WiHunter: Enabling Real-time Small Object Detection via Wireless Sensing

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***Abstract*—Rodent infestation is a great danger to human society, continuously threatening food safety and inducing disease spread. Existing methods to deal with rodent infestation are mainly based on passive bait traps and poisoning. These methods lack timeliness and effectiveness due to the missing of real-time detection. In this paper, we develop WiHunter, a new wireless sensing system to discover small objects (e.g., rat). Our idea is to exploit reflection signal effect of wireless channels induced by the movement of small objects around the receiver antenna. However, existing wireless sensing works usually employ customized or costly device-dependency Network Interface Cards(NIC), which are impractical to be densely deployed in reality. We implement WiHunter with several CSI-enabled standalone IoT nodes. We show how such devices enable moving small object detection via WiFi signal. The rationale behind this is 1) thanks to the widespread deployments of WiFi infrastructures and IoT devices, the WiFi signal covers almost every location of the corner, 2) the signal amplitude of each device is related to the small object near the receiver antenna. This ability gives us the opportunity to sense object as small as a rat. We implement WiHunter with ESP32 microcontroller on Espressif IoT Development Framework (both of them are cheap commodity off-the-shelf (COTS) devices) and design a practical small object intrusion detection system. Comprehensive and real-world experiments demonstrate that our system is effective in detecting the presence of small objects with an average accuracy of 92.1%.**

***Index Terms*—small object detection, CSI, IoT, wireless sensing**

I. Introduction

Rodent infestation is one of the most terrible plagues in the world. Crowds of rat would destroy commodity, steal grain, and even spread disease. From 1347 to 1351, the *Black Death* resulted in more than 25 million deaths. The spreading of this disease is most likely caused by the fleas living on the black rats [1]. Thus, it is of significance to dispel the rat activity in the place (*e.g.*, the kitchen) related to human health. All along, trap and poison are two major countermeasures for the inhibition of reinfestation. Although easy to implement, they are inefficient because they are passive manners. Meanwhile, they may be harmful to humans themselves. Fortunately, if we can actively sense the movements of rats (i.e., localizing them), the rat traps can be placed in a targeted manner, thereby improving the efficiency of rodent control.

Previous proposal [2] has demonstrated the feasibility of camera-based small object (e.g., rat) detection. However, rats are prone to act in dark environments, where cameras usually do not work. Meanwhile, rats often hide in surroundings. In such a non-line-of-sight (NLOS) scenario, these light-of-sight (i.e., cameras) based approaches are ineffective. Therefore, there is an urgent need for an obstacle-free small object detection system that can perform well under NLOS and dark conditions.

One promising way to overcome these limitations is the Radio Frequency (RF) based sensing [3], [4]. RF signals, e.g., WiFi, have become ubiquitous in recent years. Meanwhile, the wide deployments of WiFi infrastructures (including numerous access points (APs) and routers) make it possible to utilize the pervasive WiFi signals for uninterrupted and noninvasive sensing. In particular, researchers find that the channel state information (CSI) derived from the WiFi signals is able to sense objects in many applications, such as indoor localization [5], [6], human tracking [5], [7], and hand sign recognition [8]. CSI can be estimated in wireless communication via commodity WiFi devices, e.g., network interface cards (NICs), offering convenient deployment and scalability in real implementations. Unlike camera-based approaches that are susceptible to dark and NLOS environments, the penetrability and pervasiveness of WiFi signals allow them to bypass (via reflection, diffraction, or diffusion) and pass through most obstacles. Hence, WiFi-based wireless sensing meets the need for online small object detection under poor lighting conditions and complex environments, such as kitchen and warehouse.

Previous studies [9]–[11] have demonstrated that WiFi signals can be exploited to probe the dynamics of human bodies as well as some small motions (e.g., respiration rate [10] and finger motion [11]). However, these approaches are inapplicable to our sensing scenarios, i.e., detecting moving small object. Specifically, prior works can be grouped into learning-based approaches [10] and modeling-based approaches [9], [11]. The former ones need to collect a batch of training data (usually in a large volume) to learn the relationship between the sensing object and WiFi signals, while the latter ones rely on modeling the signal propagation to form such relationship. If adopting a learning-based approach, it would be extremely inconvenient to collect training data from rats. So, using modeling-based approach is wiser. Nevertheless, ex-

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isting modeling-based methods are unsuitable for small object detection, because they are primarily designed for humans. Particularly, they require the sensing object either to stay in a fixed sensing area (i.e., crossed Fresnel Zones [11]) or to have a large reflection surface (e.g., human chest). The former requirement is for maintaining a stable relationship between the signal variations and the dynamics of the sensing object. The latter requirement is to guarantee sufficient received signal strength (RSS) of reflected signals. Both requirements are easy to meet if the sensing objects are humans because they are cooperative and with large reflection surfaces, but hard to satisfy when detecting small and uncooperative objects, like rats.

In this work, we aim at using standard WiFi signals to detect moving small objects with weak reflection. Intuitively, we can achieve this by placing the receiver near the small object, because smaller distance between them leads higher RSS to the signals reflected from the small object. To verify our conjecture, we conduct a preliminary experiment. The results show that it is feasible to capture the dynamics of the small object once it presents within a certain range (e.g., within 0.5m).

Based on the above observations and analysis, we can densely deploy the WiFi infrastructures in the corners that small objects (e.g., rat) are prone to pass. However, current NICs used for wireless sensing are relatively expensive and cumbersome (requiring to be connected to extra computing components like personal computer). Thus, these NICs are not suitable for dense deployment in small object detection. The essential challenge turns into designing a low-cost and small-volume CSI acquisition device.

To this end, we devise an ESP32 microcontroller-based [12] device, named WiFi-functioned node (WiFN), to acquire CSI. WiFN bears the advantages of small volume, low cost, and the ability of operating independently. Thus, it can be densely deployed in cramped environments. Given the fact that IoT devices are pervasive and WiFN supports IoT framework, WiFN can be ubiquitously deployed like other WiFi infrastructures. Specifically, we rebuild the data acquisition function on the ESP32 board, such that WiFNs can be deployed in a distributed manner and collect the CSI from multiple positions at the same time, which cannot be done by previous CSI acquisition approaches. Besides, we modify the data stream of original ESP32 design, which allows the obtained CSI to be uploaded to the internet in real time. This facilitates the subsequent real-time object detection.

Then, we meet another challenge, that is, it is difficult to accurately detect the small object by raw signals. Due to the inherent defects of the WiFN, the raw measurements of WiFN are noisy, which may lead to false detection of the small object. To address this challenge, we first extract the low-frequency components that characterize the dynamics of the small object to mitigate the interfering signals. Then, we leverage the feature of signal variation caused by the movement of the small object to enhance the detection accuracy.

We build a prototype of WiHunter with WiFNs to evaluate its performance on small object detection. Extensive experiments are conducted with a live Fancy Rat in real scenarios. The experiment results show that WiHunter can achieve 92.1% average detection accuracy. To demonstrate the good quality of service (QoS) of the system, robustness studies are conducted and the results show that WiHunter is robust against harsh environments, such as NLOS conditions. The main contributions of this paper are summarized as follows:

- We propose a WiFi-based small object sensing system named WiHunter. It can detect the presence of any moving small objects, such as uncooperative small animals.
- We develop and implement a CSI acquisition device called WiFN, which can collect standard WiFi signals and upload estimated CSI to the internet in real time. Unlike expensive and large-volume traditional WiFi sensing hardware (i.e., NIC), the low cost and small volume allow WiFN to be densely deployed even in cramped environments. Last but not least, WiFN can work merely based on battery supply.
- We prototype WiHunter and carry out extensive experiments in real scenarios. The results show that WiHunter can accurately detect the small object's presence. Besides, it performs well under various environments with good QoS.

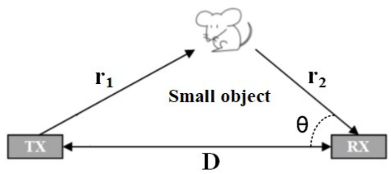
II. Preliminary and Feasibility Study

A. Why WiFi?

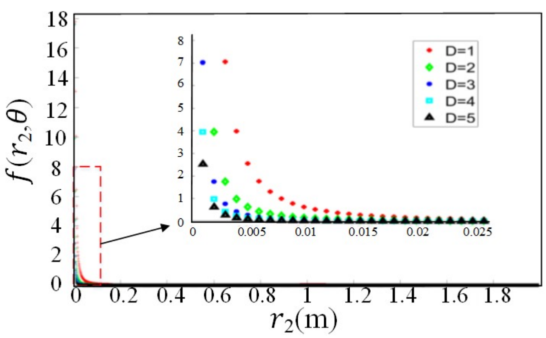
A lot of efforts have been made in the past to deal with rat infestations. Placing large quantities of traps and rat poison is the most intuitive and easiest method. However, blindly placing rat traps and other facilities to capture/poison rats is not only inefficient but also easy to accidentally injure humans. Fortunately, on the premise of understanding the movement trajectory/habit of the rat, the targeted arrangement of rat traps in right positions will effectively avoid this problem. Thus, rat tracing is of importance to the control of rodent infestation. Meanwhile, since rat is a very alert animal, it would be better to track them in a non-intrusive way, e.g., wireless sensing.

Devices that use wireless signals for object sensing include camera [2], [13]–[15], acoustic device [16]–[19], and radio frequency (RF) device [20]–[22]. The first two kinds of devices have been well developed to achieve fine-grained sensing. However, they have their drawbacks towards sensing small objects. Cameras need light to capture the image or video of objects, but rats prefer to come out in dark environments (e.g., at night), leading to capture failure due to insufficient light. Besides, rats also like to move along the corners such that they are easily obstructed, i.e., cameras cannot function in NLOS situations. To capture object dynamics without disturbing humans, sound-based approaches usually opt to emit ultrasounds whose frequency exceeds the range of human hearing. Nevertheless, the auditory system of rats has a significantly wider frequency spectrum (1000-70KHz [23]) than that of human. High-power ultrasonic pulse will make rats uncomfortable and away from the device, making them unable to perform sensing task.

Recent years have witnessed the rapid development of RF-based sensing techniques [5], [6], [9], [24]–[28]. RF signals in various frequency bands are exploited to achieve light-free



(a) Setup illustration.



(b) The objective function vs. distance r_2.

Fig. 1. Increasing the power of the reflected signal by decreasing the distance between receiver and object. (a) Small object sensing setup illustration. (b) The objective function increases drastically when the distance is less than 10cm.

sensing. Due to their good penetrability, RF-based systems usually can work well under NLOS conditions. Among these RF signals, WiFi is a special and appealing one because of its prominent ubiquity, i.e., nearly covering everywhere. Besides, existing research shows that WiFi signals can be utilized to achieve fine-grained sensing applications, such as sign language recognition [8], respiration detection [9] and finger motion tracking [11]. Therefore, in this work, we aim at leveraging ubiquitous and non-intrusive WiFi signals to detect moving small objects.

B. Small Object Sensing Near Receiver

In general, WiFi sensing relies on capturing the signals reflected of the object surfaces. According to [29], the power of the received reflection signal can be expressed by the following:

$$y_r = \frac{xG_t}{4\pi r_1^2}\sigma\frac{1}{4\pi r_2^2}A \tag{1}$$

where G_t is transmitter antenna gain, r_1 is the distance between transmitter and object, r_2 is the distance from object to receiver, σ is radar cross-section of the object, and A is effective area of the receiver antenna.

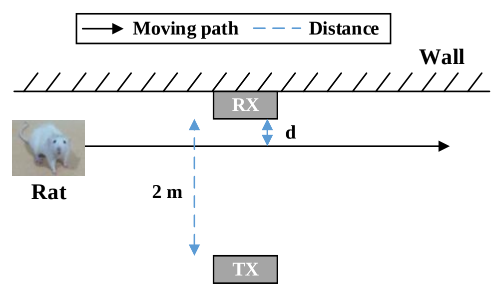
Previous works can achieve remote human sensing because human body has large reflection surface. In our sensing scenario, however, the reflection surface of the sensing object is very small. That is, σ of human is much larger than that of rat ($\sigma_{rat} \approx 0.01m^2$, $\sigma_{people} \approx 1m^2$ [30]). To enable small object sensing, we need to maximize the power of the signal reflected from the small object. However, transmitter power and antenna gain cannot be increased due to FCC regulations for WiFi signal. The effective area of receiving antenna also cannot be very large for the convenience of deployment. The radar cross-section cannot be changed as well since it is the inherent property of the object. Thus, the most reasonable solution is to decrease the distances to maximize reflected signal power. The objective function can be described as:

$$\underset{r_1,r_2}{Maximize}\, f(r_1,r_2) = \frac{C}{16\pi^2 r_1^2 r_2^2} \tag{2}$$

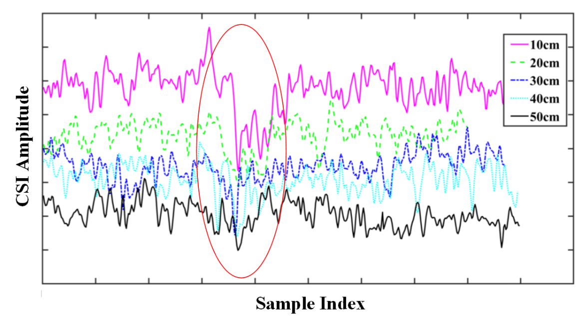
where $C = xG_t\sigma A$. Note that C is a constant when the sensing object is known. We assume that the distance between the transmitter (TX) and receiver (RX) is D. The angle between D and r_2 is θ. As illustrated in Fig. 1(a). We can express r_1 by r_2 and θ according to the law of cosines. Therefore, Eq. 2 can be expressed as:

$$\underset{r_2,\theta\in(0,90)}{Maximize}\, f(r_2,\theta) = \frac{C}{16\pi^2(r_2^4 + D^2 r_2 - 2Dr_2 cos\theta)}. \tag{3}$$

Apparently, the value of the objective $f(r_2,\theta)$ varies with r_2 and θ. To obtain the maximum of $f(r_2,\theta)$, as shown in Fig. 1(b), we calculate its value by varying r_2 and θ. It can be found that, as the distance r_2 decreases, the value of $f(r_2,\theta)$ increases. Specifically, there is a drastic increase when r_2 is less than 10cm. Therefore, reducing the distance of the rat from the receiver can greatly increase the reflected signal power. Thus, we can sense the small object as long as the distance between it and the receiver is small enough.



(a) Experiment setup for feasibility validation.



(b) CSI samples with different distance r_2.

Fig. 2. The amplitude will change drastically when a small object passes by RX. (a) Experiment setup. (b) CSI amplitude collected when small object passes by RX.

To confirm the validity of the above analysis, we conduct a validation experiment[1]. We focus on the amplitude of the collected CSI as the amplitude can reveal the strength of the signal power. In order to observe the signal variation when the small object gets close to the receiver, we lead a

[1]Note that this experiment and those presented in the following sections are conducted by adhering to the approval of Zhejiang University's Institutional Review Board (IRB).

Fancy Rat to pass by a receiver along a straight line with a constant speed, as shown in Fig. 2(a). The distance between the transmitter and the receiver is set to 2m. Fig. 2(b) shows the amplitude variations when the rat is 10cm, 20cm, 30cm, 40cm, and 50cm away from the RX. It can be observed that the signal changes rapidly and obviously when the rat just passes by the RX. In addition, the signal changes become smaller as the rat's distance to the RX becomes larger. When the distance exceeds 50cm, we can hardly observe the drastic signal change. Therefore, it is feasible to detect the presence of small object by capturing drastic amplitude variations. Meanwhile, by arranging the layout of the RX reasonably, e.g., densely deploying the RX with the distance between any two adjacent RX less than 1m, we are able to monitor a large area.

III. System Overview

We develop a WiFi-based moving small object detection system named WiHunter. As shown in Fig. 3, WiHunter is composed of two primary modules: *CSI acquisition* and *object detection*. In the CSI acquisition module, to enable multi-position CSI collection in cramped environments, we devise a small-volume device called WiFi-functioned node (WiFN) to measure CSI from WiFi packets and upload the CSI to the internet. The WiFN is developed on IoT framework and enables further development for other IoT applications. Since WiFN has small volume (3cm length and 2.5cm width) and low cost (<\$5), they can be densely deployed in corners, where small objects like rats are prone to pass. In *object detection* module, we collect CSI from WiFNs and process the CSI of every WiFN to detect small object.

CSI acquisition. In this module, a signal transmitter sends WiFi packets to several WiFNs. WiFNs perform CSI estimation and transmit the CSI to a router. The router further uploads the CSI to the Internet. The signal transmitter is built up over an ESP32 board with AP mode that has the same size as the WiFN. It conforms to the 802.11g protocol [31] and can transmit signals in WiFi frequency bands. All the WiFNs will listen to the open wireless channel and capture the packets sent by the signal transmitter. Once a WiFN captures one packet, it will immediately estimate CSI from the packet and send the CSI to the router, which relays the CSI to the local device (e.g. PC) for further processing. However, if all the WiFNs directly send their CSI to the device, the device cannot figure out the source of the CSI. To solve this problem, we add the MAC address as an identifier to the end of each CSI, such that the device can determine which WiFN the CSI belongs to. The CSI acquisition module and design of WiFN will be detailed in Sec. IV.

Object detection. This module can be further divided into three sub-modules: *data preprocessing*, *presence detection* and *positioning mapping*. The first sub-module is for removing object-irrelevant components from the raw CSI flows. Considering that the system collects and stores the CSI data flow in real time, we cannot directly use the data stream for object detection. We need to use the signal change on a data segment to detect the presence of the small object. So, we first utilize

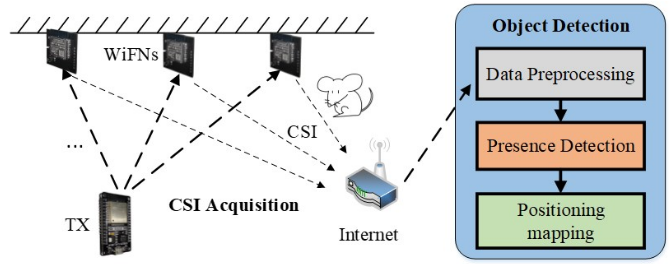


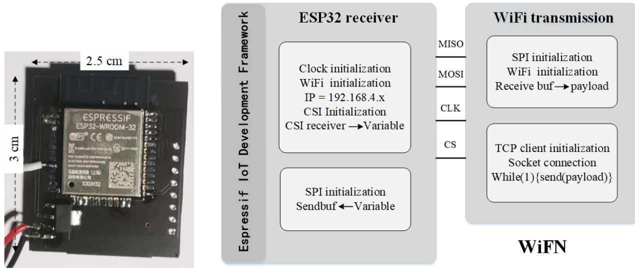
Fig. 3. Overview of WiHunter. The CSI acquisition module collects WiFi packets from multiple WiFNs. The CSI estimated from these WiFi packets sends to object sensing module. The detection result and location of WiFN indicate the physical location of small object.

a sliding window to segment the CSI stream. Each segment is termed as a CSI sample. Then, we perform data cleaning on the CSI sample to remove the outliers induced by environmental noise and hardware imperfection. Afterwards, to remove high-frequency noise while retaining the components that reflect the dynamics of the small object, we perform filtering on the CSI sample and preserve the low-frequency components. The details will be presented in Sec. V-A. Afterwards, in the *presence detection* sub-module, WiHunter detects the presence of the object by determining whether there is a drastic change on the CSI sample. For doing so, we propose an improved medium absolute deviation (MAD) [32] algorithm to detect such drastic change. If there is a drastic variation on the CSI sample, WiHunter confirms that there was a small object appearing near the corresponding WiFN. The details of the detection algorithm will be introduced in Sec. V-B. In the *positioning mapping* sub-module, once the presence of a small object is detected, this result is marked to the location of the corresponding WiFN. The physical location of the WiFN to which the detection result belongs can be known by setting a MAC address in advance.

IV. CSI Acquisition with WiFi-Functioned Node

Considering that small objects like rats are prone to act in cramped environments (e.g., corners) and the sensing device needs to be deployed densely, the volume of the sensing device should be small enough. However, existing mainstream devices used in WiFi sensing must be equipped with NICs that require additional computing units (e.g., PCs) to drive. Thus, these devices are too large in size to be adopted in WiHunter. Although some researchers [33], [34] try to reduce the volume of them, the modified devices are still large (10cm$\times$15cm), not to mention the relatively high price (>\$100). What hinders the miniaturization of these devices is that NIC needs to be installed on Linux kernel-based operation platforms that usually work on computing-resource-rich hardware. Therefore, existing NIC-based WiFi acquisition devices are not suitable for small object detection in our sensing scenario.

Recently, researchers in [35] developed a CSI tool that can be implemented on ESP32 microcontroller. ESP32 microcontroller bears the advantages of small volume (5cm$\times$3cm) and low cost, so it can be densely deployed in cramped environments. Furthermore, we choose ESP32 for it supports IoT development framework. Since the current version of



(a) (b)

Fig. 4. Hardware and functional block diagram of WiFN. (a) Hardware. (b) Functional block diagram.

this CSI tool only supports the packet transmission between multiple transmitter (TX) and single receiver (RX), we need to deploy a TX at each position if we want to capture the CSI of multiple positions.

However, there raises a challenging issue, i.e., CSI loss. In the ESP32 like platforms, due to the limited computing resource of RX, RX can only estimate the CSI of one packet at each sampling period even if it captures multiple packets from multiple TX. In this case, the CSI of some packets would be lost. Intuitively, we can deploy multiple RX in a one-to-one TX-RX manner to solve this problem. But this will introduce extra hardware and deployment overhead. Thus, with current CSI tool, it is hard to collect the CSI of multiple positions at the same time. To tackle this issue, we seek to use one TX to send packets to multiple RX simultaneously, such that each RX can obtain the CSI near its position. However, we find that it is unable to switch the TX-RX pattern from one-to-one to one-to-many in ESP32. We conduct an in-depth analysis on the codes of the CSI tool. We notice that the current version of this tool uses two modes to actively estimate CSI: station (STA) mode as TX and access point (AP) mode as RX. According to the specification of WiFi standards [36], one STA cannot be connected to multiple AP simultaneously. Thus, we modify the packet transmission manner of the TX and RX in ESP32 by applying AP mode as TX and STA mode as RX.

Nevertheless, it is still hard to obtain the CSI of multiple RX in real time to achieve online small object sensing, because the CSI estimated by the RX component must be transmitted to an extra computing device (e.g., PC) in a wired transmission mode. This leads to large delay and overhead. To deal with this issue, we modify the hardware of the existing ESP32 board. Specifically, we integrate a WiFi transmission board on the ESP32 board (i.e., RX). This WiFi transmission board receives the CSI of the RX via SPI bus [37] and sends the received CSI to a router through WiFi channel. In this way, we can obtain the CSI of multiple RX at multiple positions in real time. We integrate this hardware into the WiFN. With such design, WiFN is cheap and small, i.e., worth $4 and with a size of 3cm × 2.5cm. The hardware and functional block diagram of WiFN are shown in Fig. 4. We also release the code of modified CSI tool at GitHub [2]. In addition, WiFN can be used as an IoT node to support IoT application or work only with a battery supply.

[2]https://github.com/ZouXiang2019/WiFi-functioned-node

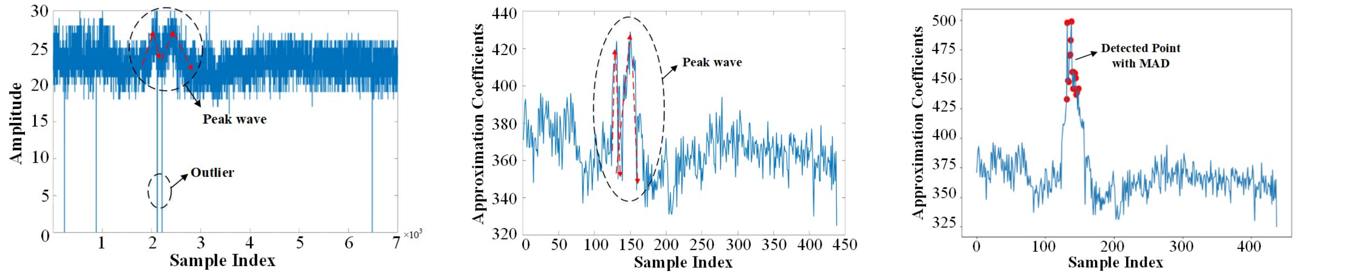
V. Small Object Sensing

A. Data Preprocessing

Signal segmentation. In order to extract the change of the signal when the small object passes by the WiFN, we need to perform signal segmentation on the real-time CSI stream, so as to facilitate the object detection of the *presence detection* sub-module. The segmented signal should not be too long, which may lead to two signal changes in one segment, thus judging that the object appears in two positions as one. The segmented signal should also not be too short, which would lead to undetectable signal changes, resulting in missed detection of the presence of objects. To do so, we adopt a signal segmentation window. It slides on the CSI series for detecting the sudden signal change caused by rats. Specifically, we need to determine a proper length for this window, denoted as L_w. Considering that the signal change is caused by rat movements and the speed of rat is not very fast (about $0.15m/s$) [38], the window length can be set to $L_w = Fs * (L/s) = 250 * (0.5/0.15) \approx 800$, where Fs is the received packet rate of the WiFN, L is the detectable range of WiFN, and s is the rat's speed. The CSI readings of all subcarriers in a window form a CSI sample. Besides, the sliding stride L_s can be set to half of the window length.

Data denoising. As aforementioned, we use the amplitude of CSI to detect small objects. However, raw amplitude series are noisy, i.e., there are some outliers with extremely large values. These outliers may impact the subsequent filtering. We empirically set a value that is $3 \times Std$ larger than M as the outlier threshold, where Std and M are the standard deviation and mean of a subcarrier signal, respectively. For those CSI readings larger than this threshold, we remove them for data denoising, as shown in Fig. 5(a). Since each CSI sample has 64 subcarriers [35], we perform outlier removal for every subcarrier alternatively.

Signal filtering. In addition to the outliers, raw CSI also contains some high-frequency components (HFCs) irrelevant to the dynamics of the small object. These HFCs are caused by environmental noise and hardware imperfection. To eliminate the impacts of HFCs, we select several commonly used filters to perform filtering. To be specific, we opt to use Butterworth and discrete wavelet transform (DWT) filters, which are often applied in radio signal processing. Butterworth mainly retains the signal components within a specified frequency range. Different from Butterworth filter, DWT is commonly used to discretize the scale and shift of basic wavelet. It is helpful to highlight the characteristics of the low frequency component of the signal. Both of these filters have the ability to remove high-frequency noise and obtain low-frequency components of signal characteristics. In detail, we use the low pass function of Butterworth to obtain low frequency components of the signal. For DWT filter, we extract the approximation coefficients vector. Empirically, we use db15 Daubechies and level 4 for DWT, 10Hz and level 4 for Butterworth. We will evaluate the performance of these two filters in Sec. VI-B. Visually, the effectiveness of signal filtering is shown in Fig. 5(b). It can be observed that the HFCs are well filtered out.



(a) Outlier in original signal. (b) Signal smoothing. (c) Variation detection.

Fig. 5. Signal preprocessing and variation signal. (a) Example of outlier. (b) Signals filtered by a level 4 DWT. (c) Signal variation detection by improved MAD algorithm.

B. Presence Detection

The received signal strength (i.e., amplitude) of WiFN is related to the distance between the WiFN and the small object. It seems that we can leverage this relationship to estimate the position of the small object precisely. However, the frequency selective fading, multi-path effect, and hardware noise would destroy such relationship, disabling precise positioning with only one WiFN. Therefore, we opt to monitor the amplitude change to detect the presence of the small object instead of direct positioning.

Before detailing our detection method, we perform analysis on the signal recording the presence of the small object. As shown in Fig. 5(a) and Fig. 5(b), the signal has a sudden and drastic change when the small object passing by the WiFN. The signal series described by red dots (looks like ‘M’) represent the presence of the small object near the WiFN. The reason causing such signal changes is that: Radar cross-section (σ) [30] is a measurement of an object’s ability to reflect RF signals in the direction towards the receiver. σ measures the area of an object that reflects RF signals. As small object approaches the receiver, σ increases dramatically [39], resulting in increased received signal strength. On the other hand, shortening the distance between the object and the receiver also increases the received signal strength. However, the amplitude will decrease when the small object blocks the main path between the signal transmitter and the WiFN. When the small object is far away from the main path, σ becomes larger and the amplitude increases again. Finally, the small object moves away from the WiFN and the signal amplitude decreases. From the above observation, we can conclude that the movement of the small object would induce sudden and large-scale amplitude changes. Therefore, we can detect the presence of the small object by finding out such amplitude changes.

Here, we propose an improved MAD outlier detection algorithm to find out such drastic amplitude variation. We do not choose other outlier detection methods like isolation forest [40] and one-class support vector machine [41], because they require either pre-training or prior knowledge of the data distribution, to achieve which is very inconvenient in our sensing scenario. Since MAD [42] is a robust statistic scale, MAD is able to effectively and stably detect the presence of the small object.

Algorithm 1 Presence detection using improved MAD

Input: Signal samples S
Output: Detection result
$D \leftarrow |diff(S)|$
$index \leftarrow find(D > mean(D))$
start point $\leftarrow S(index(1))$
end point $\leftarrow S(index(end))$
$M \leftarrow$start point to end point
$index(M_{left}) \leftarrow find(max(1 \text{ to } \frac{M}{2}))$
$index(M_{right}) \leftarrow find(max(\frac{M}{2} \text{ to } M))$
$V \leftarrow S(index(M_{left})) \text{ to } S(index(M_{right}))$
for $i \leftarrow 2$ to $length(V)$ **do**
  if $V(i) - V(i-1) < 0$ **then**
    $R(i) \leftarrow R(i-1) + (V(i-1) - V(i))$
  else
    $R(i) \leftarrow R(i-1) - (V(i) - V(i-1))$
  end if
end for
$S(index(M_{left})) \text{ to } S(index(M_{right})) \leftarrow R$
$result \leftarrow MAD(S)$
if result >threshold **then**
  return YES
else
  return NO
end if

Generally, MAD algorithm is used to detect unimodal signals with large variance. It uses the absolute deviation of the median as the reference value for variation detection. The MAD algorithm can be described as:

$$MAD = median(|S_i - median(S)|) \tag{4}$$

where S is the signal samples. Recalling that the signal will exhibit an ‘M’ shape. Such a bimodal shape would degrade the detect performance of MAD algorithm because the decline in the middle of ‘M’ would flatten the key metric–medium. To solve this issue, we need to transform the bimodal signal into a ‘Λ’ like unimodal one.

Specifically, we increase the deviation of the sample in our improved MAD algorithm by reversing the valley of the bimodal signal as a peak. We first find the start point and end point of the peak wave by calculating the differences between adjacent elements of samples. Then, we get the two peak values of the 'M' shape signal. Next, we reverse the samples between these two peak values. Finally, MAD algorithm is used for outlier detection. The improved MAD algorithm is described in Algorithm 1. The detection effectiveness is shown in Fig. 5(c). As long as one of the deviation calculated by MAD is greater than a threshold we set in advance, the system is considered to have detected the object. It is noteworthy that each CSI sample contains the signal readings of 64 subcarriers. As long as a rapid and large-scale amplitude variation is detected on any of the subcarriers, we consider that a small object is present.

C. Position Mapping

To optimize the timeliness of message delivery across multiple WiFNs, we use Socket protocol in our system. Socket ensures the real-time message transmission of the whole system. Meanwhile, the sensing result of each WiFN and the corresponding device's MAC address are transmitted to a process of the Socket server via static IP. We apply multiple proceeds to receive the detection result and map each result to a location of WiFN. In this way, we can know the physical location (i.e., WiFN) of the rat in real time.

VI. Evaluation

In this section, we first introduce the experiment setup and metrics. Then, we detail the overall performance of small object detection. We also conduct several experiments in complex scenarios to evaluate WiHunter's robustness. Finally, the overhead and latency are talked to show the low cost and practicality of WiHunter.

A. Experiment Setup and Metrics

Experiment setup. We implement prototype of WiHunter based on one ESP32 at AP mode as the transmitter, several hand-soldered WiFNs as receivers, and a router as relay. Each WiFN is equipped with a PCB printed antenna. The modified codebase is implemented in C language. The CSI is automatically estimated when WiFN is connected to the AP, and it transmits CSI to the connected router. We receive the CSI on a PC (with i7-10870H CPU and 16 GB RAM) connected to the same router. The PC runs socket server with multiple threads to receive the CSI from multiple WiFNs simultaneously. The packet sending rate of transmitter is set to 1000 Hz.

Experiments are conducted at a corner of a wall in a warehouse. In the default setting (as shown in Fig. 6), we deploy six WiFNs along the wall, which are 5cm off the ground. Any two adjacent WiFNs are placed 0.5m away from each other. The signal transmitter is placed 2m away from the midpoint of the line consisting of the six WiFNs. To collect CSI samples that record the movement of the small object, we lead a Fancy Rat (small object) to move along the wall. The distance between the small object and the wall is 10cm.

Metrics. Three metrics are defined to quantify the performance of WiHunter: accuracy, false accept rate (FAR), false reject

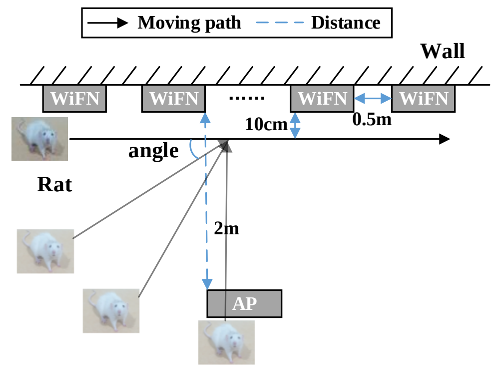


Fig. 6. Experiment setup.

rate (FRR). Specifically, accuracy represents the probability that our system can detect the presence of the small object correctly. FAR is the probability that WiHunter mistakenly detects the presence of the small object while there is no small object actually. On the contrary, FRR denotes the probability that WiHunter does not detect the presence of the small object when the small object is actually present. We pay more attention to FRR than FAR, because false accepts can be avoided in manual inspection. Hence under the same accuracy, we prefer lower FRR.

B. Overall Performance

To evaluate the overall detection performance of WiHunter, we first vary the threshold of the MAD outlier detection algorithm from zero to five to calculate the FAR and FRR. The results are shown in Fig. 7. It can be found that the FAR decreases with the threshold, while the FRR increases with the threshold. When the threshold reaches 3.77, the FRR is equal to the FAR, where we get equal error rate 14.1%. Such equal error rate is low, indicating the good detection performance of WiHunter. Since we prefer a lower FRR, we set the threshold to 3 in the following experiments, where the FRR is only 1.28%. To evaluate the overall detection performance of WiHunter, we assess the detection performance with different filters and distances between the small object and the wall. Specifically, we conduct experiment under three filter settings (only Butterworth, only DWT, and the combination of Butterworth and DWT) and five distances (10cm to 50cm in step of 10cm). The combination of the two filters means that the small object is regarded as presence once the signal processed by any of the two filters shows the presence of the small object. Fig. 8 depicts the accuracy under these settings. It can be observed that when the distance increases, the accuracy under Butterworth filter decreases obviously. But the accuracy under the combination of Butterworth and DWT is stable and always high. From a global perspective, better performance can be achieved when both Butterworth and DWT filters are used. The highest accuracy is 98.7% when the distance is 10cm. The average accuracy is 92.1%. Even the lowest accuracy is higher than 85%. Therefore, WiHunter has outstanding small object detection performance.

We also assess the performance of WiHunter with multiple WiFNs. Specifically, we lead a rat to pass by six WiFNs

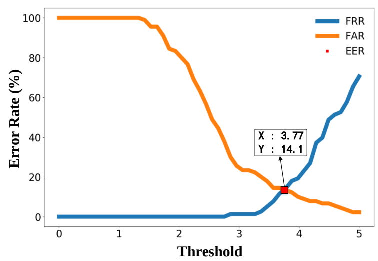


Fig. 7. FARs and FRRs under different thresholds.

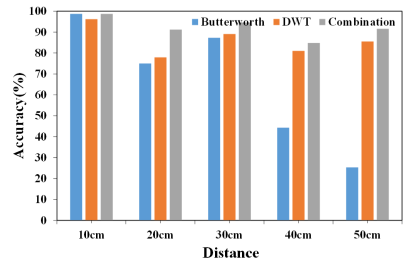


Fig. 8. Accuracy under different distances between WiFN and object.

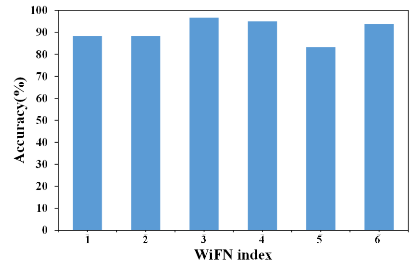


Fig. 9. Detection accuracy of 6 WiFNs.

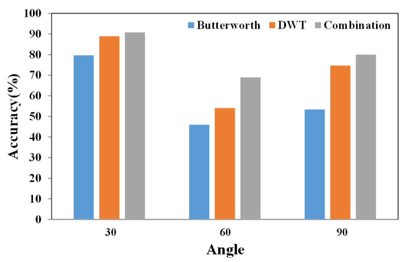


Fig. 10. Accuracy under different angles.

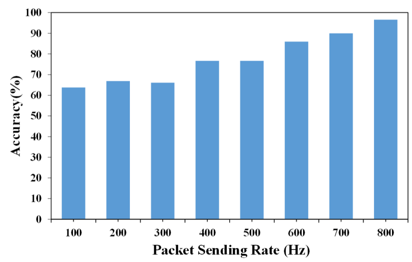


Fig. 11. Accuracy under different packet sending rates.

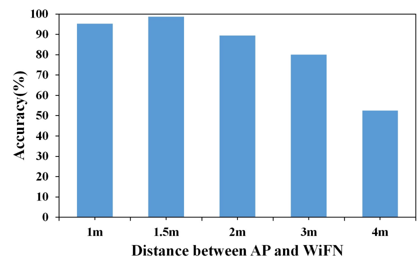


Fig. 12. Accuracy under different distances between AP and WiFN.

and calculate the detection accuracy of the six WiFNs. We set the detection distance of 50cm and the filter of the combination. The detection results are shown in Fig. 9. The results indicate that WiHunter can achieve maximum detection accuracy of 96.7% and average detection accuracy of 91%. Therefore, WiHunter is able to accurately detect small object with multiple WiFNs.

C. Effect of Related Factors

Effect of angle. To evaluate the performance of WiHunter under different angles, we vary the angle from 30 degrees to 90 degrees in step of 30 degrees (shown in Fig. 6). Meanwhile, we take into consideration the filter. The detection accuracy is shown in Fig. 10. It can be observed that the accuracy under different angles is disparate, e.g., the accuracy of 30 degrees is 90.7 while that of 60 degrees is 68.9%. However, the accuracy increases to 80% when the angle is 90 degrees. Thus, WiHunter can detect the presence of the small object more accurately when it moves along the wall instead of away from the wall.

Effect of packet sending rate. In this experiment, we vary the packet sending rate from 100 Hz to 800 Hz in step of 100 Hz. The detection accuracy is shown in Fig. 11. We can see that the accuracy increases as the increase of the packet sending rate generally. Surprisingly, the accuracy is already higher than 60% when the packet sending rate is only 100Hz. When the packet sending rate increases to 800Hz, the accuracy becomes larger than 95%. Hence, we prefer a larger packet sending rate to get higher accuracy, while the performance under low packet sending rate is also decent.

Effect of AP-to-WiFN distance. To assess the effect of AP-to-WiFN distance, we vary it from 1m to 4m in step of 0.5m and calculate the detection accuracy. It can be seen from Fig. 12 that the accuracy generally decreases with the distance. However, when the distance is as large as 3m, the accuracy is almost 90%. Thus, WiHunter is robust against the distance variation. Users can select suitable distances according to the environments and their demands.

D. Robustness Study

Cross environment test. We test the detection accuracy in three environments: office, warehouse, and outdoors. The experiment results in Fig. 13 demonstrate that the detection accuracy in indoor environments (office and warehouse) is higher than that of outdoor environment. This is reasonable because the multi-path effect in indoor environment can help get more signals reflected by the small object.

Impact of human movement. In this part, we conduct experiments when a person is walking within one to two meters with respect to the WiFN. From Fig. 13 we can see that human movement indeed impacts the detection accuracy of WiHunter. Fortunately, rats prefer to be active when people are resting at the night.

NLOS sensing. To assess the performance under NLOS conditions, we place a large wooden board (5m length $\times$ 3m width $\times$ 2cm thickness) between the signal transmitter (AP) and WiFNs. We totally conduct two experiments with: the board near the AP and the board near the WiFNs. The results are shown in Fig. 14. It can be found that the accuracy remains high when the board is near the AP or WiFNs, which means that WiHunter is able to perform well under NLOS conditions.

Impact of metal. To explore the impact of metallic objects near the WiFNs. We put some metal chairs and metal cabinets in front of the WiFNs. The experiment result is shown in Fig. 14, which indicates that the detection accuracy is still around 90%. Hence, even when the metal objects around the WiFNs impact WiHunter a little, the accuracy is still high.

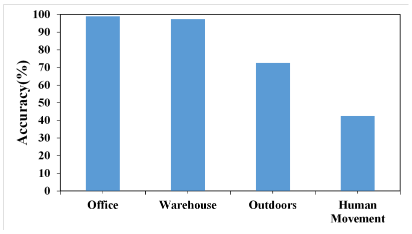


Fig. 13. Accuracy under different environments and the impacts of human movement.

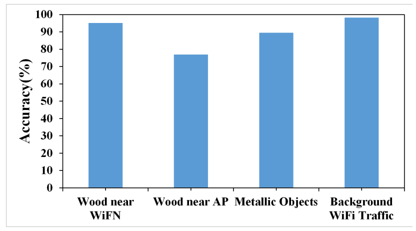


Fig. 14. Accuracy under NLOS conditions and impact of metallic and background WiFi traffic.

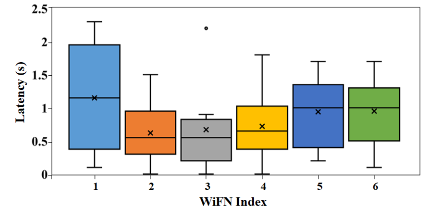


Fig. 15. Data collection latency of 6 WiFNs.

TABLE I
COMPARING *WiHunter* WITH THREE RELATED WORKS.

System	Learning -free?	Hardware volume/price	Suitable for dense deployment?	Sensing area	Requirements for sensing object
ResFi [10]	×	Large/expensive	×	Large	Cooperative, keep still
SpiroFi [43]	✓	Large/expensive	×	Large	Cooperative, keep still
FingerDraw [11]	✓	Large/expensive	×	Small crossed Fresnel Zones	Cooperative
WiHunter	✓	Small/cheap	✓	Large	No constraint

Impact of background WiFi traffic. In this experiment, we report the detection accuracy with background WiFi traffic. When WiHunter is monitoring the movements of the small object, we use a smartphone connected with a WiFi router to watch online videos. The experiment result is shown in Fig. 14. It can be found that the background WiFi traffic does not affect the accuracy of WiHunter. Meanwhile, we find that WiHunter will not degrade the user's experience of watching videos. This is because WiHunter and the router are working in different WiFi channels (frequency bands). Once the router finds that there is a channel collision, it will automatically change its channel, according to WiFi standard.

E. Cost and Latency

Cost. The cost of WiHunter comes from three components: an ESP32 board working at AP mode, WiFNs and a router connected internet. Therein, an ESP32 board, a WiFN and a router cost 2 dollars, 4 dollars and 10 dollars, respectively. These devices are all very cheap. Since a WiFN can monitor a $\sim 1m^2$ area, the deployment cost of WiHunter is ~52 dollars per $10m^2$.

Latency. The latency of WiHunter comes from two parts: data acquisition and detection algorithm. The latency of six WiFNs used to collect CSI is shown in Fig. 15. It can be seen that the median latency is less than 1.5s. The results indicate that our system can achieve real-time data collection. As for the detection algorithm, the data preprocessing and presence detection respectively take only 0.008s and 0.187s. Therefore, WiHunter has outstanding real-time performance in terms of small object detection.

VII. COMPARISON WITH RELATED WORKS

Since there is no WiFi-based detection system specially designed for small object, we compare WiHunter with three small motion detection systems: ResFi [10] (the latest WiFi-based respiration estimation system), SpiroFi [43] (the latest WiFi-based pulmonary function monitoring system), and FingerDraw [11] (the state-of-the-art finger tracking system). In Tab. I, we list the differences among them in terms of the necessity for learning, hardware, deployment fashion, sensing area, and requirements for the sensing object. It can be seen that ResFi is learning-based, yet the other three systems are learning-free. In terms of the hardware, the signal transceiver (NIC) used by ResFi, SpiroFi, and FingerDraw is relatively large and expensive, while that adopted by WiHunter (WiFN) is small and cheap. Therefore, different from traditional NICs, WiFN is suitable for dense deployment, allowing WiHunter to work in cramped environments. Meanwhile, the sensing area of ResFi, SpiroFi, and WiHunter is large, but in FingerDraw, the sensing object needs to stay in a small crossed Fresnel Zones. Most importantly, ResFi, SpiroFi, and FingerDraw require the sensing object to be cooperative. On the contrary, WiHunter does not impose any constraints on the sensing object. Even for uncooperative objects like rats, it can accurately capture their dynamics.

VIII. CONCLUSION

In this paper, we demonstrate the feasibility of moving small object detection using WiFi devices. For doing this, we develop a CSI acquisition module that is composed of several low-cost and small-volume WiFNs. With the CSI obtained by WiFNs, we propose an improved MAD algorithm to detect the presence of the small object. Unlike existing small motion detection techniques that require the sensing object to be cooperative, our system does not impose any constraints on the sensing object. Real-world experiments show that our system can achieve high detection accuracy which provide good QoS for the small object detection.

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