ma is given by:

$$P_{N \to Ma} = p_1 p_2 \sum_{f=0}^{\lceil \frac{n}{2} - 1 \rceil} C_n^f (p_1 p_2)^{n-f} (1 - p_1 p_2)^f,$$

in which f is the number of abnormal features. The probability of a normal CSI feature being regarded as M_i is given similarly:

$$P_{N \to Mi} = p_1 p_2 - P_{N \to Ma}.$$

The probability of a normal CSI feature being correctly labeled is in Eq. (2).

Similarly, we can derive the probability for an abnormal CSI feature being correctly labeled $P_{An \to An}$. The sensing accuracy of weighted hierarchical majority voting method is calculated by $P_{N \to N} + P_{An \to An}$, indicating the probability of an activity being correctly classified. Specifically, an activity might be sensed as abnormal when it appears in the first time, however, it may be considered as normal when more and more instances are observed.

$$\begin{aligned} P_{N \to N} = p_1 p_2 \sum_{m=1}^{n} C_n^m (\sum_{a=0}^{\lceil \frac{m}{2} - 1 \rceil} C_m^a P_{N \to Ma}^{m-a} P_{An \to Ma}^a) \\ \sum_{b=0}^{n-m} C_{n-m}^b P_{N \to Mi}^b P_{An \to Mi}^{n-m-b} + P_{N \to Ma} \sum_{c=0}^{n} C_n^c P_{N \to Mi}^c P_{An \to Mi}^{n-c} \end{aligned} \quad . \quad (2)$$

V. Empirical Evaluation

A. Device and Network

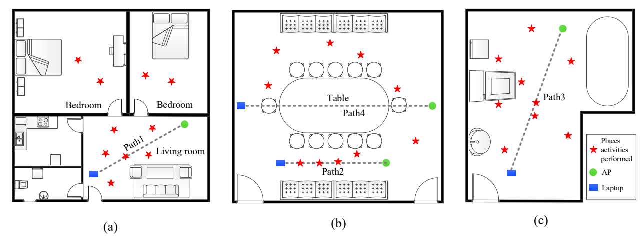
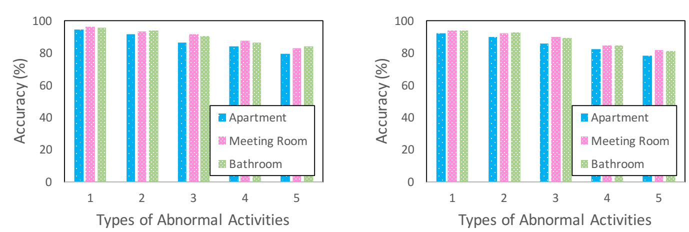


Fig. 4: Apartment (a), Meeting Room (b), Bathroom (c).

Experiments are conducted on one *Think-pad X200* laptop with IEEE 802.11n WiFi network device and a router *TP-LINK TL-WDR4300*. Laptops equipped with Intel 5300 *network interface card* (NIC) are to establish orthogonal links. The router which is set as *access point* (AP) runs on 5 GHz, while the laptop runs Ubuntu 10.04 which is set as receiver. We chose the 5 GHz band because its wavelength is shorter and it gives better resolutions than 2.4 GHz band. We extract the CSI values of 30 *Orthogonal Frequency Division Multiplexing* (OFDM) subcarriers from IEEE 802.11 data frames using a modified driver as described in [24]. The pair of WiFi devices communicate with 100 $pkts/s$. We use MATLAB to analyze the CSI data.

B. Experimental Methodology

Our primary focus in *WarnFi* is smart spaces abnormal activity sensing, we then choose three different indoor environments for our evaluation as shown in Figure 4: (a) an apartment covering about 9×9 m^2 area with two bedrooms and a living room. (b) a meeting room covering an area of around 9×10 m^2 with a table, dozens of chairs and two groups of sofas; (c) a



(a) LOS (b) NLOS

Fig. 5: Abnormal activity sensing accuracy in different scenarios.

TABLE II: Top abnormal activities sensed by WarnFi.

	Abnormal Activity	Time
1	Jump	03:05 PM
2	Running fast	02:43 PM
3	Falling down	03:35 PM
4	Slipping on the ground	04:17 PM
5	Breath pausing	03:56 PM

bathroom covering about $3 \times 4\ m^2$ area. The length of “Path1”, “Path2”, “Path3” satisfies that $l1 = l2 = l3$. 7 volunteers are recruited to observe the activities performed by testers via video. The arriving activity will be labeled as normal when most of the volunteers label it as such. If the labeled abnormal activity reoccurs frequently, it will be regarded as normal.

C. Evaluation Metrics

1) True Positive Rate (TPR): the proportion of instances that *WarnFi* senses the abnormal activities correctly among all the abnormal activities.
2) False Positive Rate (FPR): the proportion of instances that *WarnFi* gives false alarm when actually no abnormal activity exists.

D. Accuracy of WarnFi

1) Feasibility of Abnormal Activity Sensing: The accuracy of *WarnFi*’s abnormal activity sensing is evaluated by asking the human to vary activities and location as shown in Figure 4. In Table II. we display the top 5 abnormal activities of *WarnFi*. The results in Figure 5 show that overall *WarnFi* in NLOS has an average accuracy of 85.7% in apartment, 88.6% in meeting room, and 88.2% in bathroom environment. This accuracy in LOS can be increased to 87.2% in apartment, 90.2% in meeting room, and 90.1% in bathroom environment. The meeting room and the bathroom environment are in higher accuracy. The reason is that while we adopt PCA to discover the correlations between CSI streams, the environment is still faced with complex electromagnetic interference, especially for apartment. The accuracy indicates that *WarnFi* is robust in different environments.

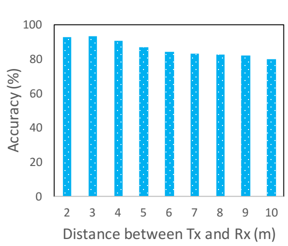


Fig. 6: Impact of different distances between Tx and Rx.

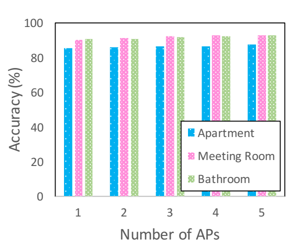


Fig. 7: Impact of different APs.

The meeting room is chosen to evaluate the performance under different distances between the transmitter which is abbreviated to Tx and the receiver which is abbreviated to Rx. As expected, the sensing error becomes worse when it is more than 5 meters in these scenarios. It is clear that shorter distance leads to higher accuracy, because the received WiFi signals are stronger with shorter communication distances, providing more reliable extraction of CSI to capture the human body movements.

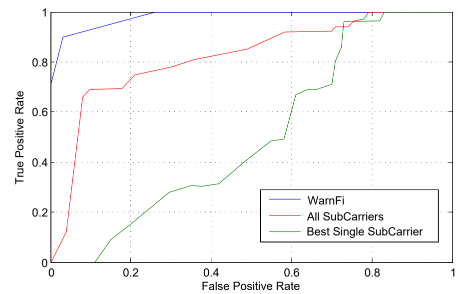


Fig. 8: ROC curves of *WarnFi*, compared with two baseline methods.

2) Comparision with the Baseline Methods: We use the *Receiver Operating Characteristic* (ROC) curves to quantitatively evaluate the overall performance of *WarnFi* against two baseline methods: using *all subcarriers* without grouping and analysing the *best single subcarrier*. The CSI values of all subcarriers are directly added up as *all subcarriers*, and we choose the single subcarrier which has best performance as *best single subcarrier*. Figure 8 gives ROC curves, which depicts the tradeoff between TPRs and FNRs. The performance for *best single subcarrier* scheme is worst among them. This is because the wireless signals affected by human activity are scattered in multiple subcarriers, and the fine-grained information can not be easily captured by a single subcarrier.

3) Non-parametric Clustering Accuracy: We compare non-parametric clustering with existing well-known parametric method including *k-means*, *gaussian mixture*, *DBSCAN* [25] and *mean-shift* clustering. Parametric clustering methods need some predefined parameters. By assuming there are two activity patterns, we set 2 clusters for *k-means*, and *gaussian mixture* clustering. For *DBSCAN*, the minimum cluster size is set to 1. For *mean-shift* clustering, we set the bandwidth to 0.6.

Figure 9 demonstrates the clustering accuracy of all these methods. The result demonstrates that when the true number of activity patterns and clusters is the same, all these methods perform well. As the number of abnormal activity types increases, the *DBSCAN*, *mean-shift* and *non-parametric* clustering methods outperform the others slightly.

4) Impact of Different Number of APs: We change the number of transmitter for up to five to illustrate that our measurement accuracy is good enough for abnormal activity sensing. We place the laptop at the center of apartment, meeting room, and bathroom, while APs are placed at the corner of the scenarios. From Figure 7, we have the observation that *WarnFi* can achieve an average sensing accuracy of 90.2%,

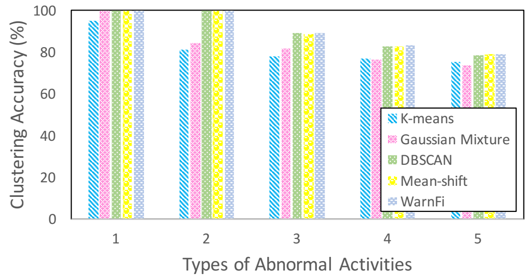


Fig. 9: Comparison of *WarnFi* with existing clustering methods.

and the accuracy reaches 91.2% on average when there are more APs. The reason is that there will be more direct path measurements when more APs are included.

VI. Conclusion

In this paper, we propose *WarnFi*, a non-invasive WiFi-based abnormal activity sensing system with only two *commodity off-the-shelf* (COTS) WiFi devices. First, we present a *Channel State Information* (CSI) grouping algorithm to reduce the overall computation cost. Then we utilize a density-based mean-shift clustering method that requires no supervised information as input parameters to sense abnormal activity. Specifically, an activity might be sensed as abnormal when it appears in the first time, however, it may be considered as normal when more and more instances are observed. We compare *WarnFi* with the baseline methods and extensive experimental results demenstrate that *WarnFi* has made some progress by proposing an abnormal activity sensing system that simultaneously satisfies the *non-invasive*, *device-free*, *accurate*, *easy for installation*, and *comprehensive*.

In addition, we aim to extend this work to achieve that it easily distinguishes the furniture with static target. *WarnFi* may need a training period to recognize the background of the environment [26]. Besides, *WarnFi* may separate different humans by tracking them respectively in different dimension [7]. This work will contribute to the development of a comprehensive non-invasive WiFi-based sensing system. Furthermore, building a non-invasive WiFi-based higher accuracy monitoring system is our future work.

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