# Artificial Intelligence Empowered Mobile Sensing for Human Flow Detection

Fu Xiao, Zhengxin Guo, Yingying Ni, Xiaohui Xie, Sabita Maharjan, and Yan Zhang


## Abstract

Intelligent human detection based on WiFi is a technique that has recently attracted a significant amount of interest from research communities. The use of ubiquitous WiFi to detect the number of queuing persons can facilitate dynamic planning and appropriate service provisioning. In this article, we propose HFD, one of the first schemes to leverage WiFi signals to estimate the number of queuing persons by employing classifiers from machine learning in a device-free manner. In the proposed HFD scheme, we first utilize the sliding window method to filter and remove the outliers. We extract two characteristics, skewness and kurtosis, as the identification features. Then, we use the support vector machine (SVM) to classify these two features to estimate the number of people in the current queue. Finally, we combine our scheme with the latest Fresnel Zone model theory to determine whether someone is in or out, and thus dynamically adjust the detected value. We implement a proof-of-concept prototype upon commercial WiFi devices and evaluate it in both conference room and corridor scenarios. The experimental results show that the accuracy of our proposed HFD detection can be maintained at about 90 percent with high robustness.


## Introduction

With the rapid development of wireless technology and vast deployment of WiFi networks, a great deal of device-free sensing applications have emerged in recent years, including indoor positioning, activity identification, respiration detection, and line-of-sight recognition. These interactive applications are changing our lives, improving our quality of experience (QoE), and leading us into a new era.

Since human movement has a strong randomness, technically it is not an easy task to realize exact crowd counting. However, the corresponding people counting applications have remarkable business values. For example, we can provide recommendation services dynamically based on the current number of people in the queue. Similarly, the number of customers in a store can be indicative of the peak sales in a store. The above applications reveal good business prospects of head count detection. Therefore, many human recognition applications have emerged and gained popularity. These applications are implemented mainly based on two types of techniques: video-based recognition and signal-based recognition.

Video-based recognition (e.g., [1]) has several shortcomings. The method needs dedicated camera equipment. Moreover, the captured area is limited and a tremendous amount of storage space is required. Signal-based identification methods normally function upon radio frequency identification (RFID) tags [2], mobile phone or sensor nodes, which requires dedicated sensing equipment, and these are not easy to deploy either.

At present, a promising method for detecting the number of people is to utilize the widespread WiFi signal to extract the received signal strength (RSS) or channel state information (CSI). The advantage of using RSS-based detection schemes (e.g., [3]) is that it is easier to extract RSS. But compared to CSI, RSS offers low sensitivity and no ability to reflect real-time characteristics. CSI is the fine-grained value derived from the physical layer and refers to the known channel attribute of the communication link. It consists of the attenuation and phase shift experienced by each spatial stream on every subcarrier in the frequency domain. CSI is therefore more sensitive to environmental change and is more efficient compared to RSS.

In practice, the detection of the number of people suffers from numerous factors, for example, a change in the environment and human interaction. Most of these factors are random. In our model, we detect the number of persons along the line-of-sight path from the receiver to the WiFi access point (AP). For scenarios with people standing in a line, we propose a human flow detection (HFD) scheme that can be applied to detect the number of queuing people in dynamic scenarios, such as queues of withdrawals in a bank and queues of payments in a mall, which can then be utilized to provide appropriate recommendation services.

HFD is a complete number detection scheme. First, we use a denoising method based on sliding window to remove the outliers. Then following the analysis of CSI amplitude, we can determine whether someone is in the current scene. When someone is present, the relationship between the feature and the number is analyzed from CSI, and the support vector machine with good classification effect is used to identify the number of people in the current queue. Finally, combined with the Fresnel model proposed in [4], our scheme reveals the change of CSI when a person enters and leaves the detection area, so as to dynamically correct the number of people in the current scene.

In summary, our main contributions are as follows:

- We propose HFD, an integral scheme for device-free queuing head count detection using commodity WiFi devices. As far as we know, this is the first scheme that uses the

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*Fu Xiao, Zhengxin Guo, Yingying Ni and Xiaohui Xie are with Nanjing University of Posts and Telecommunications; Sabita Maharjan is with Simula research Laboratory; Yan Zhang is with the University of Oslo.*

CSI signal of commercial wireless devices for robust human flow detection.
- Different from other related schemes, HFD is a complete solution that can dynamically identify the number of people in current queues. We extract the lightweight kurtosis and skewness characteristics of the denoised CSI signal with different numbers, and quickly estimate the number of people in current queues. Then we combine with the Fresnel Zone model to dynamically correct the current number of persons.
- We prototype the HFD on commodity WiFi devices and verify its performance from multiple dimensions, which include the different sampling times, the different kernel functions and for two different scenarios (conference room and corridor). The experimental results show that HFD can achieve a detection rate of about 90 percent.

The rest of this article is organized as follows. We first review the related work. Then we present an overview of the system architecture, while the detailed design of each component is provided. Following that we present the performance evaluation. Finally, we conclude the article.

## Related Works

The design of HFD is closely related to the following categories of research.

### Device-Free Detection Based on CSI

A number of human detection schemes based on CSI have been proposed in recent years. In [5], Wu *et al.* exploited the advantages of both amplitude and phase information of CSI to detect moving targets, and implemented a non-intrusive detection scheme for a moving and stationary person on a commercial WiFi device. R-TTWD [6] is a scheme that leverages the CSI of commodity devices for device-free through-the-wall human detection. WiFinger [7] uses CSI to achieve number text input by recognizing a set of finger-grained gestures. LiFi [8] extracts different CSI characteristics to carry out the detection of line of sight. These works based on CSI perception can provide a theoretical reference for our proposed scheme.

### Fresnel Zone

In [4], the authors proposed the concept of a Fresnel Zone model. Fresnel Zone is a series of concentric ellipsoidal regions of alternating reinforced strength and weakened strength of a wave's propagation, as shown in Fig. 1. The ellipses in black solid and red dashed lines indicate the most reinforced and degraded locations of the reflector, respectively. When people walk in different directions, the reflection of their signal is different. Based on this theory, the authors combined the model of the Fresnel domain with the WiFi signal to estimate the walking direction. Wang [9] introduced the Fresnel Zone model to indoor environments, and then used commodity WiFi devices to detect people's breathing depth, location and orientation.

### Human Flow Detection Schemes Based on Wireless Signals

The existing schemes for human flow detection by wireless signals can be divided into two categories: RSS-based and CSI-based. Most of the schemes are based on RSS. For example, SCPL [10] utilizes RSS to count and localize multiple objects in indoor environments. Yuan [11] divided the crowd density into different levels according to the RSS data from WSNs using the K-means algorithm. Wang [12] proposed a multi-target location method based on compression perception of RSS signals. Compared to RSS, the physical-layer CSI data are more granular and more sensitive to changes in the environment. At present many researchers have turned their attention to CSI. Electronic Frog Eye [13] is a program for counting the number of people by using CSI. It uses non-zero element percentages (PEMs) in the expanded CSI matrix to detect the number of people. However, if applied in a queuing scenario, the detection rate of this scheme is relatively low, and its calculation complexity is high. In contrast, our scheme HFD is more lightweight and has strong robustness, which is described in following chapters.

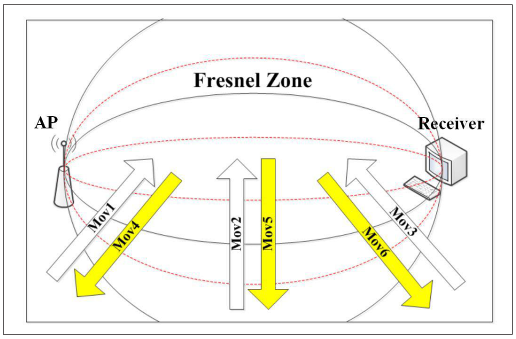

FIGURE 1. The Fresnel Zone model.

## System Model

In this section, we introduce the overall architecture of our HFD scheme. As shown in Fig. 2, HFD initializes by collecting CSI with a commodity off-the-shelf WiFi network interface card (NIC) such as the Intel 5300 network card. As the original CSI measurements contain unknown noise, we first process them through a data preprocessing module. The sliding window filtering method is used to filter the original signal, making the CSI change in a consistent manner, and then some special outliers are removed. Although the noise filtering component can eliminate most of the irrelevant noise, in the experiment we can still observe the noise of the processed CSI, which is caused by the changes in the internal state of the WiFi device. This noise can be ignored, as we discovered that it does not affect the performance in our experiment. Then we have to determine whether there are any people along the line-of-sight path. There may be other obstacles along the line-of-sight path and they can also interfere the CSI. But for simplicity, the obstacle case is not considered in this article. We extract the variance of CSI to determine whether humans exist. Next, based on the correlation between different subcarriers, we extract the skewness and kurtosis values between subcarriers as a two-dimensional recognition feature, input this feature set into the SVM classification model, and determine how many people are currently queuing.

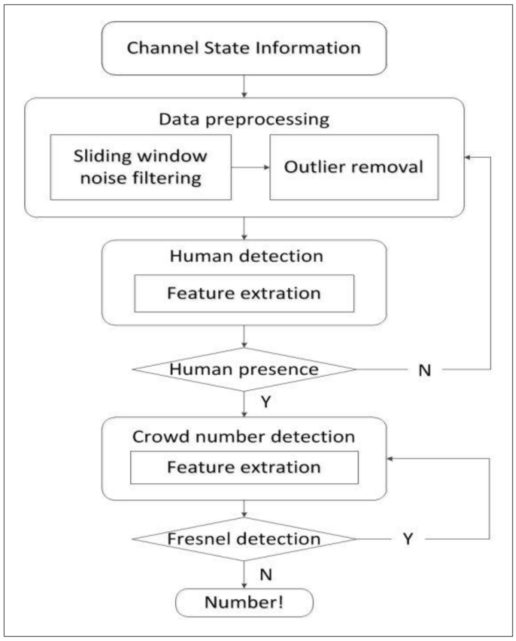


FIGURE 2. System architecture of HFD.

## Methodology

In this section, we present the methodology of the HFD as well as the experiment setup.

### Data Preprocessing

**Sliding Window Noise Filtering:** We denoise the original signal using the traditional sliding window method, to reduce the differences between subcarriers and to make the change more consistent. We collect 1000 CSI packets in four scenarios and extract from these packets the original amplitude data. Then we use the sliding window averaging method to filter the data. The size of the window is the packet rate, which is set to 50 packets per second.

According to the sliding window noise filtering, the variation trends of the CSI amplitude of all subcarriers can be filtered for consistency. As shown in Fig. 3, we plot six of these subcarriers (i.e., the 5th, 10th, 15th, 20th, 25th and 30th subcarrier). We observe that the CSI amplitude change of these six subcarriers throughout the transmission process is consistent.

**Outlier Removal:** After sliding window filtering, the CSI amplitudes of the 30 subcarriers trend consistently during the transmission, but some abnormalities may still exist. The reason for this situation is the small number of samples at the beginning when the sliding window is used. Hence, we need to use the outlier removal method to drop the beginning outlier value.

### Human Detection

We extract the CSI amplitude values in the presence of people as well as in the scenario of no persons. When someone is present in the LOS path, the difference of CSI amplitudes between the main path and the edge path will be reduced. Therefore, we only need to extract the variance between subcarriers as a feature. Then we can identify whether someone is present in that area. In our experiments, we used the variance value 5 as a threshold, as shown in Fig. 4.

### Characteristics Extraction

After noise filtering, the CSI amplitude of the subcarriers has a significant right-deviation as the number of subcarriers increases, and the peak of the subcarriers has a significant increase. Therefore, based on statistical theory, we extract the following two related characteristics.

**Skewness Feature:** The skewness is a statistic about the shape of data distribution, which describes the symmetry of a data distribution. Mathematically, skewness $S$ is defined as:

$$S = \frac{E\{x-\mu\}^3}{\sigma^3}$$

where $x$, $\mu$, and $\sigma$ denote the measurement, mean, and standard deviation, respectively. The value of skewness greater than 0 indicates that the data distribution is positive or right; a skewness less than 0 indicates that the data distribution is negative or left.

**Kurtosis Feature:** The kurtosis is a statistic about the steep degree of data distribution. Mathematically, kurtosis $k$ is defined as:

$$k = \frac{E\{x-\mu\}^4}{\sigma^4}.$$

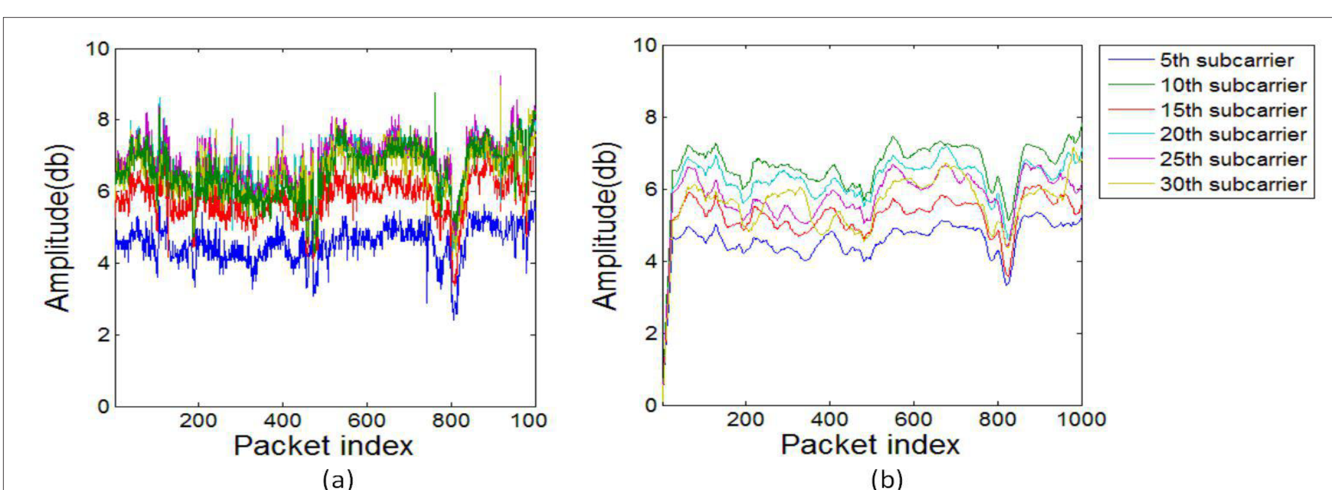


FIGURE 3. Performance comparison: a) amplitude measurements of six subcarriers in 30 before using the sliding window filter method; b) amplitude measurements of six subcarriers in 30 after using the sliding window filter method.

Normal distribution is the benchmark. A kurtosis of 3 indicates the data distribution has the same steepness as the normal distribution. If the kurtosis is greater than 3, the overall data distribution is steeper than normal distribution; if less than 3, the distribution is flatter compared to the normal distribution.

### Machine Learning Empowered HFD

After obtaining the shewness and kurtosis characteristics from the denoised signal, we use these two characteristics as a two-dimensional vector to identify the current number of queuing persons. In the field of artificial intelligence, many classifiers can produce good classification results, such as neural network used by AlphaGo, naive bayes, decision tree, support vector machine, and so on. Some deep learning algorithms [14, 15] bring ideas to our algorithm. In our experimental environment, in order to achieve good supervised classification and good visualization effect, we choose the support vector machine with the kernel as radial basis function.

The data compression process is executed before the support vector machine classification. Since our packet rate is 50 packets per second, we compress the original data and take the average of every 10 packets as one value, then generate the feature graph. If extracting characteristics from each packet directly, the error would be greatly reduced. If data from packets are compressed, although there may still exist some abnormal values, this has no significant effect on the accuracy of recognition. Since we take a mean value from each 10 packets, we can get five markings per second and obtain a result per 0.2 second. Hence, the scheme is still efficient and precise.

To choose the kernel function for the SVM classifier, we made a detailed comparison about different kernels of the SVM classifier earlier. The classification in the experiment is shown in Fig. 6a, where the black line represents the SVM classification plane. From the experimental results, we can see that the radial basis function (RBF) has a better effect. It divides our data set into four sub-planes, each plane representing a different number of persons in the queue. Then, we build the SVM classification model by the training data in our environment. In the experimental evaluation section, we will utilize the test set to observe whether different numbers fall within their corresponding regions, thus estimating the robustness of the pattern.

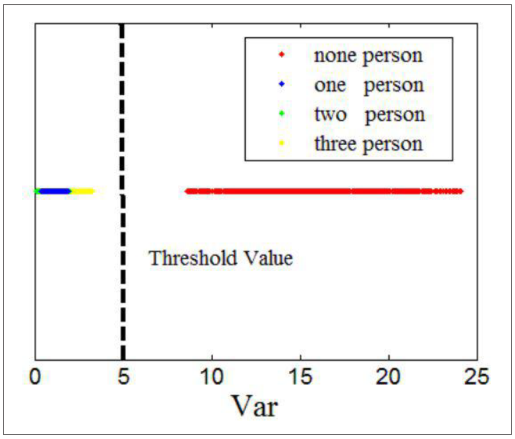


FIGURE 4. The variance characteristic of CSI amplitudes to detect whether someone exists in LOS.

### Dynamic Listening

In previous sections, we presented the process of detecting the number of queuing persons. However, this non-stop detection may not be efficient in terms of the use of computing resources. To reduce the computation complexity, based on the Fresnel Zone Model introduced previously, we add the entry and exit detection method to our scheme. Assume that people enter(Mov1, 2, 3) and leave(Mov4, 5, 6) the Fresnel Zone from three directions, as shown in Fig. 1. Mov1, 4 are close to the receiver, mov2, 5 are vertically entering and leaving, and mov3, 6 are close to the WiFi transmitter. When people enter or leave the Fresnel field from these three directions, the amplitude of the CSI changes as shown in Fig. 5. We can see that when someone enters or leaves the Fresnel field, the CSI signal will produce a big jump. According to this result, our scheme can have an additional function as follows. When the amplitude of CSI has a jumping change, we can immediately detect that someone is entering or leaving the current queue, and then we start the process of detecting the number of queuing people. By this method, we can generate a dynamic number detection scheme, saving a lot of computing resources and improving the detection rate.

## Implementation and Evaluation

### Implementation

We prototype HFD with commodity WiFi devices and we collect data in two types of experimental environment, that is, a typical conference

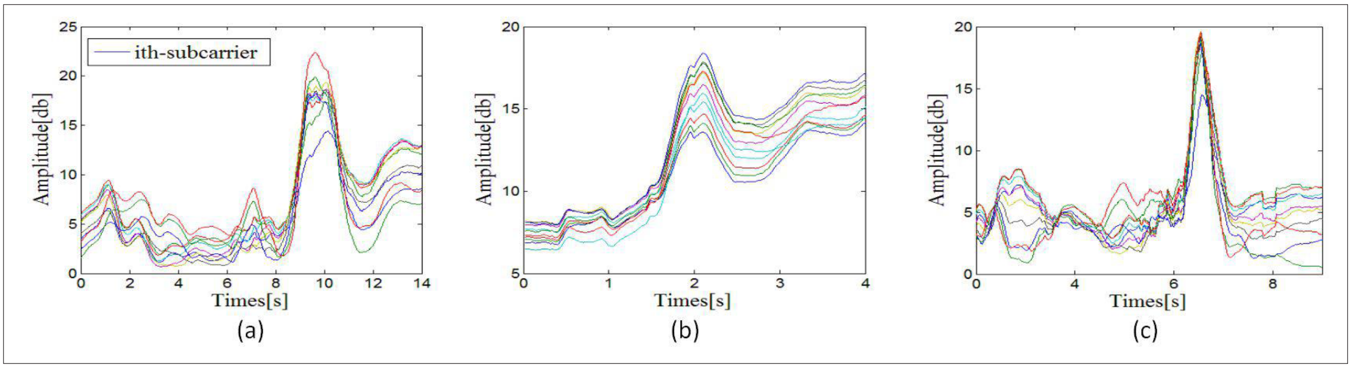


FIGURE 5. The amplitude changes when people enter or leave the Fresnel Zone in Fig. 1: a) mov 1,4; b) mov 2,5; c) mov3,6.

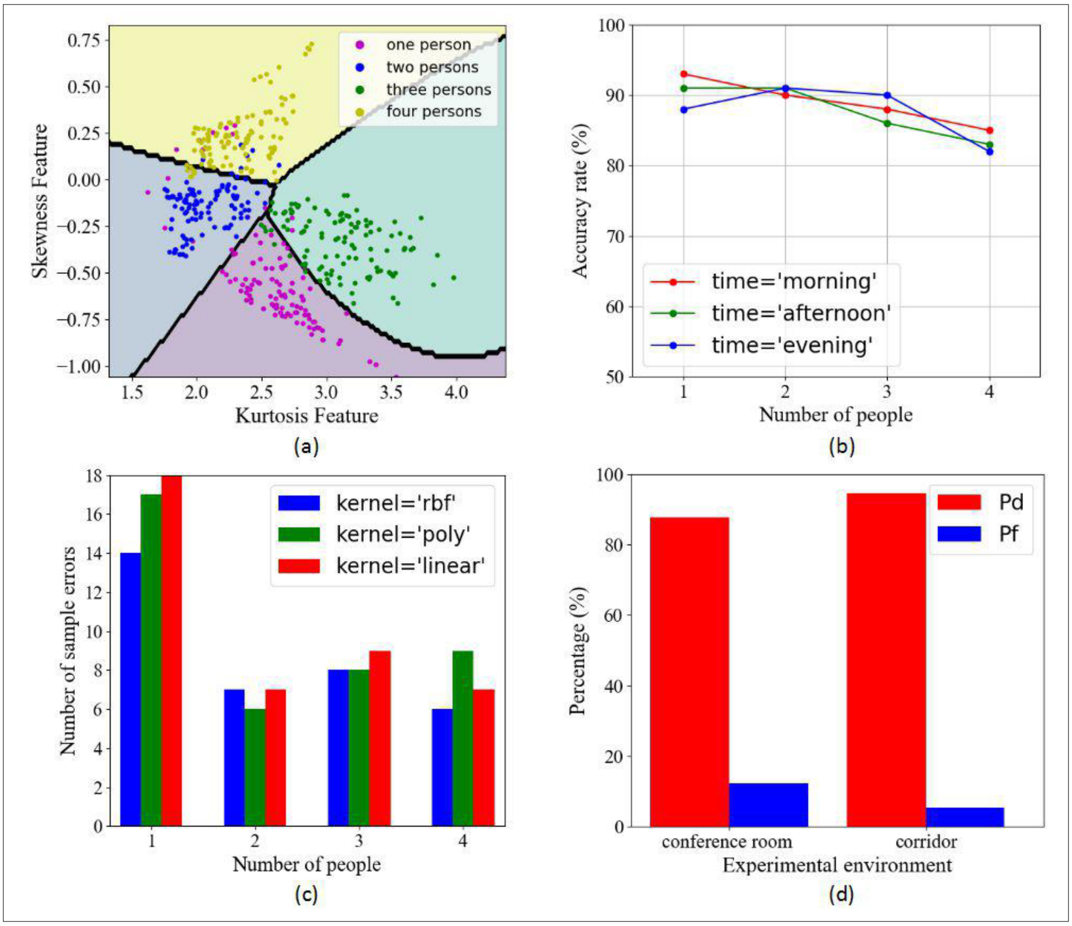


FIGURE 6. The experimental results: a) the SVM classification ; b) the test results at different time ; c) the sample number of errors by using three kinds of kernel; d) detection rate of different environment.

room whose area is 8.7 m × 5.8 m and a corridor. To obtain the measurements, we use a mini PC (physical size 170 mm × 170 mm) with three external antennas to receive pinging packets from the transmitter. The mini PC is equipped with an Intel 5300 NIC and Ubuntu 10.0 OS, and we can use the Matlab installed on the terminal to implement our algorithm. A TP-LINK wireless router with a single antenna is employed as the transmitter, operating in IEEE 802.11n AP mode at 2.4 GHz. The receiver gets ping packets from the router at a rate of 50 packets per second and records the CSI from each packet. In our experimental environment, we set the distance between the receiver and the first person in our queue as 1 m, and to make people feel comfortable we set the distance between people as 0.6 m. We discuss the effect of distance in the following sections. Due to the experimental space constraints, the maximum number of persons in our queue is 4. If we have a larger area, the maximum number of people can be increased.

## Evaluation Metrics

We mainly focus on two metrics to evaluate our HFD scheme:

- Detection Rate Pd–The case in which the number of people detected by the receiver is the same as the corresponding real number.
- False Alarm Rate Pf–The case in which the number of people detected by the receiver is different from the corresponding real number.

## Performance Evaluation

**Impact of Sample Time:** In order to test the stability of our proposed model, first we investigate whether the accuracy of the test can remain consistent in the same environment, so we need to compare the detection accuracies in different time periods. We consider three periods of time in one day, that is, morning, noon and evening, and we keep the packet rates and peoples' position unchanged in each time period. Figure 6b shows the accuracies with a different number of people in different periods. We can observe that the three periods have a similar trend of the accuracy variance, that is, with the increase in the number of persons, the accuracy trends to have a slight decline. This is due to the fact that the maximum number of queuing persons in our experiment is 4, and the queue is slightly overcrowded when the number increases, which will affect our accuracy. In the three time periods, the detection rate is about 90 percent and the false alarm rate is about 10 percent. Therefore, our experiment design is stable at different times in the same environment.

**The Impact of the SVM Classifier Kernel Function:** There are three kinds of kernel functions in a support vector machine, that is, the radial basis function, linear function and polynomial function. We test these three kernel functions to select the most suitable one for our environment. The results of SVM classification which respectively use a linear function and a polynomial function as the kernel is different; Fig. 6c shows the number of sample errors which presents the number of samples falling in areas that different form their own color. We can observe that the performance difference when using different kernel functions is small, and most error difference is about 1 or 2 people. In general, the radial basis function has the best performance, so we chose it as the kernel function for SVM classifier in this experiment. When the environment changes, the feature set values may also change. If the feature set cannot be directly separated in the linear function, or there is no polynomial function matching the classification, we recommend implementing the SVM classifier with radial basis function as the kernel.

**The Impact of Different Environments:** Although our HFD scheme shows good performance in the conference scenario, in order to verify the robustness of the scheme, we have also tested it in the corridor scenario. In the corridor, we also keep the distance between the first person and the receiver as 1 m, the distance between persons as 0.6m, and the maximum number of queuing people as 4. Figure 6d shows the results of the SVM classification based on the feature data in the corridor, suggesting that the skewness has an obvious left-leaning and becomes smaller with the increase of the number of persons while the kurtosis is gradually increasing. Compared with the detection rate in two typical scenarios, we find that the detection rates in both scenarios are about 90 percent, which proves that our detection scheme has a strong universality.

## Conclusion

With the development of wireless networks, device-free human detection has drawn great attention. In this article, we have proposed HFD, a complete human flow detection scheme. This scheme denoises the original signal through the sliding window filter, extracts the features, then uses the support vector machine to estimate the current number of queuing people, and finally combines the Fresnel Zone model to dynamically adjust the result. We have prototyped HFD in two typical environments and we sample a large amount of data with different time periods, distances and classifier kernel functions. Experimental results demonstrate the robustness of HFD in various environments, with the average recognition accuracy of about 90 percent. We therefore expect this work to be an important and  a solid step toward prospective device-free human detection.

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## Biographies

Fu Xiao [M] (xiaof@njupt.edu.cn) received the Ph.D. degree in computer science and technology from Nanjing University of Science and Technology, Nanjing, China, in 2007. He is currently a professor and Ph.D. supervisor with the School of Computer, Nanjing University of Posts and Telecommunications, Nanjing, China. He has published over 20 papers in related international conferences and journals, including IEEE INFOCOM, JSAC,TMC, TVT and so on. His main research interest is wireless sensor networks and Internet of Things.

Zhengxin Guo is a postgraduate student in computer technology at Nanjing University of Posts and Telecommunications. His current research interests include wireless sensor networks, machine learning, and Internet of Things.

Yingying Ni is a postgraduate student in computer science at Nanjing University of Posts and Telecommunications. Her current research interests include wireless sensor networks, delay-tolerant networks, and Internet of Things.

Xiaohui Xie is a postgraduate student in computer science at Nanjing University of Posts and Telecommunications. His current research interests include wireless sensor networks, delay-tolerant networks, and Internet of Things.

Sabita Maharjan is currently a postdoctoral fellow at Simula Research Laboratory, Norway. She received her M.E. from the Antenna and Propagation Lab, Tokyo Institute of Technology, Japan, in 2008, and her Ph.D. from the University of Oslo and Simula Research Laboratory, Norway, in 2013. Her research interests include wireless networks, smart grid communications, cyber-physical systems, machine-to-machine communications, software defined networks, and network security. His major research interests include wireless sensor networks and information security.

Yan Zhang received a Ph.D. degree from Nanyang Technological University, Singapore. Since August 2006, he has been working at Simula Research Laboratory. He is currently head of the Department of Networks, and an adjunct associate professor in the Department of Informatics, University of Oslo. He is a regional editor, associate editor, or on the Editorial Boards of a number of international journals. His recent research interests include wireless networks, cyber physical systems, and smart grid communications.