Device-free Crowd Density Estimation with Off-the-shelf WiFi Traffic

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***Abstract*—Crowd density estimation plays a crucial role in avoiding potential hazards in public social activities like holiday celebrations. Traditional crowd density estimation approaches leverage cameras to probe the characteristics of the crowd. Despite their high accuracy, they cannot work in bad lighting conditions and could cause visual privacy leakage, To address these problems, in this paper, we propose a WiFi-based crowd density estimation system named *WiCount*. It is deployed on a side of the entrance of the target public place and continuously collects the communication packets emitted by the access point (AP). By feeding the features extracted from the packets into machine learning classifiers, *WiCount* is able to determine the number of people passing through the entrance. To deal with the issue of lacking communication traffic for crowd sensing, we design an incentive strategy to drive the AP to transmit compensation packets without impacting the normal communication function too much. Real-world experiments show that *WiCount* has over 99% and 95% accuracy in detecting the passing through of the people and determining the number of these people.**

***Index Terms*—Crowd Density Estimation, WiFi Sensing, Signal Incentive.**

I. Introduction

With the development of city and the increase of urban popularity, people are gathering more and more in public places for various activities like conference meeting and holiday celebration. In such cases, crowd density estimation is of significant importance for the organizers to manage the crowd to avoid potential hazards [1]. For example, being aware of the crowd density timely is helpful in preventing stampede accidents and evacuation in case of fire. Traditional approaches [2] usually capture the visual information via cameras for crowd density estimation. Albeit high precision, they suffer from poor lighting conditions. Besides, vision-based methods raise the concerns of visual privacy leakage. To avoid these problems, RF signals (e,g., RFID [3] and WiFi [4]) are exploited to probe crowd density. Among them, WiFi is of special interest to researchers due to the pervasive deployment of its infrastructures.

Existing WiFi-based crowd density estimation methods can be categorized into two groups: device-based ones [1] and device-free ones [3]. The former ones usually require subjects (i.e., the target people need to be sensed for crowd density estimation) to carry some specific devices, such as smartphones.

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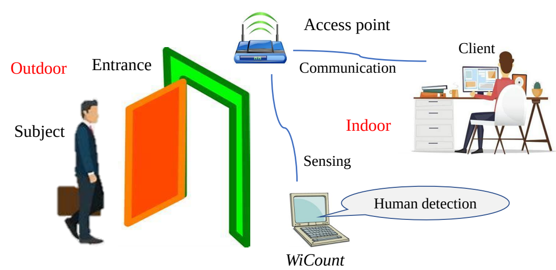


Fig. 1. *WiCount* achieves crowd density estimation by accumulating the number of subjects entering the target place.

This would bring inconvenience to the subjects. By contrast, device-free approaches do not impose any constraints on the subjects. However, current device-free WiFi-based crowd density estimation approaches suffer from two major drawbacks. First, they can only monitor the crowd in a specific area. If the crowd is scattered or the target place is very large, they cannot effectively realize the existence of every subject. Moreover, these methods are achieved through exclusive transmission facilities as well as frequency bands, in which only probing packets are emitted and communication is not allowed. This would introduce extra hardware overhead and the waste of scarce WiFi frequency band. Thus, there is an urgent need for a device-free WiFi-based crowd density estimation system that can count the number of all people in a large place by passively sniffing the communication traffic.

However, it is non-trivial to achieve such a goal due to the following challenges. (1) The propagation range of WiFi signals is limited. If the place of interest is large or the crowd is scattered, it is difficult to count the number of all people. (2) It would be ideal if we can achieve crowd sensing by only collecting the communication packets emitted by the AP. But the communication traffic only depends on the communication demands of the clients (e.g., smartphones). If the clients have no communication packets, we cannot obtain enough packets to monitor the crowd.

In this paper, by overcoming the above challenges, we propose a novel WiFi-based crowd density estimation system named *WiCount*. As shown in Fig. 1, *WiCount* is deployed on a side of the entrance to this place. It captures the communication packets transmitted from the AP to various clients. By analyzing the channel state information (CSI)

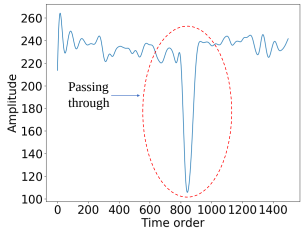


Fig. 2. Signal variation caused by passing through of subject.

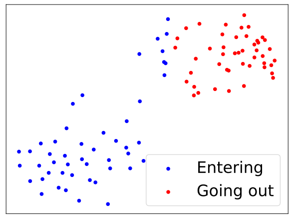


Fig. 3. Signals of entering and going out are distinguishable.

extracted from these packets, *WiCount* can detect the persons entering or going out this place. Meanwhile, *WiCount* is able to determine the number of persons passing through the entrance. Through accumulative analysis over time, *WiCount* can eventually determine the number of people in this place.

Specifically, we first heuristically propose an accumulative crowd density estimation method. Instead of directly monitoring the area the crowd stays, we place *WiCount* on a side of the entrance to the place of interest. In this way, we can count the number of people in the whole place by accumulating the number of people who enter or go out each time. A threshold-based method is proposed to detect the dynamics of people around the entrance. Meanwhile, we extract features from WiFi CSI and leverage machine learning technique to determine the number of people passing through the entrance. To tackle the issue of insufficient packets, we devise a signal incentive strategy to drive the AP to send compensation packets. By alternating between two states, our incentive strategy can provide sufficient CSI for people detection while not hurting the communication performance too much.

We build a prototype of *WiCount* and conduct real-world experiment on it. The experiment results show that *WiCount* can achieve over 99% detection accuracy and 95% subject number determination accuracy. Moreover, the experiments on incentive strategy indicate that it can provide sufficient CSI for sensing systems, while almost not impacting the communication throughput. Our contributions can be summarized as follows:

(1) We propose a novel WiFi-based crowd density estimation system, namely *WiCount*. It determines the crowd density by accumulatively counting the number of persons passing through the entrance with passively sniffed communication traffic.
(2) We propose a signal incentive strategy, allowing any WiFi sensing applications to collect sufficient CSI in communication environments, while not hurting the communication performance too much.
(3) We carry out real-world experiment with five participants. The experiment results show that *WiCount* has high detection accuracy and subject number determination accuracy.

II. Feasibility Study

We perform theoretical analysis and conduct preliminary experiments to show the feasibility of detecting the passing through of subjects with WiFi signals.

The subject detection scenario of *WiCount* is shown in Fig. 1. In this scenario. a pair of WiFi transceivers (one is AP and the other is *WiCount*) are arranged on either side of the entrance of the target place. Considering the multi-path effect [5], the CSI between these two transceivers can be formulated as:

$$H = \alpha e^{-j\phi} + \sum_{i=1}^{L} \alpha_i e^{-j\phi_i}, \tag{1}$$

where α and ϕ are the attenuation factor and phase shift of the main path. L is the number of multi-paths. α_i and ϕ_i are the attenuation factor and phase shift of the i_{th} multi-path. Once a person passes through the entrance, the paths between the transceivers would be occluded. Theoretically, when the person appears in the light-of-sight line (main path) between the transceivers, the first term of Eq. 1 would be greatly affected. That is, the strength of the received signals would significantly decrease, because most of the signals propagating through the main path would be reflected away or absorbed by the human body. Thus, when a person walks through the entrance, the amplitude of the CSI would first reduce rapidly due to the occlusion of the human body. Then, the amplitude would quickly recover owing to the departure of the subject.

To confirm the validity of the above analysis, we conduct a real-world preliminary experiment. Specifically, we let a volunteer walk into the entrance in Fig. 1 and collect the CSI at the *WiCount* end. The amplitude variation trace is shown in Fig. 2. It can be found that before the approach of the volunteer, the amplitude remains high and stable. When the volunteer starts to enter the entrance, the amplitude begins to decrease. The amplitude drops to the minimum when the volunteer blocks the main path. Afterwards, the volunteer leaves the entrance and goes into the target place. The amplitude increases to the initial level. Therefore, it is possible to detect the people passing through the entrance by finding out the sharp decline of the CSI amplitude.

In practice, there may be multiple subjects entering the target place simultaneously. To accurately estimate the density of the crowd in the target place, it is necessary to determine how many subjects are passing through the entrance concurrently. To explore if it is potential to achieve this, we invite three volunteers to participate in our preliminary experiments. We respectively let two and three volunteers simultaneously go through the entrance and record the CSI measurements. The results show that more people make the variation trace of the amplitude more complex. Hence, it is feasible to determine the number of people walking through the entrance by analyzing the variation features of the amplitude.

In addition to determining the number of the subjects, it is also indispensable to figure out whether the subjects are entering or going out the target place, as entering means the increase of the crowd density while going out causes the decrease of the crowd density. Intuitively, if the environments inside and outside the entrance are the same, the amplitude dynamics of entering and going out are the same as well. Fortunately, in most cases, such two environments are different.

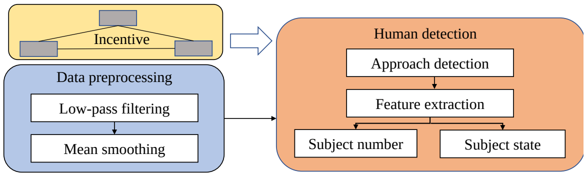


Fig. 4. Architecture of *WiCount*.

Meanwhile, it is very easy to change the environment of any side of the entrance. With different environments, thanks to the multi-path effect, the amplitude variation traces of entering and going out should also be different. To validate the correctness of the above analysis, we conduct a preliminary experiment. To be specific, we first let a volunteer to respectively enter and go out the entrance for multiple times during CSI collection. Then, we reduce the dimensionality of the CSI via t-SNE algorithm [6]. The distributions of entering and going out are shown in Fig. 3. It can be seen that the CSI of entering/going out assembles together. At the same time, the cluster of entering is far away from that of going out. So, it is possible to figure out whether the detected people are entering or going out.

In this work, we make full use of the above analysis and propose *WiCount*. The designs of *WiCount* enable the user to detect the dynamics of the subject, determine the number of people concurrently passing through the entrance, figure out the state (entering/going out) of the subjects, and eventually be aware of the number of all the people in the target place.

III. System Overview

As shown in Fig. 4, *WiCount* is composed of two modules: *data preprocessing* and *human detection*. The use of *WiCount* can be divided into two phases, i.e., training phase and detection phase.

In the training phase, *WiCount* aims to establish the mapping relationship between the CSI and the sensing objective (e.g., the number of subjects passing through the entrance). Specifically, *WiCount* first collects a batch of CSI samples as training data. In this process, *WiCount* actively 'ping' [7] the AP to obtain the WiFi packets and extract CSI from them. Then, *WiCount* extracts the features from the training data. These features can reveal the dynamics of the subjects, so *WiCount* can establish a mapping relationship between them and the number/state of people passing through the entrance via machine learning. The establishment of the mapping relationship is detailed in Section IV.

In the detection phase, *WiCount* continuously monitors the entrance to detect the subjects timely. The collected CSI sequences are first processed to detect if there is a rapid decline. If so, *WiCount* will segment the CSI sequences and get a CSI sample. By feeding the features extracted from the CSI sample into the mapping relationship established in the training phase, *WiCount* can determine how many people are passing through the entrance and judge whether the subjects are entering or going out. In the above process, our incentive strategy keeps running to prevent *WiCount* from lacking sensing packets. We elaborate on the incentive strategy in Section V.

IV. Crowd Density Estimation

In this section, we successively introduce how to 1) detect the passing through, 2) determine the number, and 3) judge the state, of the subjects.

A. Subject Detection

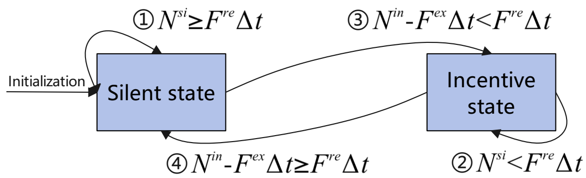
As introduced in Section II, when a person passes through the entrance, the amplitude of the CSI would decrease rapidly. Thus, we aim to detect the subjects by finding out the sharp decline on the CSI sequences.

CSI preprocessing. Raw CSI measurements cannot be directly used for human sensing because they contain much noise caused by environment interference and hardware imperfection. In order to obtain clear data to improve the detection accuracy, we first perform low-pass filtering on the raw CSI measurements. Specifically, a Butterworth filter [8] with 20Hz cut-off frequency is adopted because the frequency caused by human activities is generally lower than 20Hz. Afterwards, we find that there are some CSI readings with extremely large or small values. These readings should be regarded as abnormal values and removed. For doing so, we perform mean filtering to smooth the CSI sequences. A window is set to slide on the CSI sequences. The mean of all the values in a window is taken as the final value of this window. In this way, we can significantly reduce the impacts of those abnormal values.

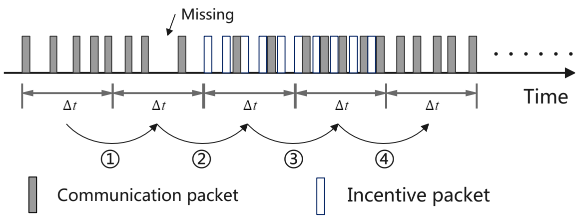
Approach detection. After that, we can use the purified CSI sequences to detect the approach of the subjects. Since the approach would introduce obvious CSI decline, we need to use a metric that can quantify the variation level of the CSI to achieve approach detection. We opt to utilize variance as such a metric. Similar to the processing manner of mean filtering, we use a window to slide on the preprocessed CSI sequence. In each window, we calculate the variance of all the values and get new sequences composed of variance. When there is no human around the entrance, the variance is low and stable. Once a person passes through the entrance, the variance would increase noticeably. Thus, we set a threshold to locate the time point the subjects start to enter/go out. If the variance of at time point is larger than the threshold, we think that the subjects starts to enter/go out the target place.

B. Subject Number and State Determination

After detecting the subjects passing through the entrance, we need to determine their number and state. Intuitively, we can directly feed the CSI sample into a machine learning model to learn the mapping relationship between the CSI and subject number. However, machine learning models usually require the sensing system to have unchanged CSI sampling rate, so that the input collected in a fixed-length of time can have consistent dimensionality. It is hard to guarantee such consistency in a communication context, because the communication traffic only depends on the communication demands of the clients. To deal with this issue, combining



(a) Incentive strategy with two states.



(b) An example for explaining the incentive strategy.

Fig. 5. Incentive strategy.

with the observations in Section II, we propose to extract the features that can reveal the signal variation complexity. To be specific, we first segment the CSI sequences to obtain the CSI sample reflecting the dynamics of the subjects. Then, we extract six statistical features (maximum, mean, standard deviation, entropy [9], interquartile range [9], and velocity of Signal Change [9]) from the CSI sample to form a feature vector with dimensionality of (1, 6). Thereafter, we leverage two random forest classifiers [10] to map the feature vector into the subject number and state, respectively.

V. Signal Incentive

We aim at utilizing the communication packets as many as possible for sensing. However, the communication traffic is insufficient from time to time. To address this problem, we design an incentive strategy based on the listened communication packets. The main idea is given in the following. If the communication packets transmitted from the AP to the clients are enough for sensing, *WiCount* only extracts CSI from these communication packets; otherwise, *WiCount* drives the AP to transmit incentive packets for making up missed packets, which can be achieved by 'pinging' the transmitter. Specifically, the state transition diagram of the incentive strategy is shown in Fig. 5(a). We define two states as follows. 1) *Silent state*: *WiCount* only collects CSI based on communication packets. 2) *Incentive state*: *SenCom* drives the AP to transmit incentive packets and collects CSI simultaneously. The initial state is *silent state* and the transition is triggered after a given period of time, denoted by Δt. Then, during one period, the numbers of collected CSI in *silent state* and *incentive state* are denoted by N^{si} and N^{in}, respectively. The incentive packets in *incentive state* should have a small and equal time interval and its transmission frequency is denoted by F^{ex} (in packets/s). Besides, let T^{re} denote the small time interval required for sensing and then $F^{re} = \frac{1}{T^{re}}$ is the required frequency. Therefore, the state transition condition can be designed based on whether there are enough communication packets during Δt. If not, the next state is *incentive state*; otherwise, the next state is *silent state*. Specifically, there are four cases based on different current states and the numbers of collected CSI, which can be given as follows. (1) If the current state is *silent state* and $N^{si} \geq F^{re}\Delta t$, the next state is *silent state*. (2) If the current state is *silent state* and $N^{si} < F^{re}\Delta t$, the next state is *incentive state*. (3) If the current state is *incentive state* and $N^{in} - F^{ex}\Delta t \geq F^{re}\Delta t$, the next state is *silent state*. (4) If the current state is *incentive state* and $N^{in} - F^{ex}\Delta t < F^{re}\Delta t$, the next state is *incentive state*.

We show an example in Fig. 5(b). It can be found that there is no missing of sensing information in the cases 1, 3, and 4, while missing is happened in case 2. It is noteworthy that the missing in case 2 is unavoidable since we cannot know the number of communication packets in advance and we can only transmit more incentive packets after observing there are no enough communication packets. But in most cases, we already can get enough CSI to support sensing.

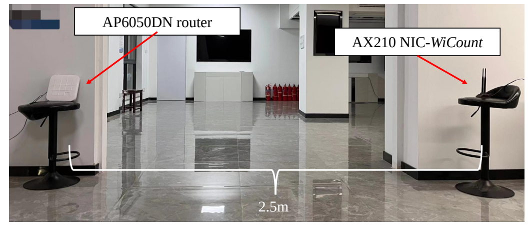


Fig. 6. Experiment setup.

VI. Experiment and Result

This section describes the real-world implementation and details the experiment results.

A. Experiment Setup and Metrics

Experiment setup: As shown in Fig. 6, we carry out experiments in a lab by mimicking an entrance with 2.5m width. An AP and *WiCount* are placed on either side of the entrance. The AP is a commercial off-the-shelf (COTS) AP6050DN router that has been commonly used by enterprises. We use an Intel AX210 network interface card (NIC) (equipped with two antennas) implemented on a Lenovo laptop as *WiCount*. In our default setting, the AP and antennas of Intel AX210 NIC are placed 0.6m and 0.65m off the ground, respectively. The required packet transmission rate is 100 packets per second. The number of subcarriers is 53. We invite five volunteers (with height from 165cm to 183cm) to participate in our experiments. We test over 700 times for overall performance evaluation in three environments, including a lab, an office, and a hall.

Metric: We define three metrics to quantify the performance of *WiCount*: accuracy, satisfaction rate (SR), and throughput. Accuracy is used for crowd density estimation evaluation. It is the probability that *WiCount* accurately detects the appearance of subjects, the number of subjects passing through the entrance, or the subjects' state. The higher the accuracy is, the better *WiCount* is. SR and throughput are defined for incentive strategy evaluation. SR is the probability that *WiCount* can require sufficient packets for sensing. Higher SR means that

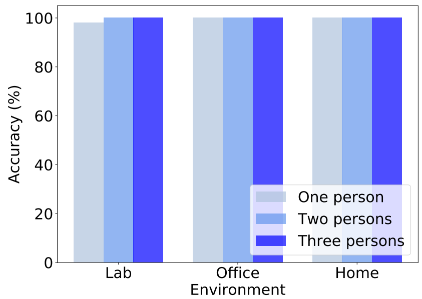


Fig. 7. Detection accuracy.

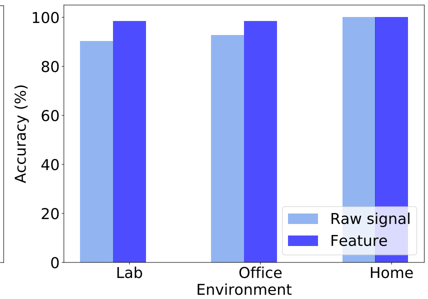


Fig. 8. Subject number determination accuracy.

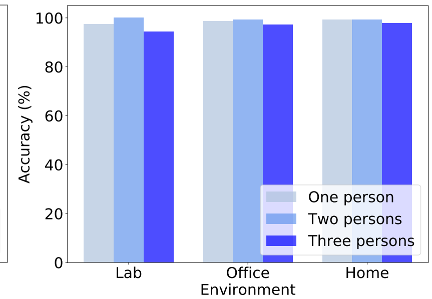


Fig. 9. Accuracy of subject state judgement.

our incentive strategy can create better sensing conditions. Throughput is the rate of successful message delivery between the AP and other clients. We prefer that the throughput of the AP before implementing *WiCount* is close to that after implementing *WiCount*.

B. Overall Performance

We first assess the detection accuracy of *WiCount* in three environments. The experiment results of one to three people are shown in Fig. 7. It can be seen that the detection accuracy is very high under all conditions. The overall accuracy of one, two, and three people is 99.3%, 100%, and 100%, respectively. Thus, *WiCount* performs significantly well in detecting the passing through of the subjects. Since the signal variation caused by one person is not as large as that caused by two or three persons, the accuracy of one person is not perfect. But 99.3% is already very high. Meanwhile, it can be observed that the accuracy in three environments is similar to each other. So, the performance of *WiCount* is stable in different environments.

Then, we calculate the accuracy of counting the number of subjects passing through the entrance concurrently. To show the superiority of our feature extraction approach introduced in Section IV, we also compare the accuracy generated by using the features with that generated by using raw signals. To make raw signals have consistent dimensionality, we perform linear interpolation before feeding them into the random forest classifier. The experiment results are displayed in Fig. 8. It cam found that the accuracy of *WiCount* in three environments is 98.4%, 98.4%, and 100%, respectively. The high accuracy demonstrates that *WiCount* performs outstandingly well in determining the number of subjects. Moreover, the accuracy generated by using features is higher than that generated by raw signals. This means that the extracted features are very effective. Furthermore, similar to the results in Fig. 7, the accuracy in three environments is close to each other. Hence, *WiCount* is fair to determine the subject number in different environments.

Afterwards, we evaluate the accuracy of determining whether the subjects are entering or going out. The results of one to three persons are shown in Fig. 9. The overall accuracy of one, two, and three persons is 98.4%, 99.5%, and 96.4%. The high accuracy demonstrates that *WiCount* can accurately judge the state of the subjects. The accuracy under different environments is similar, indicating that *WiCount* is able to adapt to various environments.

Since *WiCount* is empowered by training-driven machine learning model, its performance is related to the size of the training set. In this experiment, we vary the training set size from 10 to 50 CSI samples to explore the its effect on the subject number and state determination accuracy, respectively. The experiment results are depicted by Fig. 10. It can be observed that both the subject number and state determination accuracy increases with the training set size. When the training set size is 10, the subject number/state determination accuracy is only 68.9%/79%. But when the training set size reaches 30, the subject number/state determination accuracy increases to 91.3%/91.7%. Once the training set size increases to 50, such two accuracy becomes 95.1% and 95.4%, respectively. Therefore, *WiCount* can perform well even is supported by a small training set.

C. Incentive Strategy Evaluation

WiCount leverages an incentive strategy to drive the AP to transmit compensation packets for sensing. In this part, we evaluate the incentive strategy in terms of sensing and communication.

We first assess the SR under three common communication tasks: online gaming, playing video, and webpage browsing. As comparison, we also evaluate the SR without incentive. The experiment results are shown in Fig. 11. It can be seen that, without the incentive strategy, the SRs of online gaming, playing video, and webpage browsing are 0%, 43%, and 10.8%, respectively. A sensing system cannot work normally in such cases. When we run the incentive strategy, the SRs of online gaming, playing video, and webpage browsing increase to 100%, 100%, and 97.5%, respectively. Apparently, this incentive strategy can effectively improve the quantity of CSI needed for sensing tasks.

To validate that our incentive strategy does not impact the communication performance of the AP too much, we evaluate the throughput with clients having one, two, and three antennas, respectively. The experiment results are displayed in Fig. 12. It can be found that the throughput with *WiCount* is close to that without *WiCount*. The performance drops less than 10%. Thus, after implementing *WiCount* in a communication system, it can provide good crowd density estimation service, while not hurting the communication function too much.

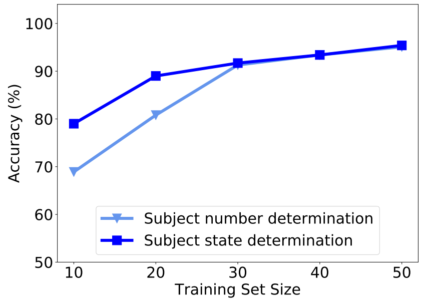


Fig. 10. Effect of training set size.

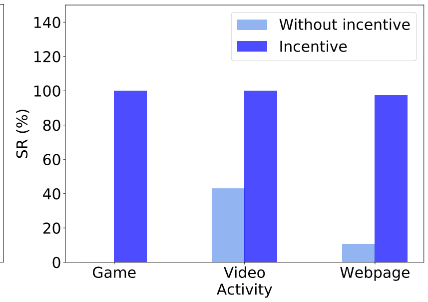


Fig. 11. SR under incentive.

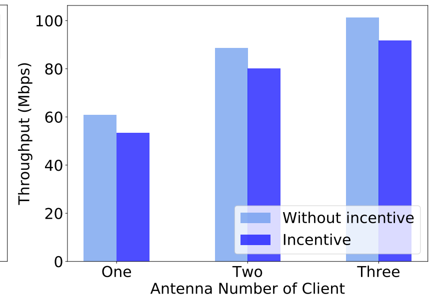


Fig. 12. Throughput under incentive.

VII. Related Work

According to whether the subjects need to carry any devices or not, existing RF-based crowd density estimation approaches can be grouped into two classes: device-based ones and device-free ones.

Device-based methods usually require the subjects to carry some devices as sensors. For example, the physical-layer characteristics of the signals of RFID tags can reveal its position information, so Zou et al. [11] and Weekly et al [12] propose to attach the tags to human bodies for crowd occupancy level estimation and indoor localization, respectively. Tang et al [1] show that the density of a target crowd can be estimated by analyzing the physical features of the WiFi packets emitted from the smartphones carried by the people. Similarly, Schauer et al. [13] demonstrate the feasibility of leveraging the Bluetooth signal leaked by smartphones to track people. These approaches have decent crowd density estimation accuracy, but the requirement of carrying devices brings inconvenience to subjects.

Thus, device-based approaches are more appealing because they minimize the interactions between subjects and the systems. Generally, these systems only need to collect the RF signal reflected off the crowd during density estimation. Since different density has varied effects on the physical-layer indicators (e.g., received signal strength and phase), the crowd density can be determined by establishing a mapping relationship (e.g., learning model and fitting function) between these indicators and the crowd density. For instance, Ding et al. [3] place a RFID tag array in front of the target crowd, so that the backscattered signal can carry the features of the crowd density. Ma et al [4] use a COTS WiFi NIC to emit active probing signals, and receive the signals reflected from the crowd to capture the density information. Nevertheless, existing device-based approaches can only monitor the crowd in a specific area. If the crowd is scattered or the target place is large, it is difficult to sense all the people in this place. In this paper, we propose *WiCount* to address this problem by accumulating the number of subjects passing through the entrance.

VIII. Conclusion

In this paper, we propose a WiFi-based crowd density estimation system *WiCount*. It is deployed on a side of the entrance of the target place. By feeding the features extracted from WiFi CSI into a random forest classifier, *WiCount* is able to determine the number of people passing through the entrance. Different from previous WiFi-based sensing systems that rely on exclusive infrastructures and frequency band, *WiCount* can directly reuse the communication packets for sensing. Experiment results show that *WiCount* can achieve very high detection accuracy with communication traffic.

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