Peripheral WiFi Vision: Exploiting Multipath Reflections for More Sensitive Human Sensing

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ABSTRACT

A large amount of energy could be saved by detecting home occupancy and automatically controlling the lights, and HVAC. Existing occupancy sensors can detect the motion of people but cannot detect people when they are stationary. In this paper, we present a system called Peripheral WiFi Vision (PeriFi), which exploits multipath reflections as individual spatial sensors to increase the sensitivity of the conventional approaches. PeriFi analyzes each multipath component independently, increasing sensitivity so it can directly sense both moving and non-moving occupants.Our evaluations for 6 physical configurations with 11 different occupancy states show that PeriFi can achieve 96.7% accuracy, which translates to nearly 30% improvement over the conventional approaches.

Keywords

WiFi, occupancy detection, CSI, multipath propagation

1. INTRODUCTION

Human presence sensing has significant potential to provide monetary and environmental benefits by saving energy. Motion sensing is often used for lighting control and, although current systems often turn off the lights when occupants are not in motion, these errors can easily be fixed by moving or waving at the motion sensor. However, they would cause major comfort issues with heating and cooling control due to the thermal inertia and resulting time lag. The ability to automatically control air conditioning has been available for over hundred years, but the potential energy saving have not been fully realized due to lack of a sensing system that can detect human presence, and not just human motion.

Recent advances in wireless techniques such as MIMO-OFDM have extended its use beyond simply a communication medium to that of a device-free human sensing tool. The previous works that have explored the possibility of inferring occupancy from WiFi signals [13, 8, 12, 7] focus on detecting motion of the target and measure the temporal variations of WiFi signals caused by target movements as an indicator of occupancy. However, they suffer from high false negative rates since they cannot differentiate an unoccupied room from a non-moving person. Rich multipath distortions in indoor environments is one of the main challenges of these systems, causing the signal disturbance produced by people to be swamped in the noise distortion subspace due to destructive interferences. This limitation is particularly problematic for long sedentary activities such as movie watching or sleeping.

To address this problem, we propose a new technique called *Peripheral WiFi Vision (PeriFi)*: using multipath signals to increase the sensing area and sensitivity levels of WiFi sensing. The basic approach is to resolve multipath reflections and leverage each path as an individual sensor, rather than treating it as just a distortion. The intuition is that analyzing each path independently allows more sensitive detection of disturbances caused on weak Non-Line-Of-Sight (NLOS) signals which would otherwise be swamped by the strong Line-Of-Sight (LOS) signal when looking only at the aggregated received signal. This allows the approach to be more sensitive to small movements of a stationary target. In addition, people affect the multipath reflections even when they are perfectly still, while other approaches require the person to be moving.

Instead of any special wireless hardware, we leverage on the ubiquity of commodity WiFi devices. The presence of several WiFi-enabled devices or plug-in modules deployed in every room of a home creates a wireless mesh, which can serve as a sensor network and provide rich information about the environment. To sense the person's presence, PeriFi firstly characterizes the multipath environment of an empty room by using subspace

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methods [5, 9], which perform eigenspace analysis of the signal's correlation matrix. Then, it looks for changes in that multipath environment such as (1) multipath variations in a time window caused by a moving person, or (2) multipath attenuation and reflections caused by a stationary (sitting or standing) person. To capture these changes, PeriFi employs supervised classification models with one-time training.

To implement PeriFi, we leverage the PHY layer Channel State Information (CSI) provided by commercial WiFi cards, which offer fine-grained channel responses at the granularity of OFDM subcarriers. We evaluate PeriFi in 6 individual physical configurations with 11 different occupancy states resulting in 66 individual conditions and 96 minutes worth of data. Our extensive analysis and experiments show that the relative phase information and multipath characteristics play a key role in determining the occupancy specifically if the target is stationary or completely still. Also, results indicate that PeriFi can detect occupancy with 96.7% accuracy, compared to the conventional solution with 56.1% and 76% accuracies.

2. RELATED WORK

Device-free passive detection with WiFi signals have drawn much attention in the past years. Recent works focus on fine-grained PHY layer CSI as a promising substitute for MAC layer RSSI. We can categorize these works into three main approaches: fingerprint-based, threshold-based, and respiration-based. Unlike PeriFi which analyzes the multipath signals individually, all of these approaches look at the aggregate CSI values, which makes them less sensitive to fine movements without relying on scenario-specific calibration.

The fingerprint-based approaches [13] measure the similarity of CSI fingerprint of an occupied room with the reference unoccupied condition. The intuition behind this technique is that the disturbance of CSI values created by human motions reduce the similarity between occupied and unoccupied fingerprints. However, similar to any fingerprinting approach, they require a large database of all occupied scenarios in different locations, which is practically impossible due to random movement behavior of occupants. The threshold-based algorithms [8, 12, 7] define an individual metric as a threshold line to differentiate occupied and unoccupied conditions based on the temporal correlation of CSI values [8, 12], or the correlation of CSI values over multiple frequencies [7]. Although these algorithms are fairly accurate in detecting human motion, they are incapable of detecting stationary or still occupants since the fine or even absence of the target movements causes no measurable temporal or frequential variation of WiFi signals.

Apart from the above works, DeMan [12] proposed respiration rate as a metric to detect stationary target by justifying a sinusoidal model and looking for desired breathing frequency component in the signal. Although the performance of this method is promising in extremely controlled scenarios, small body movements or the working distance range limit the performance and make it impractical for occupancy detection. Besides these WiFi-based occupancy detection method which use commodity devices, there some high resolution breath detection [2], and device-free localization [1] systems, which require specialized bulky hardware and radar techniques such as FMCW, thus cannot be implemented by commercial products. We build PeriFi upon noise-subspace methods [5, 6] to capture multipath reflections. Although these methods focus on better estimation of the LOS signal by discarding the NLOS signals, PeriFi leverages all multipath components and use each as a spatial sensor to infer occupancy.

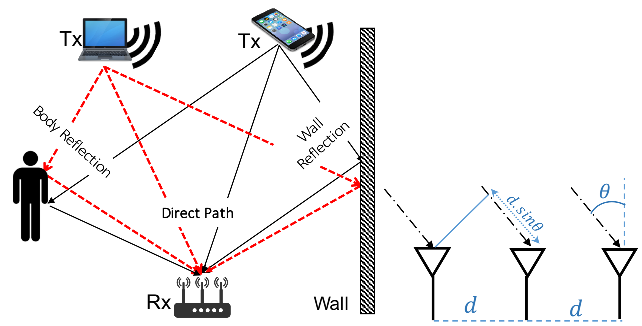

Figure 1: an illustration of (left) multipath propagation in the presence of a target, and (right) additional phase shift of the incident signal in the second antenna.

3. PERIPHERAL WIFI VISION

Complex indoor environments cause wireless signals to propagate along multiple paths, reflecting off of walls, furniture and human body (shown in Figure 1). The received signal is the combination of all these paths, thus suffering from multipath interference. In the occurrence of destructive inferences, the human body disturbance may be canceled out in the aggregated signal. In addition, the properties of the received signal are dominated by objects in the Fresnel zone of the LoS path, resulting in a linear sensing region despite the omni-directional nature of the antennas. So, in the presence of an occupant in the NLoS area, the resulting disturbances are weak and can be swamped by the LOS signal when looking at the aggregate value.

To address this challenge, we leverage multipath reflections and analyze them independently to provide peripheral WiFi vision. Each of these paths reveals information about a different part of the physical environment and acts as an additional sensor. This increases sensitivity by allowing LoS and NLoS paths to be analyzed independently, thus can differentiate between empty room and an occupied room with a stationary or completely still target. We further improve the sensitivity of this approach by leveraging the presence of several WiFi-enabled devices in a building. PeriFi takes

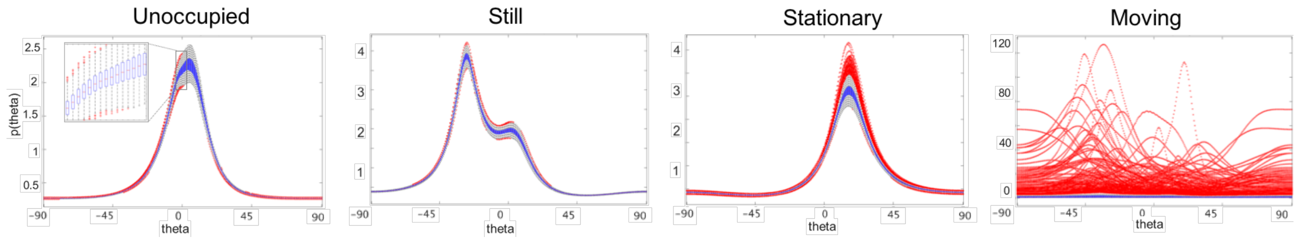

Figure 2: PeriFi detects different occupancy scenarios based on changes in multipath characteristics of empty room as well as stability of AoA spectrum in each angle.

advantage of these spatially diverse WiFi components such as personal computers, smart TV, or thermostats to create a wireless mesh that covers the home and can view different aspects of a target simultaneously.

PeriFi leverages the PHY layer Channel State Information (CSI) provided by commercial WiFi cards. CSI provides a small version of fine-grained channel frequency response at the granularity of OFDM subcarriers. While previous studies [8, 13] show that CSI suffers from arbitrary phase offsets due to Packet Detection Delay (PDD) and Sampling Time Offset (STO), we show that the effect of these noises can be eliminated by converting raw CSI values into multipath components. The intuition behind this idea is that the novel multipath resolution methods [6, 5] leverage multiple subcarriers of a WiFi channel to eliminate phase offsets caused by STO, and PDD, thus providing more accurate estimation of the stationary environment. The details of our data preprocessing method are explained in Section 3.1.

Similar to threshold-based algorithms, PeriFi requires a prior multipath characteristics of the environment with no human presence. However, unlike fingerprint-based approaches, it doesn't need scenario-specific calibrations for all possible occupancy states. So, in the first step, PeriFi characterizes the multipath components of an empty room for each Tx-Rx link and converts each path into multiple features over both time and space such as the power, Angle of Arrival (AoA), and relative Time of Flights between paths (rToF). Then, in a sliding window fashion, PeriFi monitors and scans these paths multiple times per second and uses a classifier to detect the presence of people. The details of multipath resolution algorithm and extracted features are explained in Sections 3.2 and 3.3, respectively.

3.1 Data Preprocessing

Leveraging OFDM and MIMO technologies in the current WiFi standards such as 802.11n, the commercial WiFi cards can provide the overall attenuation and phase shifts of the transmitted signal introduced by the channel. This information is represented in the form of CSI in the granularity of 30 subcarriers for 3 antennas,

$$CSI\ Matrix = \begin{bmatrix} csi_{1,1} & csi_{1,2} & \dots & csi_{1,30} \\ csi_{2,1} & csi_{2,2} & \dots & csi_{2,30} \\ csi_{3,1} & csi_{3,2} & \dots & csi_{3,30} \end{bmatrix}$$

where $csi_{m,n}$ is the CSI of m^{th} antenna and n^{th} subcarrier, which includes the received signal from all paths.

Each CSI value depicts the amplitude and phase responses of the channel. Although CSI phase values are more sensitive to small changes in the environment, they are prone to arbitrary errors caused by PDD and STO. To address this issue, we leverage the constant behavior of STO across antennas and the linearity of this offset across subcarriers. On the other hand, our observations from extensive experiments [10] show that the CSI phase is significantly noisy in the frequencies with destructive interference. So, we sanitize the phase values by using a similar technique as in [5], but for a portion of subcarriers with no deep fading.

3.2 Resolving Multipath Propagation

Our approach to resolve multipath components builds on well-established noise-subspace methods such as MUSIC [9]. The basic idea is that each propagation path is received with a specific AoA, which introduces a corresponding phase shift across the antennas due to the extra travel distance (shown in Figure 1). The introduced phase shift of k^{th} path with AoA of θ_k at m^{th} antenna is denoted as a function of AoA:

$$\phi(\theta) = e^{-j2\pi f d \sin(\theta)/c} \tag{1}$$

where d is the distance between antennas, c is the speed of light, and f is the frequency of the transmitted signal. The MUSIC algorithm uses this information and creates a measurement matrix X based on the received signal across antennas as:

$$X(t) = [x_1(t), ..., x_M(t)]^T = a(\theta)s(t) + N(t) \tag{2}$$

where M is the number of antennas, $s(t)$ is the received signal vector at the first antenna and $N(t)$ is the noise vector. $a(\theta)$ is called the steering vector and expresses the phase differences at the antenna array:

$$a(\theta) = [1, \phi(\theta), ..., \phi(\theta)^{M-1}]^T \tag{3}$$

The MUSIC algorithm relies on the orthogonality of the eigenvectors of XX^H corresponding to the noise subspace and incident signals to compute the steering vectors and deduce the AoAs. To capture reflections from the human body, PeriFi builds on this foundational technique and combines it with new innovations.

A recently proposed extension of MUSIC called Dynamic MUSIC [6] has been demonstrated to identify the AoA of multipath reflections off a moving person based on its phase incoherence with other signals due to Doppler Shift. We leverage this technique for detecting moving targets by resolving these reflections and monitoring them individually.

To detect stationary targets, PeriFi characterizes the static reflections of an empty room and monitors their disturbances in the presence of a stationary or completely still person. For this purpose, we take advantage of AoA-rToF joint-estimation MUSIC methods [5] to fuse data across multiple subcarrier frequencies and increase the resolution of AoA estimation. We omit the mathematical derivations for brevity, but refer the reader to the reference paper [5]. Figure 2 illustrates the effect of a person's presence on the resolved AoA pseudo-spectrum for a sample experiment. The figure contains the variations of the power values for each angle across 1000 packets in a boxplot per angle. The comparison of the unoccupied spectrogram with others reveals that we can detect the presence of a person inside the room either with changes in the multipath components such as changes in the resolved angles in still or stationary scenarios, or with temporal changes caused by major movements in stationary or moving scenarios.

3.3 Feature Extraction

In addition to the multipath components extracted by Dynamic MUSIC [6] or SpotFi [5] algorithms, PeriFi uses some statistical features on relative phase values between antennas and subcarriers to capture temporal and frequential variations caused by human movements. Then, it uses a machine learning classifier to convert this high dimensional feature set into a single model to infer occupancy. In summary, we can categorize the defined features as follows:

- Temporal variations: 3 max eigenvalues of correlation matrix of successive measurements of CSI amplitude, phase, and relative phase.
- Frequential variations: 3 max eigenvalues of correlation matrix of subcarriers over multiple measurements.

Mean, max, min, median, STD, and entropy of:

- AoA, rToF, and power of 3 resolved paths by Spotfi and Dynamic MUSIC across packets.
- channel components across packets: subcarrier index and the SNR value of Deep fading, 3 abrupt change points in SNR pattern across subcarriers.
- channel variation factor for CSI amplitude, phase, and relative phase across subcarriers as

$$v = \sqrt{\frac{var(x)}{\frac{1}{M}\sum_{m=o}^{M-1}|x_m|^2}} \tag{4}$$

where x is the vector of CSI measurements with length M, and $var(x)$ is the sample variance of vector x. The denominator represents the RMS value of the vector x.

- entropy of CSI amplitude, phase, and relative phase across subcarrier.

4. EXPERIMENTAL SETUP

4.1 Implementation

To evaluate our PeriFi system, we employ two laptops equipped with Intel 5300 WiFi cards and 3 external antennas as the transmitter and receiver. The CSI tool [3] is installed on them to obtain the CSI phase and amplitude values of 30 subcarriers for each received packet per antenna resulting in a 3x3x30 CSI matrix. We conducted 6 experiments with different link conditions in a typical office building shown in Figure 3. The communications are operated in 5.63 GHz frequency band employing an unused 40 MHz channel.

Each experiment includes 4 different types of the occupancy states in both LOS and NLOS: (1)*empty*: when nobody is inside the room, (2)*walking*: when someone walks randomly near or far from the LOS, (3)*stationary*: when a person is in the room, but only has fine movements such as writing, (4)*still*: when the occupant is in the room, but completely still such as sleeping or sitting still. Each experiment includes multiple scenarios for each of these occupancy states, resulting in 11 different scenarios. A sample experimental setup is shown in Figure 3. Each scenario is conducted for 1 minute, resulting in 96 minutes of data in total. For the collection of CSI, the transmission rate of 100 pkts/s is chosen and a sliding window mechanism with 2-second time window and 1-second sliding is used.

4.2 Baseline

We compare PeriFi with two recent threshold-based methods that are widely used in the literature. Both of these techniques measure the correlation of CSI values for an empty room and define a threshold line to differentiate occupied and unoccupied conditions. The temporal-base thresholding algorithms such as PADS [8] and DeMan [12] apply eigen decomposition on the CSI correlation matrices of successive measurement to extract time dimension information and characterize the temporal variations of wireless signals caused by human motions. However, they cannot detect stationary or still occupants with fine movements. On the other hand, the frequential-base thresholding algorithms [7] use the subcarrier dimension information of CSI and extract the eigenvalues of the correlation matrices of subcarriers over multiple measurements. The observations show that there is a correlation among CSI changes across subcarriers in the presence of an occupant. In both of these algorithms, the threshold value is usually obtained by employing the well-known Support Vector

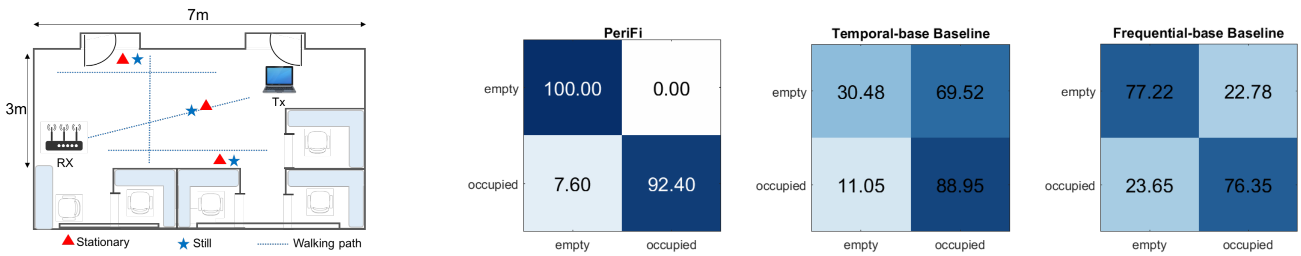

Figure 3: (Left) Floor plan and a sample experimental setup, (Right) PeriFi achieves 96.7% accuracy compared with 56.1% in temporal and 76% in frequential baseline.

Method (%)	Acc	FNR	FPR	F-Score
PeriFi	96.7	7.6	0	96.1
Temporal Base	56.1	11.1	69.5	63.8
Frequential Base	76.8	23.6	22.8	74.2

Table 1: Detailed performance comparison of PeriFi with two baselines

Machine (SVM) classification. To have a fair comparison, we use the same classification model to train PeriFi.

4.3 Evaluation Metrics

To detect home occupancy, PeriFi requires a WiFi module in every room of the home to form a wireless mesh. Therefore, the goal of PeriFi is to use all information gathered from multiple links for inferring occupancy. To address this requirement, we build one classification model for all 6 experiments to represent multiple links in home. In spite of previous works which require separate training for each link condition, PeriFi provides a generalizable and scalable solution to the size of homes. To evaluate the classification models, we use Leave-One-Scenario-Out (LOSO) to provide a calibration-free evaluation for different occupancy scenarios. In addition, we can evaluate the performance of the proposed system in detecting the occupancy of scenarios not seen in the training phase.

We measure the following metrics: (1) Detection Rate: the fraction of cases where the human presence or absence is detected correctly, (2) False Positive: where a false "human presence" is announced, (3) False Negative: where a false "human absence" is announced.

5. EVALUATION

Table 1 summarizes the performance of three methods based on accuracy, FNR, FPR, and F-Score. PeriFi performs 96.7% accurately compared with 56.1% and 76% in temporal and frequential baselines, respectively. Figure 3 elaborates these numbers in the form of a confusion matrices. We expect PeriFi to outperform the temporal and frequential baselines in differentiating empty states from occupied states with stationary or still targets, since it doesn't rely on temporal or frequential variations to detect occupancy. The results in Figure 3 show that PeriFi outperforms the baselines by 100% correctly detecting empty states, compared with 30% and 77% in the baselines. In addition, PeriFi achieves 92% accuracy in detecting occupied conditions including moving, stationary, and still scenarios, while the baselines only achieves 89% and 76%. In spite of PeriFi which performs accurately in differentiating the occupancy states, temporal baseline shifted the threshold line toward higher values, thus providing a higher accuracy in detecting occupied scenarios, while producing higher false positives. The frequential baseline could define the threshold line more balanced, however it couldn't correctly differentiate empty and occupied states in 20% of cases.

To better understand the reason of false negatives in all three approaches, we provide detection rates based on the type of occupancy states in Figure 4. As expected, all three algorithms could detect moving states 100% because of high disturbance. Low accuracy of temporal baseline in detecting empty states and frequential baseline in detecting still states indicate that a threshold-base method is not enough to detect little-movement occupants. On the other hand, PeriFi could provide a higher accuracy in detecting all types of occupancy, but it still misses 12% of low-movement still and stationary states. These misdetections could happen in scenarios where the target is not in the Fresnel zone of LOS path or any of the main reflections.

Finally, we categorize the detection rates based on whether the occupant's presence happened in the LOS or NLOS. As shown in Figure 5, PeriFi could enhance the sensing coverage by using the multipath reflections. However, it still has lower detection rate in NLOS conditions since the number of resolvable paths are limited by the size of antenna array. Although increasing number of antennas or links is a common solution for this problem, we believe part of this issue could be addressed by defining higher resolution features to detect chest movement in completely still occupancy states.

6. DISCUSSION AND FUTURE WORK

The analysis in this paper considers empty room as a static environment. Therefore, if the links conditions change such as replacement of the transmitter or receiver, or adding new links, the system requires to be

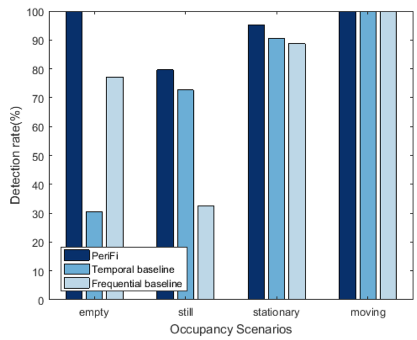

Figure 4: PeriFi achieves 93.75% averaged detection rate in all types of occupancy states compared to 74% and 72% in the baselines

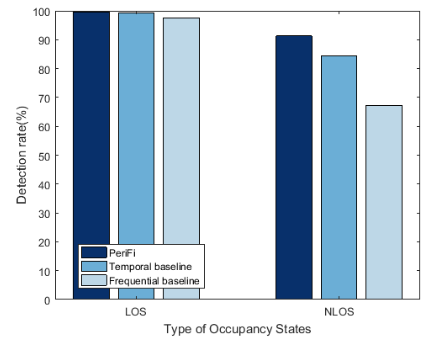

Figure 5: Although PeriFi outperforms the baselines in overall, it still has lower accuracy in NLOS conditions

recalibrated. However, to reduce the need of recalibration, we do not rely on portable devices such as cellphones and laptops. Instead, we use plug-in WiFi modules which will be deployed in every room. In addition, we didn't study the performance of our method in the presence of a moving object such as a fan or pets. In our future work, we will differentiate these conditions based on the differences in size of disturbances and breathing rates. For example, a moving animal will create low signal disturbance but high Doppler values and will affect a changing set of paths, while a stationary person will create low signal disturbance with low Doppler values, affecting only a fixed set of paths. In addition, in this paper we didn't study the effect of furniture movements. As our future work, we plan to design an automatic calibration model inspired from our previous work [11, 4] to detect empty room in offline mode and use that period to retrain the classification model.

7. CONCLUSION

In this work, we present an innovative approach for occupancy detection which converts distortions caused by multipath propagation to a useful sensing method. Our proposed approach addresses the challenge of detecting the presence of non-moving people and provides a single solution to infer home occupancy by using the concept of peripheral WiFi vision. Our analyses show that PeriFi can achieve 96.7% accuracy in occupancy detection with different occupancy scenarios including empty, moving, stationary, and still.

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