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WiFi-Tally: Crowd Monitoring and Counting

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Abstract: WiFiTally is a technology tool designed to use Wi-Fi signals to track and count people in public places. Imagine having a system that can track and detect people's movements in areas such as shopping malls, airports, and cinemas without compromising privacy. WiFiTally does this by using Wi-Fi signals emitted by smartphones and other connected devices that people carry.

Simply WiFiTally analyzes the Wi-Fi signal pattern in a designated area to gain insight into crowding and movement. The technology prioritizes privacy by using Wi-Fi signals that people want to leave on their devices, rather than relying on traditional methods like cameras. The process involves collecting anonymous data from Wi-Fi signals and turning it into useful data about population size and traffic. It does not identify individuals; instead, it focuses on all topics to help businesses and theater organizations make informed decisions about crowd management.

WiFiTally offers non-interference and privacy solutions to understand and optimize audiences. This brief aims to introduce the concept of WiFiTally monitoring and crowd counting, highlighting ease of use and respect for privacy in public spaces.

I. INTRODUCTION

Counting people and determining their walking speed and direction may have applications in many areas. For example, in a smart home, lighting, heating and cooling can be controlled depending on the number of people in the room. In retail, consumption and preferences can be determined by the number of people and the time spent in an area. Passenger traffic and traffic in public areas such as subways, bus terminals and train stations can be controlled and reported according to the number of people. Traditional census methods, including manual counting or infrared imaging, are time-consuming, expensive and sometimes impractical, especially in densely populated areas. Optical imaging with machine learning capability has been introduced and used in many cases [1, 2, 3, 4]. However, the image-based method has some disadvantages, such as the performance of optical equipment, the possibility of large blind spots, and low accuracy, and exists in complex environments due to the consistency of various objects and occlusion targets. Radio-based calculations followed. Some radio systems require humans to carry electronic devices that emit radio frequency (RF) signals to operate and extract data [5, 6, 7]; They are often inconvenient and cannot be used. Another way radio is passive: They don't require users to carry the device, but they do need to deploy early wireless sensor networks, which used to be very expensive and difficult to operate. Wireless communications for mobile communications and the Internet have become increasingly popular in recent years. Most homes and offices have Wi-Fi routers and signals. Wi-Fi signals go everywhere and are affected or scattered by objects and people. Therefore, they carry information about people and their environment and can be used to make decisions and analyze people's behavior and activities. For example, they can be used to recognize different human poses and gestures [8, 9, 10, 11, 12], identify people [13, 14], recognize statues [15], and track the position of people and objects. animals[16,17]. They can also estimate a person's breathing frequency by analyzing the modulation and phase changes of the Wi-Fi signal channel information state (CSI) [18, 19, 20, 21, 22].

Some methods of using WiFi signals have been developed, including by humans (the content of this article). Seefelding M et al. He proposed the Nuzzer system [23]. The system uses the difference in received Wi-Fi signal strength to estimate the number of people. Xi et al. proposed FCC system [24]. The system analyzes the relationship between personnel in a particular area and the situational information (CSI) it receives. It measures the percentage of non-zero points in the CSI matrix. Then use gray model theory to connect the percentage and people, get the growth curve, and count people [25]. De Patra et al. Describe the loss of absorption and the many consequences resulting from human physical disabilities and emotions [26]. They then developed a mathematical model to predict people. Fadel Adib and Dina Katabi [27] used the inverse synthetic aperture radar principle and used various techniques and various interference devices to eliminate the interference problem of fixed targets. They then proposed a method that could detect moving targets and estimate their numbers. Yang et al. proposed the first gate monitoring by analyzing the WiFi signal [28].

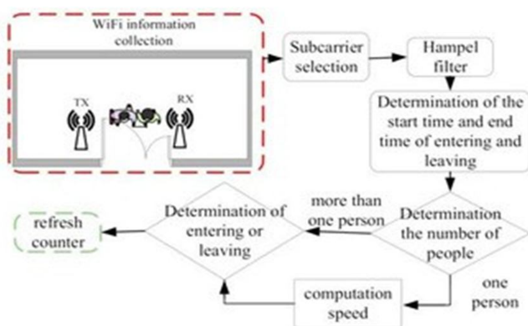
However, all these methods require training with prior knowledge of teaching materials that may not be available or possible. For this purpose, we want people to find a way based on the Wi-Fi signal. This way does not require any training data and only needs to have a design in advance. Wi-Fi signals can also estimate a person's speed.

The main contributions of this paper are summarized as follows:

1) A dual-threshold method is proposed to detect the beginning and end of entry time or exiting the room. It overcomes the inaccuracy and expensive problems associated with manual and sliding range techniques as described in [29].
2) A method for estimating human walking speed using non-linear curve fitting techniques.
3) A search method has been established to determine whether people have entered the room. Unlike deep learning algorithms, such as the gate tracking method proposed in [28], this method does not require training data, but requires building models first.
4) A different method has been proposed to determine the entrance or exit. It exploits the difference between signal variances inside and outside the room, a feature that has not been investigated or reported in the literature thus far. It enables simple communication requiring only one antenna (unlike the dual antenna approach proposed in [28]).

II. MATERIALS AND METHODS

Figure 1 is a general diagram of the proposed method. This is considered a room with a door through which people enter and exit the room. The wireless router is inside the room and placed near the door. List the subcarriers on the Wi-Fi router and select one of them for further operations. Filters are used to remove outliers for selected subcarriers. A threshold is used to determine the start and end time of entering or leaving the room through the door. Dynamic Time Rule (DTW) algorithms are used to compare and analyze the observed signal with previously generated data. Then determine how many people came to the door. After this, different methods are used to determine whether the person has entered or not. If it is a person, the speed is also estimated.



.Figure 1 General map of the algorithm

Mainstream Wi-Fi systems use 802.11 a/g/n and use orthogonal frequency division multiplexing (OFDM). It divides the 20 MHz bandwidth into 56 subcarrier bands. Subcarriers carry state information (CSI) in amplitude and phase. When encountering objects, these carriers have different wavelengths, causing the multipath signal to spread and attenuate; They result in obtaining features related to CSI amplitude and phase shift. Data transfer can be used and processed for product discovery. So a Wi-Fi router and a signal in the room are used to identify and count people entering and exiting the door. We will describe the proposed methods in the following subsections.

A. *Subcarrier Selection and filtEring*

In the proposed algorithm, we select the subcarrier with the largest variance to be detected. Since the shift number is the largest, the selected subcarrier is more sensitive to changes in CSI than other subcarriers. In the case we are considering, the frequency response of the subcarrier can be expressed as follows:

$$CSI_i = \sum_{k=0}^{K} r_k e^{-j2\pi f_i \tau_k}$$

(1) where K is the number of red multipath clusters, rk is the number signal path amplitude of the signals passing through k path, fi is the frequency of the subcarrier with the largest difference and δk is the propagation time of the signal along the path k. Figure 2 shows an example of the 15th subcarrier, which has the largest difference.

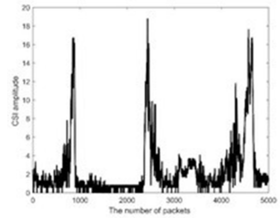


Figure 2. Signal before filtering

The signal of the 15th subcarrier is then passed to a Hampel filter [30] to remove outliers with different values from other adjacent CSI measurements. Although the CSI signal is not normally distributed in the long term, it is roughly distributed in the short term. That's why we use the Hampel filter. We also tried other filters such as the neutral filter; They are not like Hampel. This comparison directly demonstrates the necessity of using the Hampel filter. Figure 3 shows the normalized signal after filtering and removing outliers. Compared to the signal in Figure 2 before filtering, the signal in Figure 3 is cleaner.

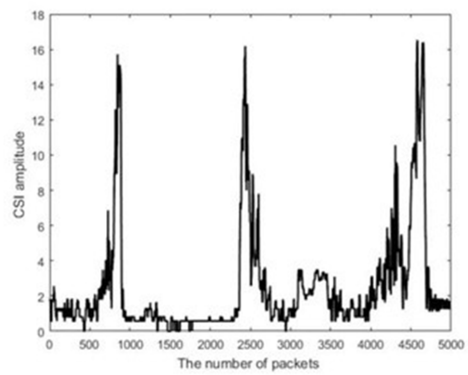


Figure 3. The signal after the Hampel filtering.

B. Determining the start and end time

The CSI signal is normalized before determining the start and end time in order to reduce the environmental impact. Figure 4a shows the positive results. The filtered signal x(n) is further windowed and segmented by the gain function and becomes y(n):

$$y_i(n) = w(n) \cdot x[(i-1) \cdot n_s + n],\ 1 \leq n \leq L,\ 1 \leq i \leq f_n,$$

where y(n) represents the segmented and windowed signal x,(n) represents the next signal filtered , w(n) represents the window function, in represents the segment length, in represents the segment change number, & represents all segments, and fo represents the number of segments in each packet.

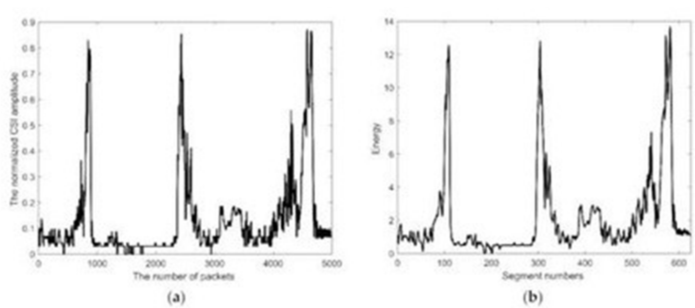


Figure 4. (a) Normalized signal. (b) Short-term strength of the normalized signal.

The short-term energy of each section is calculated as follows

$$E(i) = \sum_{n=0}^{L-1} y_i^2(n), 1 \le i \le f_n$$

where E(1) represents the strength of the signal . Figure 4b shows the short-term strength of the segmented signal.

The following two methods are for determining the start and end time of entering or leaving the room. Assuming the wireless router is at home, entering the door is considered walking outside the door, passing the router and entering the room, exiting is considered passing the room, passing the router and exiting the room. . The Wi-Fi signal inside the room is stronger and more sensitive to environmental changes (such as people walking) than the Wi-Fi signal outside and outside the room.

When people pass through the door, the reception of the Wi-Fi Fi signal will be greatly affected. Two thresholds are selected in advance to determine the start and end time of input or output to the peak amplifier, which affects the number of people passing through the router and starts the process of counting the number of people. Small area amp2 determines the start and end time of the input or output. In other words, when the signal reaches above amp 1 the plan searches the left and right side of amp1 in time to find the instance when the signal strength is equal to amp2. The time to the left of amp1 (or the time before the time of amp1) is equal to amp2 and is the start time. The time to the right of amp1 (or the time after time amp1) is the last time equal to amp2. Additionally, the minimum time for entry and exit is preselected. If the time difference between the start time and the end time is less than the minimum time, the detected signal is considered an interference problem and is ignored. Initially we set amp1 equal to half the maximum value of the amp and amp2 equal to one-eighth the maximum value of the amp. They then updated the book while creating the document. The calculation algorithm of the two attempts is as follows (Algorithm 1).

Figure 5 shows the results of using two thresholds to determine the start and end time of entering or leaving the room. Note that normalization is used for a short period of time to eliminate the negative effects of relative differences between different packages.

```
Algorithm 1:
Determination of the start and end times.
Input: amp, ampt, amp2,
Output v Begin; v. End
for n-1. length(amp)
switch status
case (0, 1)
                    If amp(n) amp
                    Identify the ontering and leaving stage, else if ampin) amp2
   .                May be the entering and leaving stage else
                          No one entering and leaving
   .               End If
case2
                  If amp(n) > amp2
                      Keep entering and leaving stage:
                 else
                      entering and leasing stage will end:
                 else
  End of entering and leaving stage.

                    End if
  case3
                 Record the current stage and look for the next stage
   .           End switch end for
```

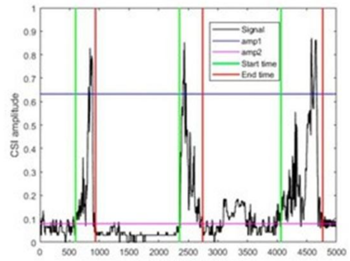


Figure 5 Determining the start and end times of entry and exit points.

C. Determine Number of People

Once the start time and end time are decided, visible signs of the start time and end time will be processed to find the people. Processing is done by comparing it with a previously generated signal. It is assumed that the database is created for eight scenarios, such as one person entering, one person leaving, two people entering, two people exiting, three people entering, three people leaving, one person entering and leaving with the child, a carrier a child.

Similarities between visual signals and data are measured and used to judge people. However, the length of the detected and analyzed signal may differ from the length of the data due to d changing with time. If you simply reduce or delay the signal length, the results will not be accurate. We use the variable time migration (DTW) algorithm to solve this problem. Metin [31] proposed the DTW algorithm to solve the speech inconsistency problem in speech recognition.

Here,we use DWT to measure the similarity between long transformed symbols and data More specifically, DTW is best. In our case it is used to find the minimum Euclidean distance between the retrieved data and the sample data in the database:

$$D = \min \sum_{i=1}^{L} d[x(i), R_k(i)] \quad k = 1, 2, \ldots, N,$$

Among them, x(t) represents the signal (the signal between the start time and end time), R) represents the A-th dataset, and represents the label of all segments in the file. N is the number of datasets. Find is to find people whose number of people gives the minimum Fuclid distance or minimum D(4).

D. Decisions Regarding Entry and Exit

When determining the number of people, their entry or exit must also be determined. A different starting method was created to do this job. The received CSI signal power when a person leaves is shown in Fig. 6a, and the received CSI signal power when a person enters is shown in Fig. 6h. Since the Wi-Fi router is placed in the room, indoor signal is different from outdoor mainly due to multipath signal. Therefore, the internal signal difference is greater than the signal difference. Therefore, the purpose of the transition method shown below is to determine the input or output status. Use the following formula to specifically determine the entry or exit status.

$$\begin{cases} \text{If } v_{t-1} \geq v_T \& v_{t+1} < v_T \Rightarrow \text{entering} \\ \text{If } v_{t-1} \leq v_T \& v_{t+1} > v_T \Rightarrow \text{leaving} \end{cases}$$

This represents the difference from the previous season and often the difference from the next season. v represents the threshold between V-1 and Vi+1

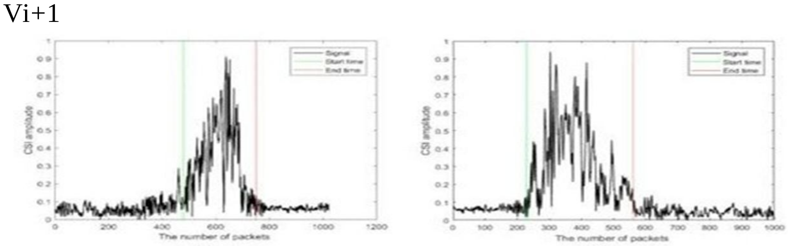


Figure 6. Time between entry and exit. (a) Leave the room. (b) Enter the room.

E. Decision Making Speed

A person's walking speed will affect the information received. Relationships are evaluated during database creation. In our case, the results are shown in Figure 7. The curve fitting method is used in this article. The algorithm proposed in this article takes 0.33 seconds. Below is the curve fit equation for speed estimation.

$$u = \frac{p_1}{L + p_2}, \; p_1 = 162.7, \; p_2 = -6.01$$

P and po are consistent when you represent the input or output rate, and L represents the number of packets received at the start and end time. MATLAB tools use straight lines. (6) can be used to determine walking speed when obtained. Then use equation (6) to determine walking speed.

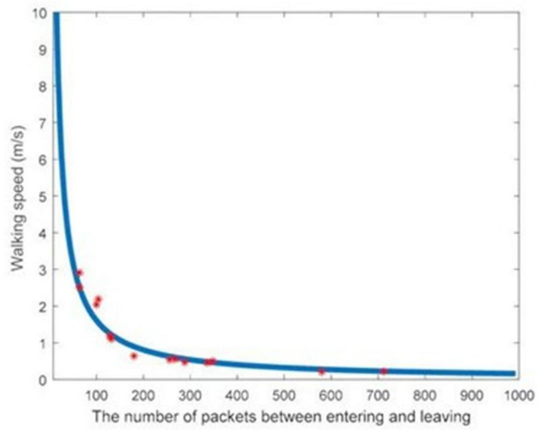


Figure 7. Curve fit of speed according to received packets.

III. RESULT

We conducted experiments using the above methods. Details are as follows.

We use the Wi-Fi transmitter on a desktop computer equipped with an Intel 5300 network card. It has an antenna that broadcasts data packets into the air. We use the receiver from a desktop computer equipped with an Intel 5300 network card. It has three antennas as a linear array. We use the Linux 802.11n CSI tool [32] to collect CSI measurements. We use channel 13 at 2.4 GHz. The packet transfer rate is set to 100 Hz. We use MATLAB to process CSI data.

We conducted the experiments in two enclosed spaces: a large empty space and a small office with furniture and students, as shown in figures 8 and 9. The transmitter and receiver were placed on either side of the door, approximately 1.2 m apart. . The laboratory has many tables, chairs and equipment. Seven volunteers (three men and four women) participated in the experiment. They enter through the door as shown in Figure 10.

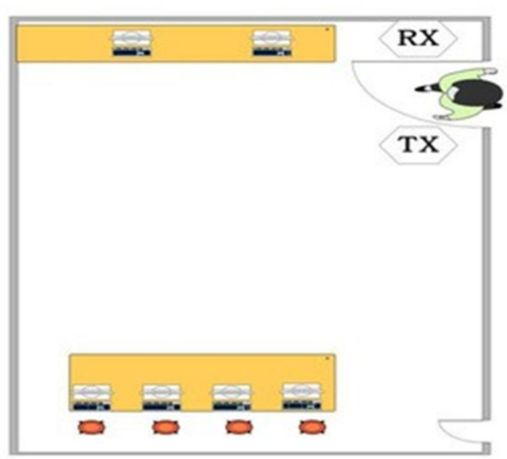


Figure 8. Experiment in a large empty area.

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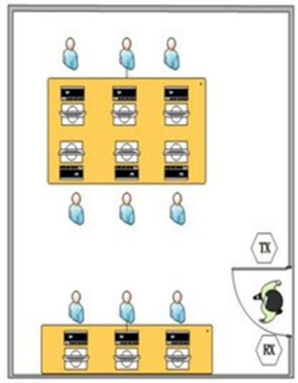

Figure 9. Experimental setup for a small office

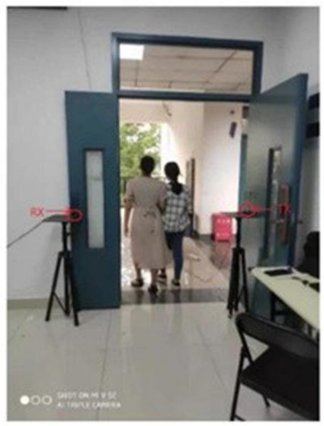

Figure 10. Participants enter through the door.

A. Traffic Detection: Entry or Exit (exit)

For a large test site, we tested the entry and exit of two people 100 times and three people 103 times. The accuracy of two commentators is 100%, and the accuracy of three commentators is 100%. The accuracy of two removers is 100%, and the accuracy of three removers is 100%. For comparison purposes, Figure 11 also shows the actual gate view [28]. The signal outside the door is weak due to the attenuation of the wall. The CSI signal change caused by people walking is smaller than the signal change at the door. The proposed algorithm using variables is robust. Unlike the model in reference [28], which uses two (or more) antennas and different phases between them, the scheme is independent of antennas and can work with one antenna.

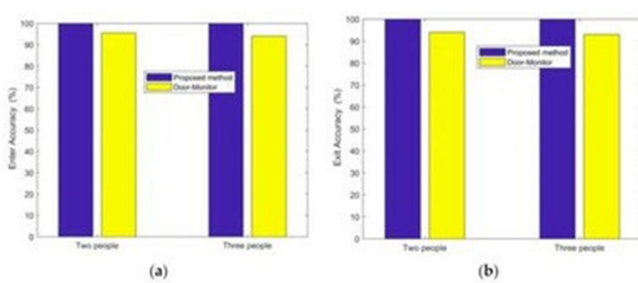

Figure 11. Accuracy of transmission direction in a large free space.
(1) Introduction. (b) Leave

Taking a small office with furniture and students as an example, we tested the entry and exit of two people 103 times, three people 100 times, four people 103 times, and five people 102 times. The accuracy of two subtractors is 100%, the accuracy of three subtractors is 96%, the accuracy of four subtractors is 100%, the accuracy of five subtractors is 100%.

The accuracy of two subtractors is 100%, the accuracy of three subtractors is 98%, the accuracy of four subtractors is 100%, and the accuracy of five subtractors is 100%. For comparison purposes, the actual gate view [28] is also shown in Fig. 12.

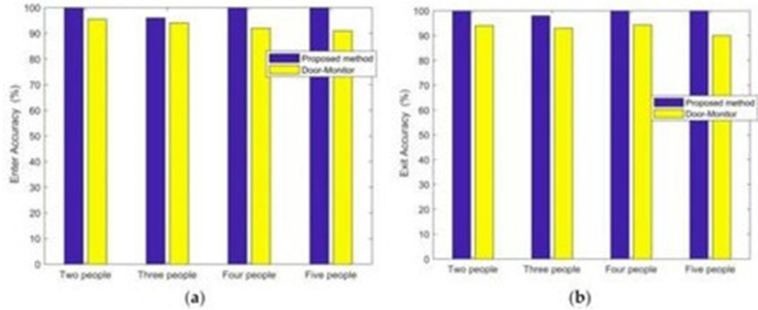

Figure 12. Proper traffic management in small offices. (1) Introduction. (b) Leave.

B. Determining the Number of People

In the large laboratory, we tested 1 person 100 times, 2 people 100 times, and 3 people 103 times. One person's accuracy is 100%, two people's accuracy is 81%, and three people's accuracy is 95%.

Table 1 shows the results from a large laboratory population. For example, the fourth column shows that for 103 tests of three people, the results were 5 tests showing 1 person (no) and 98 tests showing 3 people (yes).

Table 1. Number of people tested in the main laboratory.

Taking a small office as an example, we tested 1 person 101 times, 2 people 103 times, 3 people 100 times, 4 people 103 times and 5 people 100 times. One person's accuracy is 98%, two people's accuracy is 98%, three people's accuracy is 82%, four people's accuracy is 93.2%, and five people's accuracy is 75%.

Table 2. Test scores of residents of a small office

The above test results are valid for those entering or exiting. The proposed algorithm can determine the traffic flow (incoming or outgoing) and then the number of people. It can explain situations where new entrants differ from exiters. Since the determination of the direction of traffic was almost 100% accurate, it was determined that the number of people entering and exiting was almost the same.

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C. Walking Speed Estimation.

We tested a person walking in and out of a room 26 times. The operational speed of the prediction model is shown in Figure 13. It can be seen that the accuracy of the speed error is less than 0.241 m/s and is 75%. Accuracy is 100% for velocity error above 0.7 m/s.

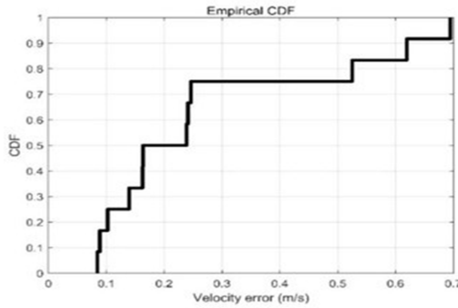


Figure 13 Accelerating the discovery of truth.

D. Effect of the Size of Objects Carried

Most of the time, people entering or leaving the room carry children or objects. Therefore, it would be useful to examine the impact of children and objects on the discovery of truth. With this in mind, we tested the following data: An adult walks with a child, holds the child, pulls a box 40 cm x 26 cm x 50 cm, and carries the letterbox on his shoulder. We performed 10 tests for each case. The results are shown in Figure 14. In these cases, our proposed method outperforms traditional SVM. Note that SVM has a previous filter step with the same conditions as the proposed method. For example, the SVM method uses the same pre- designed library. In this way, we can compare the proposed model with the SVM model.

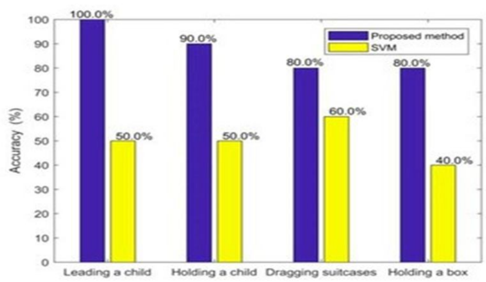
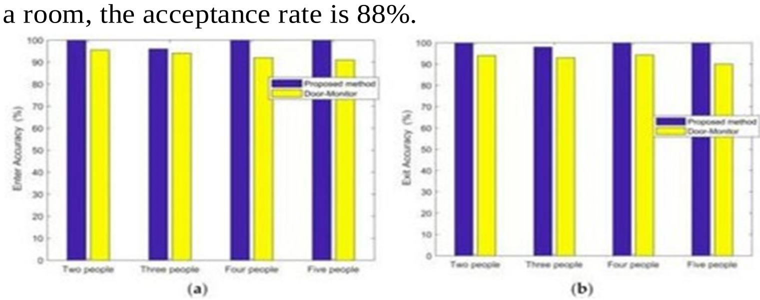


Figure 14. Accuracy of detecting people entering or leaving the room with children or objects.

From Figure 14, we can see that pulling an object (whether it is a person or an object) is more accurate than holding an object. This may be due to the separation between the person and the object and the fact that the object pulled is larger than the object held.

E. Impact of Interference

To verify the stability of the algorithm, we consider the impact of people moving around the house on the accuracy of digital authentication. The results are shown in figure 15. If the room is not affected, the average recognition rate is 95%. When someone moves into a room, the acceptance rate is 88%.



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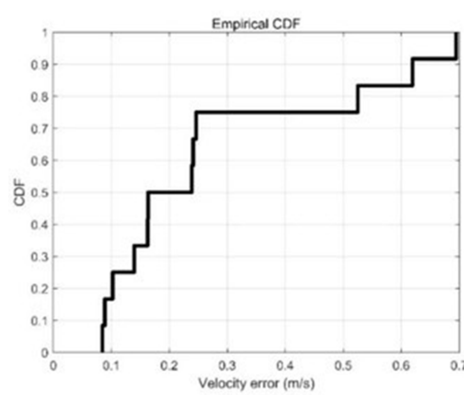

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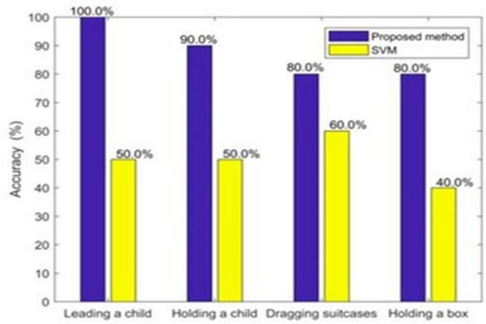

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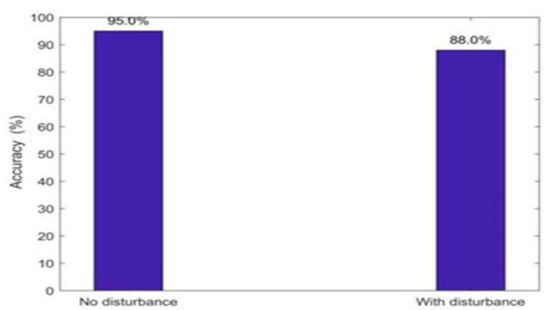

Figure 15. Movement of other people as influence.

IV. CONCLUSIONS

Counting the number of people entering and leaving a room provides important information for human traffic management and flow analysis. Few papers have used CSI signals to estimate the number of people entering and leaving a room. We found only one relevant article published so far [28]. It uses a deep learning approach and requires training with large amounts of data. Our method does not need training. It only requires a pre-developed sample database. In addition, at least two receiving antennas are used in [28] with higher cost and complexity. However, the proposed method only needs one receiving antenna. It also calculates walking speed.

Experiments show that in a large, empty laboratory, the accuracy rates for determining the number of people are 100% for one person, 81% for two people, and 95% for three people. In a small office, the number detection accuracy is 98% for one or two people, 82% for three people, 93% for four people, and 75% for five people. For walking speed estimation, the accuracy rate for a speed error of less than 0.2410 m/s is 75% for a single person. A group of five people can be considered a reasonably extreme case given the size of the door. If more than five people enter or exit the door and they are close to each other, the proposed method will present the result of five people. If they are not close to each other, the proposed method counts them separately.

The proposed algorithm is at the stage of laboratory research and is not yet ready for real use. However, the ultimate goal is to get it ready for real use and built into a Wi-Fi router - this paper is the first step to developing and validating the algorithm. Its real-time implementation and the counting of multiple persons entering and leaving simultaneously are topics for future research.

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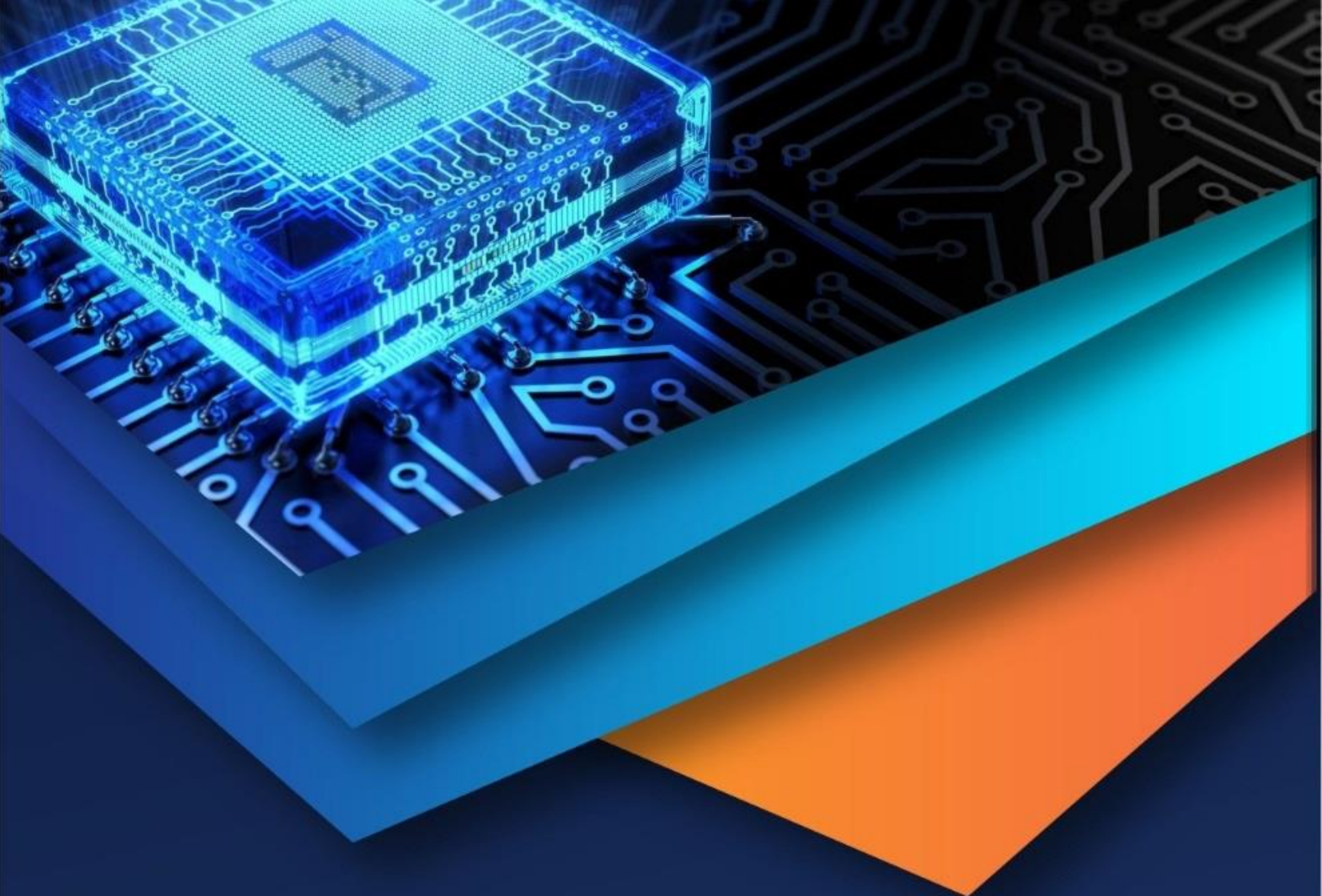

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