WiWho: WiFi-based Person Identification in Smart Spaces

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***Abstract*—There has been a growing interest in equipping the objects and environment surrounding users with sensing capabilities. Smart indoor spaces such as smart homes and offices can implement the sensing and processing functionality, relieving users from the need of wearing/carrying smart devices. Enabling such smart spaces requires device-free, effortless sensing of user's identity and activities. Device-free sensing using WiFi has shown great potential in such scenarios, however, a fundamental question of person identification has remained unsolved. In this paper, we present WiWho, a framework that can identify a person from a small group of people in a device-free manner using WiFi. We show that Channel State Information (CSI) used in recent WiFi can identify a person's steps and walking gait. The walking gait being distinguishing characteristics for different people, WiWho uses CSI-based gait for person identification. We demonstrate how step and walk analysis can be used to identify a person's walking gait from CSI, and how this information can be used to identify a person. WiWho does not require a person to carry any device and is effortless since it only requires the person to walk for a few steps (e.g. entering a home or an office). We evaluate WiWho using experiments at multiple locations with a total of 20 volunteers, and show that it can identify a person with average accuracy of 92% to 80% from a group of 2 to 6 people respectively. We also show that in most cases walking as few as 2-3 meters is sufficient to recognize a person's gait and identify the person. We discuss the potential and challenges of WiFi-based person identification with respect to smart space applications.**

I. Introduction

There has been an increasing interest in offloading the functionality of user's smart devices to the infrastructure surrounding the user. Embedding sensing, computation and communication capabilities in the environment such as home or office can allow a person to be truly "device-free" while still receiving the same services otherwise available through portable/wearable devices like smartphone. Such intelligent environments are often referred as smart spaces. Numerous applications can be enabled with the realization of smart spaces. For example, currently counting the number of steps walked by a person requires her to constantly carry a device (smartphone or fitness band) at all times even at home. Similarly, tracking sleep behavior requires her to wear a sleep tracking device even during her sleep. The need of carrying/wearing devices introduces a great deal of discomfort to the user and also inaccuracy in measurements when the user does not wear the device as suggested. With the emergence of smart space, such sensing and activity tracking functionality can be performed by the environment (home or office) itself, relieving people from the need of constantly wearing smart devices.

There are huge challenges in the true realization of smart spaces. Tracking a person's actions in smart spaces requires sensing without any physical interaction. Monitoring a person's activities like sleep and walking through audio/video is possible, however, it imposes unacceptable privacy risks. Recent research on activity tracking using RF signals of WiFi provides an attractive solution for device-free sensing. Authors in [1] demonstrated that a large set of in-home activities can be identified using WiFi. Similarly, device-free person localization using WiFi is also shown to be feasible using [2]. WiFi-based activity recognition is especially attractive due to the pervasiveness and low-cost availability of WiFi. The availability of Channel State Information (CSI) for 802.11n WiFi devices has further fueled the device-free activity recognition using WiFi.

Current state of WiFi-based activity recognition has many limitations. One of the biggest limitations of such schemes is that they cannot identify a person using WiFi in a smart space. Person identification can be considered a prerequisite for activity recognition since without that, it is not possible to associate a sensed activity to a given person. For example, if it is possible to identify the person who is in the home, detected activity (e.g. cooking [1]) can be associated with that person. Such person identification can make a way for many applications in smart spaces. When a smart home detects that one of the five family members has entered the home, it can use that identity to trigger person-specific customization such as adjust room temperature using thermostat, provide content recommendation on television, start coffee machine etc. It would also facilitate several applications related to Internet-Of-Things (IoT) that might be otherwise infeasible without knowing the person's identity.

In this paper, we investigate person identification problem using WiFi. Specifically, we address the following question - can we identify a person out of the n known people with simply the use of WiFi? We are primarily interested in scenarios such as smart homes and offices where a person currently present can be identified from the know n people sharing the home or office. As an example, our technique is applicable to a typical house or apartment complex that is shared by 4-5 family members or an office that is shared by 6-7 people. In both cases, it is reasonable to assume that there is an active WiFi connection. In this paper, we present WiWho, a framework which can monitor and mine the variations in the WiFi signals to identify a person.

Person identification using WiFi is an extremely challenging problem. One possibility is that in a small group of people, a person can be identified uniquely from her height or body mass. Sensing the impact of a person's height or body mass using WiFi signal is very difficult in indoor environments due to severe multipath. Such fine-grained sensing is not feasible using current off-the-shelf WiFi hardware and requires a dedicated software-radio or an antenna assembly (such as [2] or [3]). Our objective in this work is to use the existing WiFi infrastructure to allow pervasive, low-cost deployment of smart spaces. To address these challenges, WiWho relies on off-the-shelf WiFi hardware to measure variations in WiFi signal using detailed CSI. WiWho exploits the rich indoor multipath to understand how various reflected paths are affected when a person walks around. We show that after removing distant multipath and other noise, it is possible to detect a person's walking steps directly from the CSI. This step information in signal domain is rich enough to characterize the person's gait (manner of walking). Previous research [4], [5] has shown that gait is sufficient to identify the person. By analyzing the shape of a person's step, walking speed and overall variation in CSI due to walking, WiWho is able to identify a person uniquely from a small group of people.

WiWho is well suited for person identification in smart spaces. It does not require a person to carry any device (such as a smartphone) for identification. This is especially important in indoor scenarios as a person might not carry the smartphone with her all the time. Unlike face/fingerprint recognition methods which require deploying dedicated hardware, WiWho is low-cost as it reuses the existing WiFi infrastructure for identification. Another important advantage of WiWho is that it simply relies on person's walking and does not require her to proactively perform any activity to get identified. It also provides improved privacy compared to identification through audio/video monitoring which can also track other private activities of the person. With extensive evaluation, we show that WiWho provides moderate to high accuracy of person identification. We believe that such accuracy is reasonable for smart space applications (homes and offices) where primary purposes of identification are convenience and entertainment. WiWho is not suitable for high-risk applications (such as government identification or authentication at airports) where mis-identification can have life-threatening consequences.

The contributions of this work can be summarized as follows:

• We provide measurement-based evidence that channel state information between two WiFi endpoints can be used to identify walking steps of a (device-free) person. Similar to accelerometer-based step detection, step cycles can be constructed purely from the CSI data. This can enable various smart space applications such as a device-free pedometer.

• We demonstrate that person's step information available by monitoring CSI is rich enough to determine the person's individual walking gait. Based on the previous works which proved that gait can be used to identify the person, we analyze the CSI-based gait of different people to determine the properties that can allow us to distinguish different people. To this end, we present WiWho, a framework that can passively monitor the CSI in smart spaces, and identify a person (out of a small group of known people) based on her walking gait analysis.

• We evaluate WiWho using experiments with off-the-shelf hardware and 20 volunteers at multiple locations. WiWho can identify a person with average accuracy of 92% to 80% from a group size of 2 to 6 people respectively. In most cases, it only requires a person to walk for less than 2-3 meters in order to get identified based on the gait analysis. We discuss the potential and limitations of such WiFi-based person identification from the perspective of smart space applications.

The remaining of the paper is organized as follows. Section II provides an overview of WiFi-based sensing approaches. We discuss the design goals and system overview in Section III. Section IV provides a motivating study describing how CSI can detect steps and feasibility of person identification. Section V describes the details of walking detection and Section VI provides the details of person identification using CSI-based gait. The evaluation results are presented in Section VII followed by a discussion in Section VIII. We conclude in Section IX.

II. Related Work

Wireless Sensing: Recently, wireless signal based sensing has innovated many applications. Recent works have shown that we can leverage the wireless signals to detect human motion and activities [1], [2], [6]–[8], recognize gestures [3], [9] and other types of sensing (e.g. hearing people talk [10], counting crowd [11], estimate queue length [12], detecting fall [13] and monitoring sleep [14]). However, among these wireless sensing applications, there remains one fundamental question unsolved - person identification. This paper is the first work to achieve person identification purely using wireless signals in a device-free manner. We believe that our work can be applied with the aforementioned works to enable more practical and personalized applications in smart spaces.

Gait-based Person Identification: Gait has been recognized as a unique signature for human beings. Recent works have demonstrated that gait can be used as a biometric signature for person identification. In [15], [16], authors use video cameras to record people walking and extract gait information from the video record. These video based methods introduce major privacy concerns and require camera deployment incurring high cost. Other works leverage various sensors, such as floor sensors [17], rotation sensors [18] and accelerometer-based wearable or smartphone sensors [19]–[21], to capture gait signature. Ngo et al. [5] use the largest inertial sensor-based gait database which contains 744 subjects to further evaluate and compare different sensor based gait identification approaches. Pan et al. [22] deploy geophone on the floor and identify walking people through detected structural vibration. However, all above sensor based methods require people carrying additional devices on the body or deploy these sensors in the environment which are not convenient and require additional cost. Our work solves this problem in a convenient,

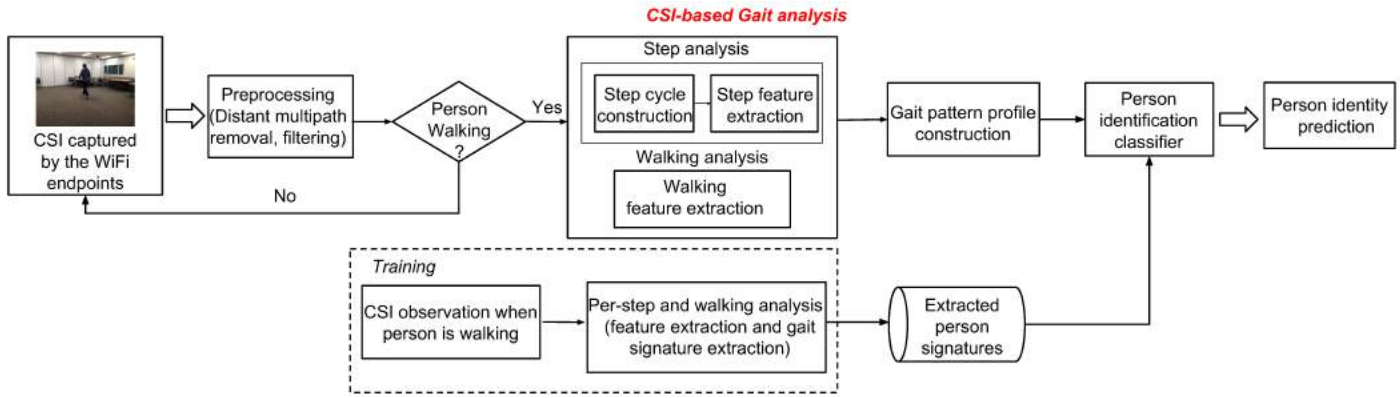


Fig. 1: System architecture of WiWho

low-cost and effortless manner leveraging the existing WiFi infrastructure.

Many other methods can be used for person identification. Unar et al. [4] did a comprehensive survey about all possible biometrics which can be used for person identification. Some biometric technologies, such as fingerprint, retina and face recognition, have higher accuracy and are more reliable. However, such kind of methods can not be directly used for smart spaces scenarios either due to their high cost or inability to operate in a device-free manner.

III. Overview of WiWho

In this section, we describe the design goals, usage scenarios and challenges of WiWho, provide an overview and discuss its limitations.

A. Usage Scenarios and Design Goals

Usage Scenarios: Our objective in this work is to design a low-cost, device-free solution for person identification using WiFi. It is necessary to point out that our objective is not to design a person identification system that provides nearly 100% accuracy. Our system should not be used in many situations/scenarios such as identifying a person at an airport or any other government identification where error in identification can lead to life-threatening consequences. Instead, our system is useful for purposes of convenience and entertainment in homes and offices where the penalty of mis-identification is not catastrophic.

Design Goals: In the view of the application context, the proposed person identification system in smart spaces should meet the following goals:

(1) Device-free and effortless: The system should not require the person to carry any device. It is expected that the person in a smart space is not carrying her smartphone or any similar device such as a wrist-band. This is inline with the design goal of a smart space itself where instead of relying on the person, more and more functionality is handled by the infrastructure itself. Requiring the person to carry a device that can provide identification credentials to the smart space reduces the overall usability and introduces inaccuracies when the person does not wear the device as intended. Furthermore, no proactive interaction from the person should be necessary in order to get identified. This means that the person should not have to perform any additional activity (such as posing for face recognition) to make the identification process as effortless as possible.

(2) Low cost and moderate accuracy: The solution should be low cost. Moderate identification accuracy is acceptable. This means that a solution which can provide very accurate identification but incurs high cost is less desirable than the one where moderate accuracy is feasible at a lower cost. An example of such system is fingerprint-based biometric authentication which is not only a high cost solution but also defeats our previous goal of effortless person identification.

(3) Privacy: Person identification process should not result in privacy leakage. Using of audio/video monitoring for identification (e.g. voice/face recognition) is not desirable, since they can track each and every movement of the person. Similar to the design goal of low-cost, it is necessary that our solution protects the person's privacy even if that reduces the identification accuracy.

B. Central Idea and Challenges

Our central idea in this work is to exploit WiFi signals for person identification. It can be claimed that WiFi-based person identification can meet all the design goals described above. WiFi is already pervasive in indoor environments such as home and office. This means that using WiFi-based sensing will eliminate the need of deploying a dedicated system.

At first, it is not clear how WiFi-based sensing can be used for identifying people in an indoor environment. One possible solution is to analyze the WiFi signals reflected from a person's body. Assuming that the person was stationary (e.g. standing without any movements), the received signal might have different signature for different people depending on his/her height, waist and body mass. The problem with this approach is that it is extremely difficult to isolate the signal that reflected from a person's body because indoor propagation is dominated by severe multipath (presence of many reflected paths). Although recently WiTrack [2] showed how body reflection waves can be used for tracking, it requires a software radio platform and custom antenna assembly. We are interested in developing a solution that can work with low-cost off-the-shelf WiFi hardware without requiring any modifications.

In this paper, we propose a novel way of using WiFi signals for person identification. We show that even though the indoor environments face severe multipath, a person's walking activity can be recognized using CSI. It is also shown that variation in the wireless channel state provides sufficient information so that it is possible to identify a person's walking gait. Similar to accelerometer-based gait analysis, we analyze the *CSI-based gait* information for different people and find that it not only can provide detailed step information but also can distinctly identify a person. This provides us a novel technique to identify a person from a small group of people without requiring the person to carry any device or perform any activity proactively.

Challenges: There are many challenges in using CSI-based gait for person identification. First of all, it is not clear whether we can detect if and when a person is walking purely using the CSI data. This is because in a rich multipath environment such as home or office, the received signal is a combination of multiple reflected paths. This requires design of a technique that can distinguish CSI variations due to walking from that of other activities. Second, even if we can determine that a people is walking, to identify the person, it is necessary to observe fine-grained gait information from the CSI. This requires that the effect of a person's walk is distilled from the noisy signal which may be affected by other reflections (e.g. people moving in the next room). Third, different from accelerometer-based gait measurement which is location-independent, CSI-based gait is highly dependent on the multipath of a given room. We will address these challenges in Sections IV, V and VI.

C. System Overview

The outline of our WiWho is provided in Fig. 1. We assume that there are two stationary endpoints in the room of the home or the office where WiWho is deployed. These endpoints communicate with each other to collect the current CSI. One endpoint can be a WiFi AP and the other can be any WiFi equipped device such as a desktop computer or a smartTV. Two endpoints are only needed to collect the CSI data, and the WiWho is only required to be operating on one of the endpoints (say the AP). It is assumed that a person (not equipped with any device) starts walking in the room. At the same time, the collected CSI samples are constantly analyzed to determine if the person is walking or not. This includes removal of distant multipath and noise filtering. If it is detected that a person is walking, the CSI samples are input to the gait analysis module. The gait analysis consists of two parts:

(1) Step analysis: In the step analysis, the step cycle is constructed from the CSI data and for each of the detected step, and various features of its shape are derived.

(2) Walk analysis: It analyzes the overall walking behavior of the person for the entire walk segment (multiple steps). This provides information on various body movements that can be different from person to person.

The characteristics of step and walk are extracted in the form of features. They are then compared to pre-trained people walk signatures using a machine learning classifier. The classifier outputs its prediction of the person's identity. An important part of WiWho is training where per-person gait signatures are built. In the training phase, each person who would like to be identified walks on a pre-determined

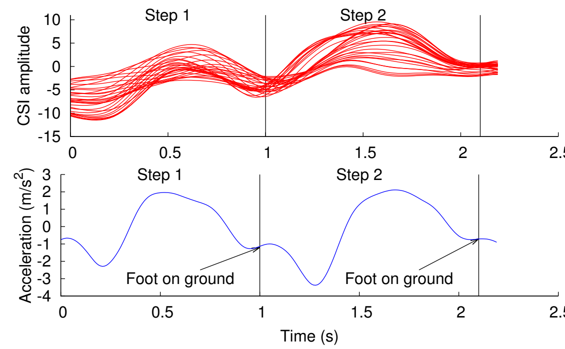


Fig. 2: Comparison between CSI Amplitude and on-body accelerometer readings while a person is walking

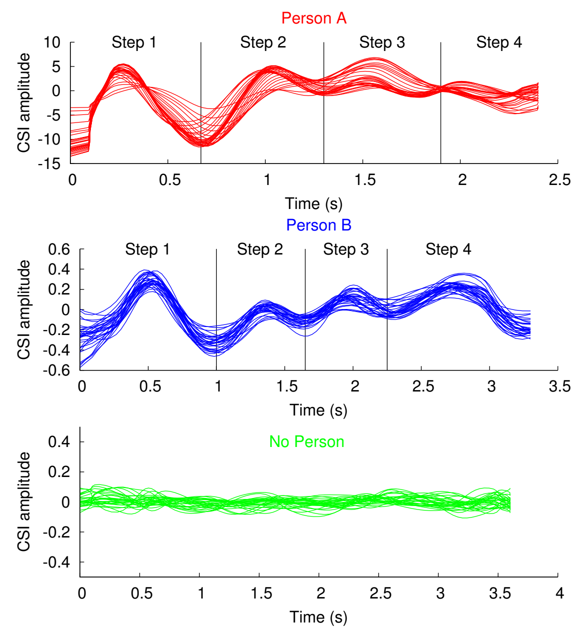


Fig. 3: Comparison between the CSI-based gait of 2 people and the static environment profile

path for fixed number of times, where the CSI samples are collected. The CSI samples are analyzed for gait and walk characteristics, and a CSI-based gait signature is extracted for each person.

Assumptions and limitations: WiWho assumes that person's walking path is a straight line. This is because CSI variations when person turns while walking make it extremely difficult to identify the steps and gait. We believe this assumption does not reduce the usability of the system. In a home or an office, a straight walkway such as a corridor or a hallway can be chosen for the purpose. In fact, choosing a walkway that leads to a home/office works better because a person can be get identified at the same time when she enters the home/office. Additionally, WiWho cannot be used to track a person because the identification is only triggered when the person enters/leaves the room. WiWho is designed and evaluated for a single person in the room at any given time, where we can associate a certain activity detected by WiFi signals to this person. However, it can remove the impact of another person's presence outside the room using distant multipath removal.

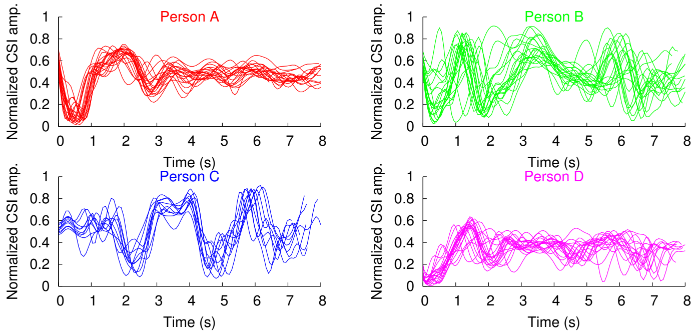
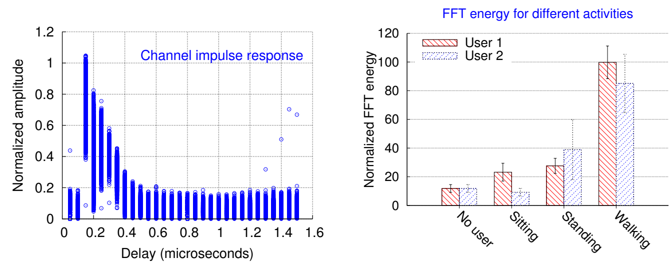


Fig. 4: Comparing CSI-based gait for different people over time



(a) (b)

Fig. 5: (a) Channel impulse response showing distant multipath (b) Comparison of FFT energy in a 6s window between different activities

IV. Measurement based Feasibility Study

In this section, we will provide some preliminary results that serve as a motivating study for WiFi-based person identification.

A. Detecting Gait from CSI

The first challenge of designing WiWho is to detect if there is a noticeable pattern in the observed CSI while a person is walking. Note that just detecting whether a person is walking or not is not enough to distinguish between different people. WiWho requires detecting the step cycle and constructing gait profile from a person's walking activity using purely observed CSI data.

To demonstrate that gait can be detected using CSI, we carry out an experiment where a person walks on a straight line in a room with two WiFi endpoints communicating and collecting CSI. For generating the ground-truth of gait, the person also carries a smartphone in the pocket. Fig. 2 shows synchronized CSI and accelerometer data for the person's walking. For CSI, we plot the amplitude of 30 subcarriers for one spatial stream, and for accelerometer, we plot the acceleration values for X axis. Note that the CSI data shown in this section is preprocessed from the raw data for removing various types of noise. We will discuss this procedure in details in Section V-A.

It is observed from Fig. 2 that the step cycles can be extracted from the CSI data. The steps observed through CSI follow a similar pattern of alternating peak and valley. Unlike accelerometer observations, the steps detected by CSI is less fine-grained i.e. various phases of gait are not clearly detected like [23]. However, we will show that this CSI-based gait information is rich enough for person identification. Since CSI-based gait is observed by nearby WiFi devices and not by a device worn on the person's body, it is dependent on location-specific multipath. This means that the gait varies at different locations as a person walks in a room. We will address these issues in Section VI.

B. Difference in CSI-based Gait for Two People

Although we are able to get the gait information from CSI, it is not clear whether such information is sufficient to uniquely identify different people. To investigate this, we perform an experiment where two people walk in a room on the same path and we capture the CSI data. Fig. 3 shows the CSI data for the initial four steps while two people are walking separately. Note that we also show the static environment CSI profile where there is no person walking in the room. By visual inspection, we can see the difference between the *shape of the steps* for the two persons and the static profile is quite clear. Also, the step lengths also observed to be different for these two people. This visually observed difference and many other underlying differences will be used for building unique gait profile for each person which will be used for identifying individual person.

C. Consistency of CSI-based Gait over Time

One of the most important question to investigate for person identification through CSI-based gait is - does the CSI-based gait for a given person remains the same over time for the same location (e.g. room)? This means that if we learn a person's CSI-based gait at one time, can we use the same gait to identify the same person at a different time? To address this, we ask 4 different people to walk one after the other for 20 rounds. To understand the consistency over time, the rounds are separated by 10 minutes. We plot the mean CSI amplitude across all subcarriers of each round for 4 different people in Fig. 4. It is observed that for any given person, the CSI-based gait remains similar between each round even over nearly 2 hours of time period.

Our preliminary study shows that CSI-based gait for one person is more or less consistent over time, and it is sufficiently different for different people. This motivates us to design a person identification system based on CSI-based gait.

V. CSI Preprocessing and Walking Detection

A. CSI Preprocessing

Current WiFi standards like 802.11n and 802.11ac use Orthogonal Frequency Division Modulation (OFDM) for their physical layer. In OFDM, the channel is divided into multiple subcarriers and the data is transmitted over the subcarriers using the same modulation and coding. The CSI information represents the amplitude and phase information of the OFDM subcarriers. It is a complex-number matrix that shows the Channel Frequency Response (CFR) of each individual subcarrier for all spatial streams. The raw CSI data can be considered noisy for direct use in person identification. Specifically, there are two types of noise we are interested in removing - (1) distant multipath and (2) high-frequency noise due to other movements.

(1) Distant multipath removal: Distant multipath is a result of reception of a strong signal due to reflection from a distant object or person. For example, in case of WiWho, such reflection can be due to person moving far away from the room where CSI is collected. The distant multipath can cause the observed CSI profile to vary in a non-deterministic manner which can affect the gait analysis. To address this, we remove the distant multipath from the CSI data. Note that the CSI contains CFR for 30 subcarriers which includes the distant multipath. We first convert the CFR to Channel Impulse Response (CIR) which provides the delay profile of signal reception. An example CIR is shown in Fig. 5a which contains distant multipath components after the delay of 1 microsecond. We remove the multipath components that have delay more than 0.5 microseconds, and convert the CIR back to CFR using FFT (Fast Fourier Transform). Note that this threshold is chosen based on the multipath delay characterization provided in previous studies such as [24]. The multipath removal allows us to focus on the reflected paths within a room which is necessary for fine-grained analysis of gait.

(2) High-frequency noise removal: Another important noise removal procedure in our case is to eliminate the high-frequency noise from time-domain CSI signal. The walking activity of a person typically exhibits energy in 0.3 Hz to 2 Hz [25] frequency band. This is attributed to arm and leg movements while walking which is known to happen at no more than 2 Hz frequency. In order to distill the step cycles from the time-series CSI data, we apply a butterworth band-pass filter with cutoff frequency of 0.3 Hz to 2 Hz. Such filter also removes the static DC component.

Note that the high-frequency filtering is only necessary for step analysis which finds the step cycles and performs step shape analysis. WiWho also performs walk analysis that extends to an entire walk segment (multiple steps). In the walk analysis, we are interested in studying the movement of body parts which may happen at a faster rate than 2 Hz. Hence, we will separately study different frequency bands (upto 10 Hz) for walk analysis in Section VI-C.

B. Walking Detection

As shown in Fig. 1, the first step towards identifying a person using CSI-based gait is to detect whether a person is walking or not. In this section, we discuss how we can detect walking activity using the CSI data and how we can distinguish it from other indoor activities such as standing, sitting, typing etc. Accurately detecting the walking activity will ensure that the gait-based person identification is only initiated when a person is found to be walking.

Our approach towards distinguishing various activities from the CSI data stems from accelerometer and gyroscope based activity recognition. Based on the previous research [25], [26] on this topic, different human activities can be identified using the frequency domain analysis of a person's movements. Typical indoor activities such as sleeping, standing, sitting, walking etc. show different characteristics in the frequency domain. These activities can be categorized as low or moderate intensity activities as shown in [25]. Since the walking detection needs to be performed constantly to check if there is any walking activity, the walking detection method should be simple and efficient. Leveraging simple features in frequency domain is ideal for the purpose.

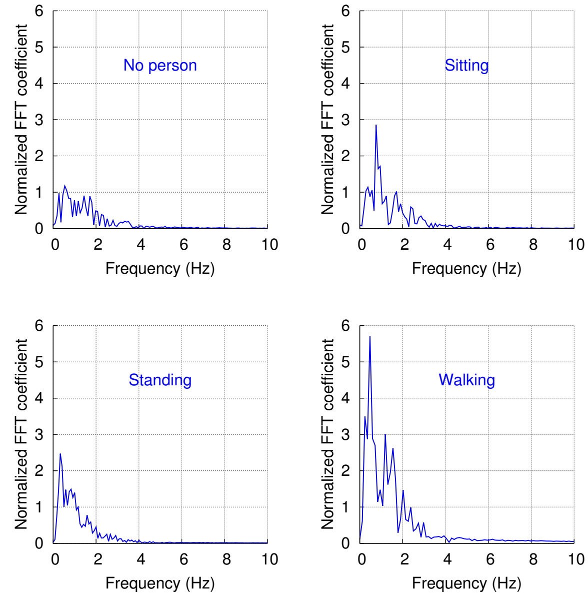


Fig. 6: Comparison of FFT coefficients for different activities

Note that the smart space scenario allows us to exclude the high intensity outdoor activities (driving, playing sports etc.) which in turn simplifies how we can detect if a person is walking or not.

To verify that frequency domain properties of different activities are also observed in the CSI, we perform experiments where (1) there is no person in the room, (2) a person is sitting and performing routine activities such as typing, moving objects on a desk, (3) a person is standing (without taking steps) using her phone, writing on whiteboard and (4) a person is walking. Fig. 6 shows the coefficients of the FFT profile for the four activities (without the DC component) observed by CSI data. As we can see, in the case where there is no person in the room, very low amplitude of FFT coefficient is observed in the low frequency band. Compared to that, sitting and standing exhibit higher amplitude values (more intensity) for the same frequencies. However, for the walking activity, the observed intensity in 0.3-2 Hz band is noticeably high. This is expected given that movement of legs and arms are known to move at that frequency while walking.

To represent the FFT profile of different activities, we use a metric referred as motion energy [25]. The motion energy (or simply energy) can be calculated as

$$\text{Energy} = \sum_{i=1}^{\text{window\_length}/2} \text{magnitude}^2 \tag{1}$$

where magnitude values are the normalized Fast Fourier Transform (FFT) coefficients calculated over the time window. Fig. 5b shows the observed energy for the four activities for

2 people. Since energy observed during walking activity is much high compared to sitting and standing, we use calculated energy as a way to detect if the person is walking or not.

VI. Person Identification using CSI-based Gait

As shown in Fig. 1, the CSI-based gait analysis of WiWho consists of two parts: (1) step analysis and (2) walk analysis. In this section, we first describe the features used for both the parts, and then explain how they are used for step and walk analysis to construct a gait pattern profile. The result of overall gait analysis is used for person identification.

A. Constructing CSI Features

Designing the feature space that can capture a person's walking gait is challenging because CSI includes amplitude and phase values for each of the subcarriers and spatial streams, and dimentionality reduction is necessary for a tractable analysis. In this work, we primarily focus on one spatial stream mostly due to significant similarity between the data from multiple spatial streams and to lower the computational cost.

Let $v_t = \{c_1, c_2, ..., c_s\}$ be the CFR vector for s subcarriers at time t. We first append additional statistics to v_t to generate v_t^* which includes v_t, and the maximum, minimum, mean, median, standard deviation, skewness and kurtosis of v_t. These statistics capture the shape (e.g. peakedness, symmetry, variation) of instantaneous distribution of CFR of all subcarriers. This process is repeated for each new sample of CSI data for the remaining of the feature calculation.

The features are calculated for a time window where the window can be for a step or for the entire walk segment. Table I describes the time domain and frequency domain features that are calculated for the window. These features are shown to be useful in accelerometer-based activity classification in [25]. For a window of size T, features of the table are calculated for each subcarrier and its statistics included in v_t^* for all $t \in T$. These features enable detailed time and frequency analysis of CSI data for a time window. We include the frequency domain features such as entropy and energy as they profile the walking activity inside the time window with high accuracy. Note that the choice of time window depends on whether we are analyzing individual steps or a walk segment. To evaluate the impact of these features on person identification, we use Information Gain(IG) [27] as a metric. Fig. 7 shows the top ten features we use to conduct per-step and walking analysis. The average IG value of selected features for walking analysis is higher than the features for per-step based analysis. We observe that the high IG features for walking consist of many frequency domain features, however, for per-step analysis, the high IG features are mostly time domain features.

• **Time domain:**
- Minimum (Min); min10th; maximum (Max); max90th; mean; variance (Var); standard deviation (Std); range
- CV: ratio of standard deviation and mean times 100; skewness (3rd moment); kurtosis (4th moment)
- First, second and third quartiles
- Inter Quartile Range (ICR): difference between the third and the first quartile
- Mean Crossing Rate (MCR): number of times the signal crosses the mean value)
- Area under the signal curve (Area) and autocorrelation
• **Frequency domain:**
- Energy: measure of total energy in all frequencies (Equ. 1)
- Entropy: measures the impurity in the CSI signal
- DomFreqRatio: calculated as the ratio of highest magnitude FFT coefficient to sum of magnitude of all FFT coefficients
- FFTPeaks: 5 largest frequencies in the signal and their magnitude

TABLE I: Time window features

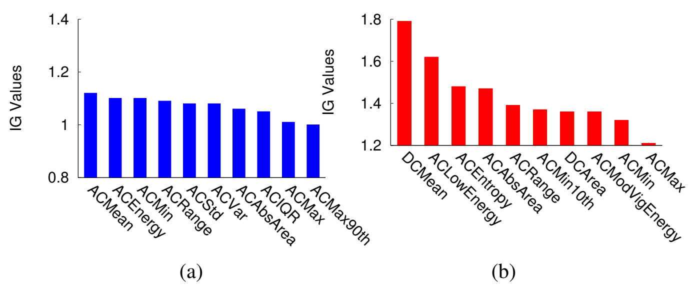


Fig. 7: Information Gain value of selected features for (a) step and (b) walk analysis, where AC means the features are calculated after a band pass filter of 0.3Hz to 2Hz and DC means processing using a low pass filter of 1Hz.

B. Analyzing Person's Steps

The step analysis evaluates how steps differ from person to person as observed by CSI. Previous research [5] has shown that the *shape* of the step varies noticeably for different people. This has led to design of person authentication methods [19] where smartphone's accelerometer signal is analyzed to differentiate between people. The challenge with the use of CSI is that the shape of a typical step of a person is highly dependent on the static multipath of the environment. The shape of a person's step changes at different locations in a room depending on the multipath at that location. When the person walks from one point to another point in a room, the shape of steps also change depending on relative position of WiFi endpoints and changing in multipath.

Step Cycle Construction: The step analysis requires finding the step cycle of the first step. However, finding the step cycle is not trivial. Let us consider that we have a time-series CSI data starting from time T_s to T_e. The number of steps taken during the time period is unknown and we would like to find out the step cycle of each step in the time period. One possible solution is to create step template of different people from the training data and compare it with CSI data in $(T_e - T_s)$ window using Dynamic Time Warping(DTW) to find out the step cycles. However, this requires a brute-force, since every person's step template has to be compared with current window. Such brute-force incurs a prohibitively large computation cost given that DTW requires solving an optimization problem with dynamic programming. Further more, due to the step shape for each person will vary at different locations along the walking path, such template matching method will have a very low accuracy for constructing step cycles.

Instead of using DTW, we rely on a peak-valley detection algorithm for step cycle construction. The peak-valley detection algorithm uses local minimum and maximum of time-series

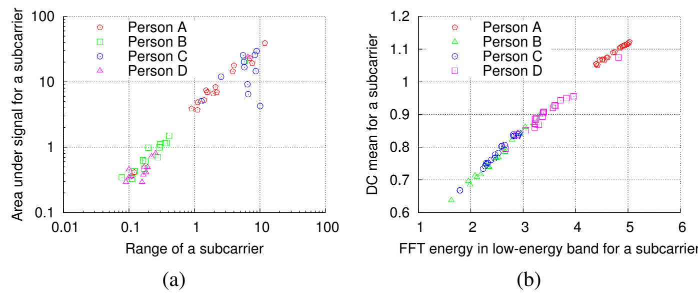


Fig. 8: Selected features for (a) step and (b) walk analysis

data along with the significance constraint [28]. Using this method, we denote the time from the start to the first valley to be the duration of the first step (Fig. 2). Immediately after we have detected that a person is walking, we start detecting the step cycle. We also set up an expected step cycle time range of 0.8s to 1.8s [29]. If we detect a step cycle which is less than 0.8s, we will further include the next peak or valley. If the detected step cycle is greater than 1.8s, we will start a new detection. The duration of the first step is then used to detect the rest of the step cycles. This assumes that the step duration does not vary significantly during the walk segment. This is reasonable since we assume that person walks on straight line path without any turns or breaks. Note that peak-valley detection algorithm does not detect trivial peaks/valleys since the input CSI data is already filtered to remove high-frequency noise.

Per-Step Feature Calculation: After the step cycle of each step is determined from the input walking segment, the CSI data in the time window of each step is used to calculate the features. We first apply the 0.3-2 Hz band pass filter to remove high-frequency noise, and then calculate the time domain features of Table I. We do not calculate frequency domain features as they provide only a little information within a small time window. The time domain features represent the shape of the person's steps in the form of statistics. Given that the shapes of different people's steps are likely to be different even at the same location, this will allow us to perform step based person identification. Fig. 8a shows how two of the features - area under the curve and range - are different for the steps of different people. The results are shown for one representative subcarrier only which is not enough for classification, but all the features calculated for all subcarriers provide sufficient information for identifying the person.

C. Analyzing Person's Walk

The step analysis helps in identifying the typical pattern of each step of a person. However, it can not capture the overall walking behavior that changes at a time scale faster or slower than the step duration. For such analysis, it is necessary to perform frequency domain analysis in order to understand various other characteristics such as the amount of energy in the walk segment across different steps, high frequency movement such as movement of arms, minor posture changes and etc. Such characteristics found using walk analysis can also help us to distinguish different people along with the step analysis. To perform the walk analysis, we calculate the features presented in Table I for the entire walk segment. For calculation of frequency domain features, we first identify three activity bands (subset of bands proposed in [25]) as

(1) Low-energy band: 0 - 0.7 Hz
(2) Activity band: 0.3 - 2 Hz
(3) High-energy band: 0.7 - 10 Hz

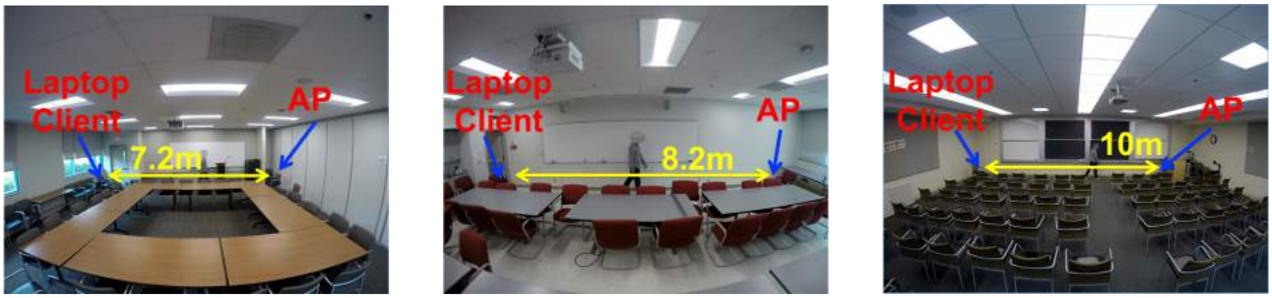
The low-energy band has been found to be useful to profile slow-moving activities such as posture change. It also includes the static DC component. The activity band is of primary interest as it identifies the impact of arm and leg movement while walking, and the energy (intensity) by which a person performs these activities. The high-energy band mostly captures the fluctuations in the CSI that is caused by movements of the person that are much faster in time. The frequency domain features of Table I are calculated for all three bands described above, while the the time domain features are only calculated for the activity band. These features characterize each person's walking behavior which will be used along with the step analysis to construct a complete gait pattern profile for person identification. Fig. 8b shows the effectiveness of the frequency domain features applied to three frequency bands. It plots energy in the low-energy band along with the mean of DC component to show that such features can distinguish different people based on the pattern of their walking segment.

Apart from these features of step and walk analysis, we also include one additional statistic for each person which is number of steps per second captured by CSI. This represents the walking speed of each person.

D. Person Identification using CSI-based Gait

After calculating step based features and walk segment features, we combine them to build a complete gait pattern profile for individual person. Note that in order to reduce the computation when the walking segment is long, WiWho only considers first few steps for step analysis.

WiWho uses decision tree-based machine learning classifier to identify people based on the step and walk analysis. The procedure to train the classifier requires the same set of features as for the testing phase. In the training phase, a person walks on a pre-determined straight line path for a certain number of times. The CSI data is collected for these instances and features are calculated. The process is repeated for all the people who would like to be identified in the smart space (e.g. home, office). As mentioned before, the person identification classifier is specific to a given room in a home or an office. This is because the changing the room and location of WiFi endpoints changes the observed multipath, which in turn affects how a person's step is observer through CSI. However, since the location of WiFi endpoints do not change in a smart space once they are deployed, the classifier is only required to be trained once for that location for all people. Since different locations might have different constraints on indoor space and possible length of walking segments, we will evaluate the performance of WiWho in the cases where person can walk for only a few steps in Section VII.



(a) (b) (c)

Fig. 9: Location (a)1, (b)2 and (c)3 layouts and device setup

We note that machine learning algorithms other than decision tree can be used in order to improve the identification performance. However, our objective in this work is to demonstrate the feasibility of person identification using CSI-based gait, and we leave the further optimization of performance to future explorations.

VII. Performance Evaluation

A. Implementation and Experiments

Devices and Setup: We implement WiWho using off-the-shelf commercial WiFi devices. Our setup consists of an AP-client pair. The AP is Asus RT-AC66U 802.11n WiFi router which has 3 external omnidirectional antennas. The client is a Dell laptop equipped with Intel 5300 802.11n WiFi NIC with 3 external omnidirectional antennas. The laptop runs Ubuntu 10.04 LTS with modified Intel driver and firmware [30] to collect the CSI data. In our setup, the pair of WiFi devices constantly communicate with 100 ping packets per second to retrieve CSI at that sampling rate. Note that the active data traffic generated by other WiFi devices have little impact on our system. Our experiment is conducted during working hours of the university. For each packet, the laptop records a CSI sample with CFR of 30 subcarriers. We implement both online and offline versions of WiWho which include preprosseing, gait analysis and person identification modules with over 3000 lines of Python code.

Experimental Scenarios: Since our primary focus in this work is smart spaces such as homes and offices, we choose three different indoor locations for our evaluation. All the three location layouts are depicted in Fig. 9. The three chosen rooms have different sizes and furniture layouts. A total of 20 volunteers were chosen to collect their CSI while walking in the three locations. The walking path is in parallel to AP-client LOS link at a distance of 1m. We consider different group sizes starting from 2 to 7 people at each location. These group sizes were chosen based on the typical number of people sharing a home (3-4) or a small office (5-7). For each group size, we conduct the experiments for 10 different combinations of people. In each combination, every person of the group walks along the pre-determined path (as shown in Fig. 9) in a round-robin manner for 20 times. Note that we do not ask people to remain constant speed while walking. The experiment lasted for 4-7 hours and the consistency of CSI profile over time is reflected in our date set. These experiments result in over 180 combinations of people with different group sizes at different locations.

A person's walking pattern is known to depend on her height, weight and age [5]. In our experiments, we selected 20 volunteers with both male and female, age from 22 to 32, height from 5'4 to 6' and weight from 120 lbs to 190 lbs.

Evaluation Metrics: We will use the following metrics in evaluation of WiWho.

(1) True Positive Rate (TP rate): TP rate of identification of person A is the fraction of walking instances of person A that are correctly identified as person A. The overall *accuracy* of person identification is the weighted average of TP rate of all the people in consideration.

(2) False Positive Rate (FP rate): FP rate of identification for person A is the fraction of walking instances that are incorrectly identified as person A.

Apart from TP and FP rates, we will use confusion matrix to detail how many times each person gets incorrectly identified as (which) other person. In a confusion matrix, the rows indicate the true identity of the person and columns indicate the identity as predicted by WiWho, and each element of the matrix is the fraction of the times the person in the row was classified as the person in the column.

B. Walking Detection Validation

It is crucial for WiWho to detect the start of walking activity from relatively stationary environment. Before performing the gait analysis, WiWho has to recognize that either a person entered the smart space or a person who was sitting or standing with relatively low movements started walking. When the walking is correctly recognized using the techniques presented in Section V-B, the person identification module can be triggered to identify the person walking. An important expectation from WiWho is that it detects that person is walking in a very short time. This evaluation of detection time and average walking detection accuracy is shown in Fig. 10. We observe that even at 0.2 second detection time, WiWho can detect the walking activity with 92% TP rate and 6% of FP rate. It can detect the walking with 97% TP rate just after 1 second of start of the walking activity. After 4 seconds, the accuracy of detection is 100%.

Fig. 11 shows the confusion matrix for walking activity detection at 0.6 seconds. We observe that walking is often mis-classified as standing with 15% of standing is mis-classified

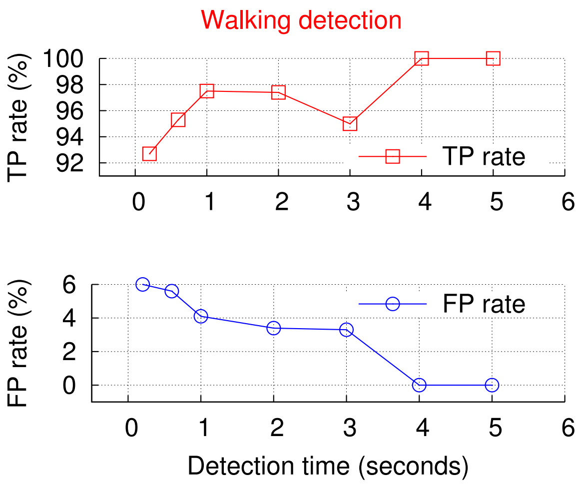


Fig. 10: TP rate and FP rate of walking detection

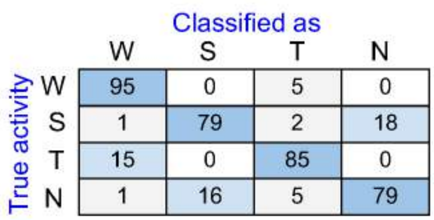


Fig. 11: The confusion matrix of walk detection with 0.6 second detection time. W is walking, S is sitting, T is standing and N is without person

as walking and 5% of walking is mis-classified as standing. This is expected since standing and walking both require the person to be in the same posture and standing is necessary before starting the walk. Since a typical step takes nearly a second for completion, 0.6 second of detection time allows us to capture the gait starting from the first step itself. We choose 0.6 second detection time in the rest of the implementation as it already achieves 95% detection accuracy.

C. *Person Identification with Different Group sizes*

In this section, we will evaluate the performance of person identification with different group sizes. As we discussed, the application of WiWho is targeted towards smart homes and offices, we only consider group of people in the range of 2 to 7. For each of the group size, WiWho uses gait analysis (step and walk analysis) to detect the person's identity. Fig. 12 shows the average accuracy and FP rate of person identification with different group sizes for the 3 locations. We observe that as the group size increases, the accuracy of person identification decreases for all 3 locations. This is expected since introducing more people in person identification increases the chances of people having similar gait. For the same reasons, the average and maximum accuracy of person identification is as high as 92% and 97% respectively with the group size of 2 (binary classification). The average accuracy decreases to 75% when the group size of 7 is considered. WiWho achieves nearly 80% of person identification accuracy for group size of 6 or lower for all 3 locations.

Person	A	B	C	D	E	F
Height	5'10	5'7	5'6	5'7	5'8	5'6
Weight(lbs)	175	130	170	145	125	165
Gender	M	M	M	M	F	M
Age	30	30	28	27	30	29

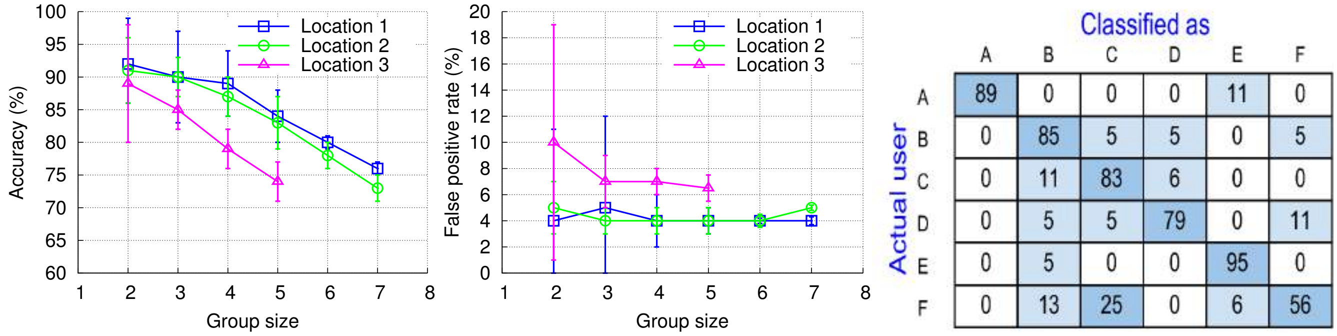
TABLE II: Characteristics of 6 volunteers

It is observed from Fig. 12b that the FP rate of person identification varies only a little with the variation in group size. For Locations 1 and 2, the average FP rate remains lower than 6% irrespective of the group size, and for Location 3, the average FP rate is observed to be close to 8%. It can be claimed that for smart space applications in homes and offices where typical group size is close to 5 people, WiWho achieves high accuracy of person identification while meeting the design goals.

Now we take a further look at the confusion matrix for the case of group size of 6 people. The confusion matrix is presented in Fig. 12c. It is known from the previous research [5] that a person's gait is loosely correlated to his/her height, weight and age. Table 2 provides these characteristics for the 6 volunteers to understand the misclassifications in the confusion matrix. It can be observed that person F and person C have similar height and weight which can be related to frequent misclassification of person F to be person C. From the confusion matrix, it can be said that person E is found to be most uniquely identifiable among the group. From Table 2, we notice that E is the only female in this group. In general, we claim that identification using CSI-based gait have similar properties as the acclerometer-based gait in terms of overall accuracy.

D. *Step Analysis vs. Walk Analysis*

As discussed before, the gait analysis in WiWho is a combined module of step analysis and walk analysis. In this section, we show how well the step and walk analysis modules can perform person identification individually. The walk analysis does not require the walk to be divided into steps, however, it requires FFT computations for frequency domain analysis (Section VI) of the walk segment. The step analysis requires step cycle construction and calculation of time domain features for each of the detected steps. Fig. 13 compares the identification accuracy for only step or only walk analysis, as well as the combined performance. It is observed that walk analysis individually works better to identify different people compared to step analysis. The step analysis applied individually achieves lower accuracy of person identification. This can be attributed to the fact that CSI provides more information on how person walks and body movements during the walk (frequency analysis of walk segment). In all cases, we observe that the combined analysis always improves the accuracy ($\approx 5-10\%$) over simply using walk analysis which means that both step and walk analysis modules are essential to achieve high person identification accuracy.



(a) (b) (c)

Fig. 12: (a) The accuracy and (b) FP rate for person in identification with different group sizes (c) The confusion matrix of person identification with 6 people

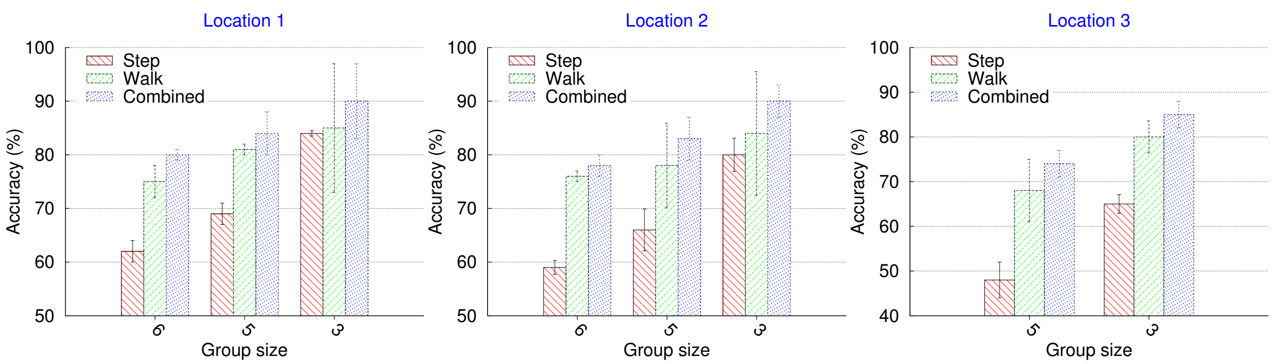


Fig. 13: The performance with different feature calculation methods and different group size at different locations

E. Robustness with Different Walking Lengths

Another important factor in evaluation of WiWho is that the length of walking segment that a person walks. In practical scenarios, the layout of rooms and indoor spaces impose the restriction that a use can walk only few steps without taking a turn. We evaluate this situation using experiments at Locations 1 and 2. Specifically, we repeat the experiments of Section VII-C with a restriction on the distance a person can walk before getting identified. The experiments are repeated at for group size of 3, 5 and 6 (10 rounds each). The length of walking segment is set to multiples of 2.4 meters ($\approx$ 4 steps) and 2.7 meters ($\approx$ 5 steps) for Location 1 and 2 respectively. The results of person identification accuracy are shown in Fig. 14. The accuracy either increases or remains similar with increase in the length of walk segment. This means that WiWho can identify person with high accuracy even with CSI data for a few steps, increasing its applicability in space-constrained indoor environments.

VIII. Discussion and Limitations

We now discuss the potential, challenges and limitations of our WiFi-based person identification system.

(1) Feasibility: Our system requires fixed deployment of both AP and the associated client. We believe that this does not pose any issue since in typical scenarios, change in the position of an AP is rare and it is possible to use stationary WiFi devices (such as a smart TV) as the client. We also assume that a person always walks on a straight line path. In a home or an office environment, a straight walkway such as a corridor or hallway can be chosen for the purpose, where a person can get identified at the same time when she enters the home/office. Changes in a person's attire (e.g. clothes, shoes etc.) should not affect system's performance, however, we have not studied the impact of other factors that can result in changes in person's gait (for example person carrying a heavy backpack or injured limb).

(2) Detecting a person outside the group: We also evaluate WiWho to detect if a person is not within the training group. WiWho can achieve over 80% accuracy to detect whether the person is "stranger" or not for a group size of 4 or less.

(3) Number of people: Majority of WiFi-based sensing research assumes a single person system like ours. However, this limitation is less severe in our case since it can be assumed that WiWho is deployed in a hallway or a corridor where typically only one person enters the premises at a time.

(4) Diverse set of people: WiWho is currently evaluated only for the age group of 25-30 years. Previous research such as [5] has shown that a person's gait is dependent on the person's age which means that the attainable accuracy of WiWho is likely to be higher when evaluated with other age groups (e.g. kids or elderly people).

IX. Conclusions

In this paper, we presented WiWho, a framework for identifying a person using the gait information detected via

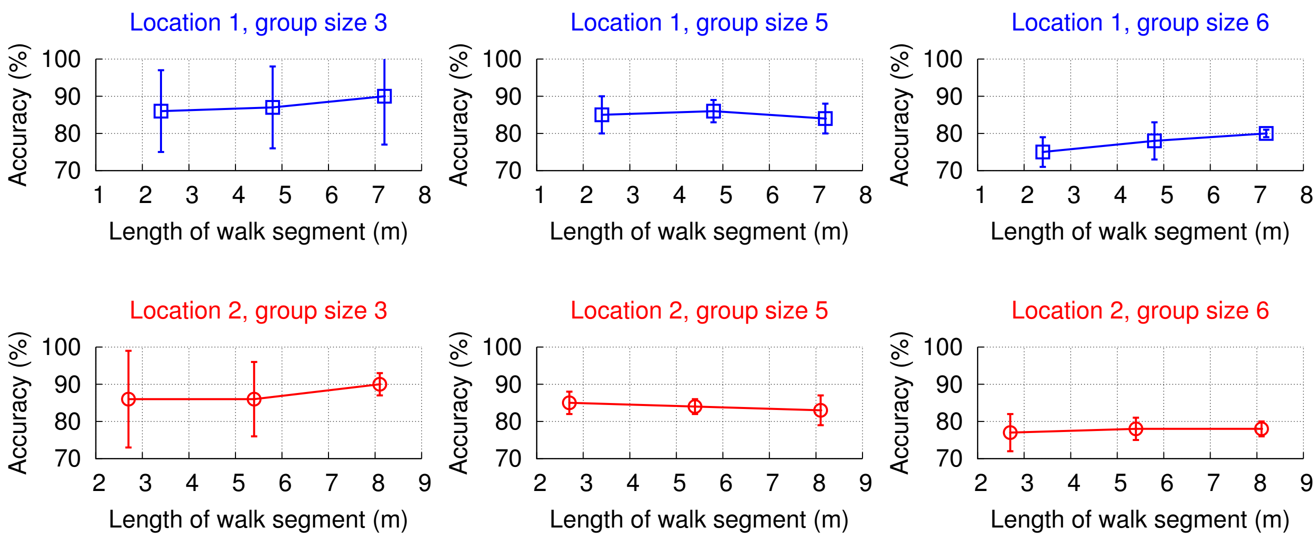


Fig. 14: The accuracy of identification for different group sizes with different walking lengths

WiFi. WiWho enables a device-free, effortless, low-cost and pervasive solution for person identification in smart homes and offices. We showed the feasibility of gait identification through CSI and discussed necessary characteristics of CSI-based gait that can identify a person. WiWho achieves an identification accuracy of 92% to 80% for a group size of 2 to 6 respectively and only 2-3 meters walking length is necessary. The limitations and potential of WiFi-based person identification system are also discussed.

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