Device-Free WiFi Human Sensing: From Pattern-Based to Model-Based Approaches

Dan Wu, Daqing Zhang, Chenren Xu, Hao Wang, and Xiang Li

Abstract

Recently, device-free WiFi CSI-based human behavior recognition has attracted a great amount of interest as it promises to provide a ubiquitous sensing solution by using the pervasive WiFi infrastructure. While most existing solutions are pattern-based, applying machine learning techniques, there is a recent trend of developing accurate models to reveal the underlining radio propagation properties and exploit models for fine-grained human behavior recognition. In this article, we first classify the existing work into two categories: pattern-based and model-based recognition solutions. Then we review and examine the two approaches together with their enabled applications. Finally, we show the favorable properties of model-based approaches by comparing them using human respiration detection as a case study, and argue that our proposed Fresnel zone model could be a generic one with great potential for device-free human sensing using fine-grained WiFi CSI.

Introduction

Radio-based human behavior sensing has become an active research area due to the pervasiveness of such wireless signals. While most existing work focuses on device-based scenarios,[1] recently device-free sensing solutions have been increasingly popular because they significantly improve the usability and practicality of indoor applications, such as intrusion detection, elder care, and healthcare. The earliest work on device-free human sensing, called "sensorless sensing," was introduced by Woyach *et al.* in 2006 [1]. By observing human motion and the resultant signals in a wireless sensor network, Woyach *et al.* noticed that the motion of a human can cause a series of signal fading spots, and further demonstrated the possibility and promise of using wireless sensors for human presence detection in a contact-free manner. Soon after that, in 2007, Youssef *et al.* [2] experimentally verified that human motion causes variations on the received signal strength indicator (RSSI), and simple features like moving average and moving variance on RSSI can be used to detect human presence. They also demonstrated that it is possible to track people's location exploiting the fact that the RSSI patterns of different locations behave differently, and thus can act as a fingerprint to estimate a subject's probable location. Meanwhile, Zhang *et al.* proposed a geometric-model-based method of localization and tracking [3] by relating a link's RSS variance to its line-of-sight (LoS) location relative to the human subjects present. These early works show the possibilities that both the RF variation pattern and the physical model can be used for human tracking and localization. However, as the first step toward RF-based human sensing, these works are still relatively preliminary.

Exposed at the physical layer, channel state information (CSI) provides finer-grained information (with amplitude and phase) than RSSI [4]. With the CSI measurements accessible to the public in 2010 in commodity WiFi chipsets (Intel 5300, Atheros 9580, etc.), the research in WiFi-based device-free human sensing has accelerated. Some RSSI-originated human sensing applications, such as indoor localization [5], are enhanced with CSI information and gain great performance improvement. Many other human behavior recognition applications, which are hard to differentiate using RSSI, also benefit from the capability of fine-grained CSI, including gesture control [6], gait identification [7], fall detection [8, 13], tracking [9], activity recognition [10, 11], vital signs monitoring [12, 14], and so on. From a technical perspective, research efforts have been devoted not only to feature engineering and pattern classification (pattern-based approach) [5, 6, 8, 10, 12, 13] but also to modeling the relationship between signal space and human activity space [7, 8, 11, 14, 15] (model-based approach) to achieve more fine-grained human behavior sensing using WiFi signals. The above works can be categorized according to two dimensions: the problem domain and the solution domain, as shown in Fig. 1. While most of the works fall into pattern-based or model-based approaches, some [7, 11] use the combination of the two approaches as the solution.

In this article, we argue that while pattern-based approaches are intuitive and straightforward for coarse-grained sensing applications, more complex and fine-grained human behavior recognition requires a more general RF model to accurately characterize the relationship between human motion and the resultant signal variations. In this regard, we first introduce the Fresnel zone model for indoor human sensing, and would like to show the superiority of Fresnel-zone-model-based human sensing over pattern-based approaches. We argue that Fresnel-zone-model-based approaches have obvious advantages

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[1] Assume that human subjects will always carry the device on which the sensing task is performed.

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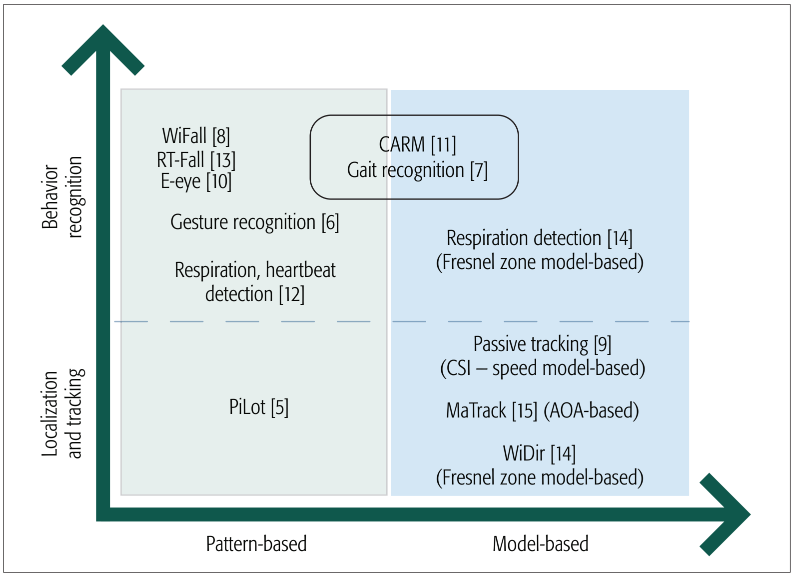

Figure 1. Design space of existing works: problem domain vs. solution domain.

and great potential in achieving centimeter and even millimeter scale human activity sensing [14], enabling a wide spectrum of applications.

Pattern-Based Approaches

Generally speaking, human sensing techniques aim to detect one's rich context information, including presence, location, moving trajectory, activity, gesture, identity, vital sign, interaction with objects, and so on. The goal of RF-based human sensing is behavior recognition based on the radio signals collected on the RF receiver.

To build a human behavior sensing system using radio signals, the connection between signal variations and human activities must be established. If the signal variation patterns have unique and consistent relations with certain human activities, it is possible for a pattern-based (or learning-based) method to recognize human behaviors accurately from signal patterns.

Feature Selection

The key to designing pattern-based approaches is to observe and find discriminative patterns to construct features and differentiate different human behaviors of interest. The features can be very simple or sophisticated, depending on the complexity of the recognition task and the required granularity.

For simple sensing tasks, feature selection is often based on intuition or direct observation. When the number of behaviors that need to be distinguished is small, it is often easy to find regular but differentiable signal patterns. In this case, one or two features may be enough to distinguish among behaviors. For example, for motion detection [2], we observe that any motion causes signal fluctuations. Features such as moving average and moving variance are good indicators; these simple features are often enough for presence sensing purposes.

As both the number of human behaviors and the sensing granularity increase, it becomes challenging to find one-to-one mappings between behaviors and signal patterns. One or two simple features are not enough for this task anymore. In this case, more features are needed to increase the dimension of feature space. For example, WiFall uses seven features for fall detection [8], and WifiU employs a total of 170 features for gait recognition [7]. Meanwhile, a simple threshold-based method may no longer work, so more powerful non-linear classifiers are needed. Often, advanced techniques such as Dynamic Time Wrapper (DTW) are applied to increase the robustness of classification, as shown in [6, 10]. Signal statistic characteristics, such as normalized standard deviation, median absolute deviation, and amplitude histogram of the CSI waveform, are the most common candidate features [8, 10]. More sophisticated features could be obtained with the help of physical models [7, 11]. These features are then fed into general-purpose classifiers such as support vector machines (SVMs) [8] or specially designed classifiers for classification. For pattern-based algorithms with big numbers of features, people began to lose understanding of the relationship between signal features and human behaviors. Therefore, designing a human behavior sensing system requires many rounds of feature adjustments in the feature selection process, which is often labor-intensive but with bounded classification accuracy.

Pattern Consistency

Pattern-based human sensing approaches rely on consistent and differentiable signal patterns for behavior recognition. This means the same patterns are always expected for a specific behavior. If the signal patterns are inconsistent for the same behavior(e.g., the same activity performed at several different locations), the sensing system may face severe performance problems. Different from wearable sensors that are attached to human bodies in fixed positions, contact-free passive sensing with WiFi signals does not assume a fixed position for a human body with respect to WiFi devices. As a result, even the same activity causes very different signal patterns at different locations. Besides the fact that the distance between a subject and WiFi devices affects the signal amplitude received at the receiver, the subject may interact with multipath differently at each location by blocking different path components. Even worse, the orientation of the subject also matters [3]. For example, in E-eye [10] the activity profiles are requested to be associated with a few locations in the home, so activities performed at different locations might not be well recognized.

The converse problem exists in the case when several behaviors share similar signal patterns. This is becoming common in today's sensing tasks, which require fine-grained sensing capabilities. For example, in gait recognition [7], conventional statistical indicators cannot be used as features because the values are almost identical for subtle movements. More discriminative features such as gait cycle length, estimated footstep length, the maximum, minimum, average, and variance for torso and leg speeds during the gait cycle, as well as spectrogram signatures are extracted from the time-frequency domain with the help of models.

In the above two cases, the pattern-based approaches face limitations. However, if certain features can be found through accurate models — for instance, the histogram distribution feature used in E-eye [10] is replaced by the CSI frequency feature in CARM [11] with the help of the CSI-Speed model — the performance of activity recognition is less affected by the subject's relative location. Please note that this is not an easy job using pure empirical observation.

Scalability

The performance of pattern-based approaches relies on the data samples trained and tested. Often, a pattern-based sensing system is built on top of the model learned from a small training dataset of a few people collected at a few locations, and it is thus difficult to scale, suffering performance degradation when deployed in rooms with different sizes or layouts, or changing the positioning of each WiFi device.

Despite the drawbacks in feature selection, environmental dependence, and scalability, pattern-based approaches have been very popular and successful in device-free human behavior sensing applications because they are not only conceptually intuitive but also relatively simple to design, for both data collection and algorithm development.

Model-Based Approaches

Different from pattern-based approaches, which often involve nontrivial training effort and could only recognize a limited set of pre-defined activities, model-based approaches are based on the understanding and abstraction of a mathematical relationship among human locations and/or behaviors, the received signals, and the surrounding environment. In the case of device-free human sensing with WiFi CSI, the aim of modeling is to relate the signal space to the physical space including human and environment, and reveal the physical law characterizing the mathematical relationship between the received CSI signals and the sensing target.

Models in the Wild

Compared to the study of pattern-based approaches, there has been much less research on model-based device-free human behavior sensing with WiFi devices. In this section, we first briefly present the few model-based human sensing research works that have appeared in recent years, and then introduce our proposed Fresnel zone model and its applications in human sensing.

CSI-Speed Model: Wang *et al.* proposed the CSI-speed model, which quantifies the correlation between CSI power (amplitude) dynamics and the speed of path length change of the reflected paths caused by human movement [11]. They find that the total CFR power is the sum of a constant offset and a set of sinusoids, where the frequencies of the sinusoids are functions of the speeds of path length changes.

The importance of the CSI-speed model lies in the fact that it mathematically links the CSI with the speed of reflected path length change due to human body movement. In such a way, the path length change rate information can be extracted from CSI power amplitude by methods like short time Fourier transform (STFT). However, there is no mathematical mapping from the path length change rate to the human motion speed and human activities. As a consequence, approximated speed information is used as input to a pattern-based learning algorithm for behavior recognition. In the CSI-speed-model-based activity recognition system CARM, Wang *et al.* assume that the human motion is half the path length change speed. Although this approximation is not very accurate, for a total of eight predefined daily activities, CARM can differentiate and recognize them well [11].

Based on the CSI-speed model, *Widar* by Qian *et al.* attempts to build a CSI-Mobility model that quantifies the relationship between CSI dynamics and a user's location and velocity for precise tracking [9]. The CSI-Mobility model tries to fill the gap between the path length change rate and the human moving velocity. As the CSI-speed model provides no direction information, the CSI-mobility model estimates the velocity by formulating it into an optimization problem. With the extended model capability, *Widar* is capable of tracking a human's walking direction and velocity. However, the lack of initial position prevents the precise mapping from speed to velocity, hindering accurate trajectory tracking.

Angle of Arrival Model: Angle of arrival (AoA) measurement is a method of determining the direction of propagation of an RF wave incident on an antenna array. AoA can be estimated by the phase difference pattern across antennas of the array. The resolution of AoA grows with the number of antennas. Normally, five to eight antennas are required for a good AoA estimation. Recently, subspace-based methods such as the MUSIC algorithm have been adopted to obtain finer angle estimation. With two or more AoA measurements from known points, the location of the signal source can be computed by triangulation.

In device-free WiFi sensing, the received signal via different reflected paths off a moving person can be viewed coming from one virtual source with the same angle. For a person to be successfully located using the AoA method, the target's angles to two RF receivers should be obtained. Li *et al.* proposed a device-free localization system, *MaTrack* [15]. The rationale for obtaining the AoA of a moving target is that the signals reflected from it keep changing in angle and time delay, which are incoherent with the reflected signals from environmental static objects. Although MaTrack can be used to infer the AoA of a moving target, its angle resolution is not fine enough to separate the reflected paths of the human body, which limits its application in human sensing tasks other than localization.

Fresnel Zone Model: The Fresnel zone concept originated from Augustin Fresnel's research on light's interference and diffraction in the early 19th century. When applied in a radio propagation area, Fresnel zones refer to the series of concentric ellipsoids with two foci corresponding to the transmitter and receiver antennas. Radio waves traveling through the first Fresnel zone are all in-phase, enhancing the signal strength received at the receiver. Successive Fresnel zones alternately provide destructive and constructive interference to the received signal strength at the receiver side [14].

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human sensing, our Fresnel zone model expands the sensing range to the vast regions outside of the first Fresnel zone. In the device-free passive sensing scenario, a pair of WiFi transceivers are placed at the fixed location. When an object appears in the Fresnel zones in free space, the radio signals can be viewed as traveling from the transmitter to the receiver via two paths: one that goes directly (the LoS path) and another that is reflected by the object (the reflected path). The two signals combine to create a superimposed signal at the receiver side. When the object moves, while the signal traveling via the LoS remains the same, the signal reflected by the object changes over time. As the length of the reflected path changes, the relative phase difference between the LoS signal and the reflected signal changes accordingly, and the received signal will present peaks or valleys when the object crosses the boundaries of the Fresnel zones. The situation is similar in a real multipath-rich environment. In this case the Fresnel zone model can be approximated in such a way that the LoS signal is superimposed with the multiple reflected signals from the environmental static objects, and the signals reflected from the moving object are unified and simplified into one dominant signal component that changes over time. Mathematically, the Fresnel zone model characterizes the relationship between the geometrical position of the sensing target and the induced CSI power amplitude variations caused by the motion of the target.

The power of the Fresnel zone model is that it not only reveals the relationship between the centimeter-scale or even millimeter-scale human activities and the received WiFi signals, but also describes how the received signals vary for a human activity performed at different locations and orientations [14]. This capability makes the Fresnel zone model location-aware, different from the CSI-speed or CSI-Mobility model.

In order to show how the Fresnel zone model can be used for human behavior recognition, we leverage the properties of multiple subcarriers in the WiFi received signals and build the human indoor walking direction and distance estimation system *WiDir* [14].

For multiple subcarriers with different wavelengths in commodity WiFi devices, their corresponding Fresnel zones are of slightly different sizes. As a consequence of a person moving inward/outward, it would cross the Fresnel zone boundaries of different subcarriers in sequence and generate increasing/decreasing time delays between a fixed pair of subcarriers. Then the inward/outward walking direction can be determined by inspecting the CSI time delay between two WiFi subcarriers. Furthermore, as crossing Fresnel zone boundaries corresponds to a series of peaks and valleys in the CSI waveform, WiDir counts the peaks and valleys in each axis for distance estimation. With two pairs of WiFi devices, both direction and distance in the 2D plane can be estimated directly and accurately. The WiDir example showcases that sensing the indoor human walking direction can be achieved leveraging only the Fresnel zone model. It is different from the CSI-speed or CSI-mobility model for human behavior recognition, where only the reflected path change rate is extracted from the model, while the human speed or human activities are approximately obtained using the path change rate and other information.

Discussion

Through the introduction of the above three lines of model-based human sensing research, it can be seen that model-based approaches have the advantage of leveraging physical laws and having clear physical interpretations. Hence, we could use the derived models to accurately extract certain parameters from the received signals and solve a class of problems. For example, the CSI-speed model can precisely sense the speed information, which can support applications such as activity recognition, gait recognition, and tracking. The AoA model is geometry-related, which suits localization applications. While the above models generally target at obtaining a specific output such as speed, velocity or angle, Fresnel Zone model seems to be more general as the basis for understanding how human motion affects the received RF signal and further designing various human behavior recognition systems, as can be seen in the walking direction sensing application as well as the human respiration detection application, which is presented in the next section.

Case Study: Respiration Sensing

In order to demonstrate the generality and potential of our proposed Fresnel zone model in human behavior recognition, in this section we use human respiration detection as an application example to show how the existing pattern-based approaches and our proposed solution achieve the goal. We further compare the advantages and drawbacks of these approaches, and argue that our proposed Fresnel zone model is not only general in supporting a wide spectrum of applications, but also very powerful in revealing the sensing limit as well as the complex relationship among human motion/location/orientation, the received CSI of different subcarriers, as well as the physical environment including WiFi devices.

Human respiration detection using commodity WiFi CSI has been explored in recent years. In [12], by observing the obvious periodic sinusoid-like patterns that appear in the received WiFi CSI across different subcarriers, which seemed to have a high correlation with human respiration, Liu *et al.* developed a WiFi CSI pattern-based vital sign monitoring system. In this work, it is assumed that the sinusoid-like pattern exists in at least one of the subcarriers; they focus on proposing methods for signal processing and respiration rate extraction, which include the steps of filtering, peak-to-peak time interval measurement, and power spectral density (PSD)-based K-means clustering. To ensure that the appropriate subcarriers are selected, a variance with a predefined threshold is employed before processing [12].

With the Fresnel zone model, we reexamined the same human respiration sensing problem [14]. According to the WiFi signal propagation properties in the Fresnel zones, when an object crosses a series of Fresnel zones, the received signal shows a continuous sinusoidal-like wave. If a moving object causes a reflected signal path length change shorter than a wavelength (e.g.,

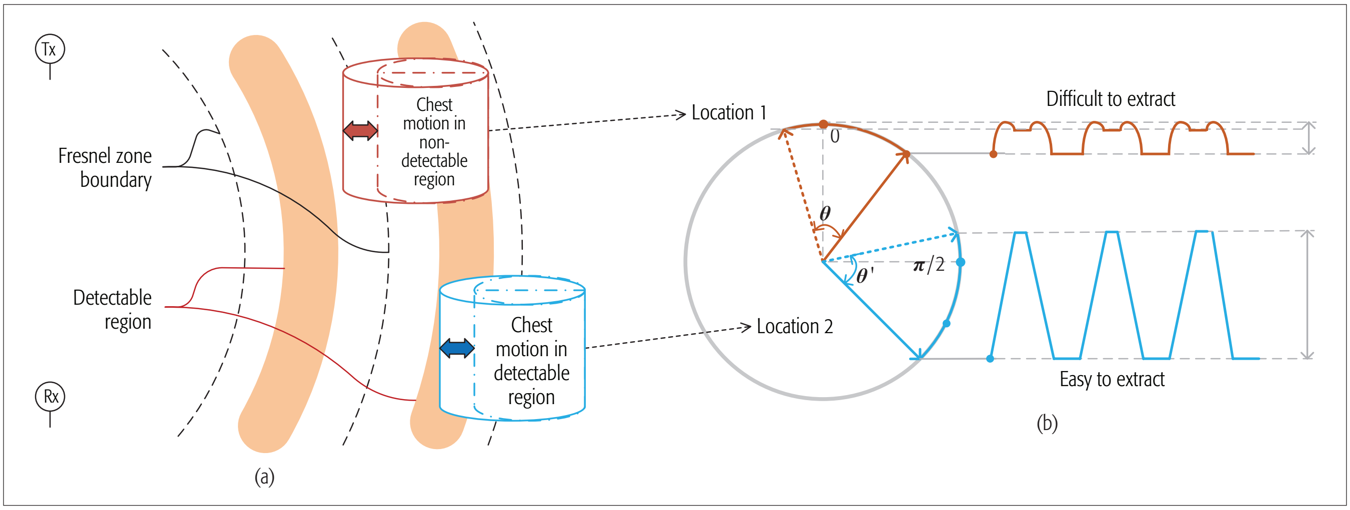

Figure 2. a) Human respiration detection at two locations in Fresnel zones; b) their corresponding CSI waveforms.

5.7 cm for 5.24 GHz), the received signal is just a fragment of the sinusoidal cycle depending on the location of the object in the Fresnel zones. As the human chest motion displacement due to respiration is around 5 mm and the resultant reflected path length change is far less than a wavelength, it roughly corresponds to a phase change of 60° in one sinusoidal cycle [14]. Given the phase change in a sinusoidal cycle (as shown in Fig. 2b), both the angle of phase change and its position affects the shape of the resultant signal waveform. Apparently, in order to make the respiration rate easy to extract correctly, it is expected that the angle not only covers a large range but also lies fully in the monotonically changing fragment of the cosine wave. Based on the above study, Zhang *et al.* conclude that within each Fresnel zone, the worst human location for centimeter-level motion sensing is around the boundary, while the best location appears in the middle of the Fresnel zone, as illustrated in Fig. 2. By further considering the multi-frequency diversity of subcarriers, a respiration detection map can be constructed to instruct where respiration is detectable by different subcarriers, as illustrated in Fig. 3. According to this map, Zhang *et al.* found that in the inner Fresnel zones, there are many places where human chest movement cannot be detected by any subcarrier, while a short human body move outwards would make the human respiration detectable; in the frequency diversity-enabled region, at least one subcarrier can be used to detect the human respiration according to the ideal Fresnel zone model. Besides the impact of location, they also show that the orientation of the human body also matters. Different orientations lead to different effective chest displacements with respect to a pair of transceivers, thus influencing the detectability of human respiration [14].

To validate our observation, we conducted extensive experiments in an apartment. The experiment settings are illustrated in Fig. 3b. A subject laid on the bed facing up. In order to validate that the detectable and undetectable regions alternatively appeared in the shape of ellipses in the geometrical space, we mounted a COTS WiFi transmitter and receiver pair on two vertically placed slide rails. We examined six consecutive Fresnel zones and collected 2 hours' CSI data at a sampling rate of 20 packets/s. The results show that the detectable and undetectable regions indeed appear alternatively by fixing the human posture and moving the LoS away from the human continuously, and the estimation performance in the detectable regions is consistent. In our case, the median estimation errors of respiration rate in the three detectable regions are about 0.09 breaths per minute (bpm), 0.15 bpm, and 0.06 bpm, respectively, compared to the overall mean estimation error of 0.4 bpm reported in [12]. Please note that our experiment results show that human respiration cannot be monitored reliably in the three undetectable regions, which were not reported in the previous work.

By comparing the above two human respiration sensing approaches, it can be seen that the pattern-based respiration detection method used in [12] is intuitive and works well as long as the assumption holds, that is, at least one subcarrier is able to sense the human chest movement. However, our proposed Fresnel-zone-model-based approach could explain when the pattern-based system works or not, why some locations and subcarriers are not able to detect human respiration effectively, and how WiFi devices should be positioned for better respiration monitoring [14]. With these findings and understandings, designing a practical respiration monitoring system should consider many factors such as the location of the subject, the posture of the subject, and the positioning of WiFi devices for effective continuous monitoring. These considerations also apply to situations where more than one person's respiration rates are monitored.

From the above case study we can see that not only can the Fresnel zone model interpret where and at what orientation a person's respiration can be sensed, but it can also guide the sensing system design. However, the pattern-based respiration sensing approach can only sense respiration when there are obvious and clear signal patterns. It can neither answer the question why sometimes human respiration cannot be sensed, nor provide guidance on how to design a robust monitoring system.

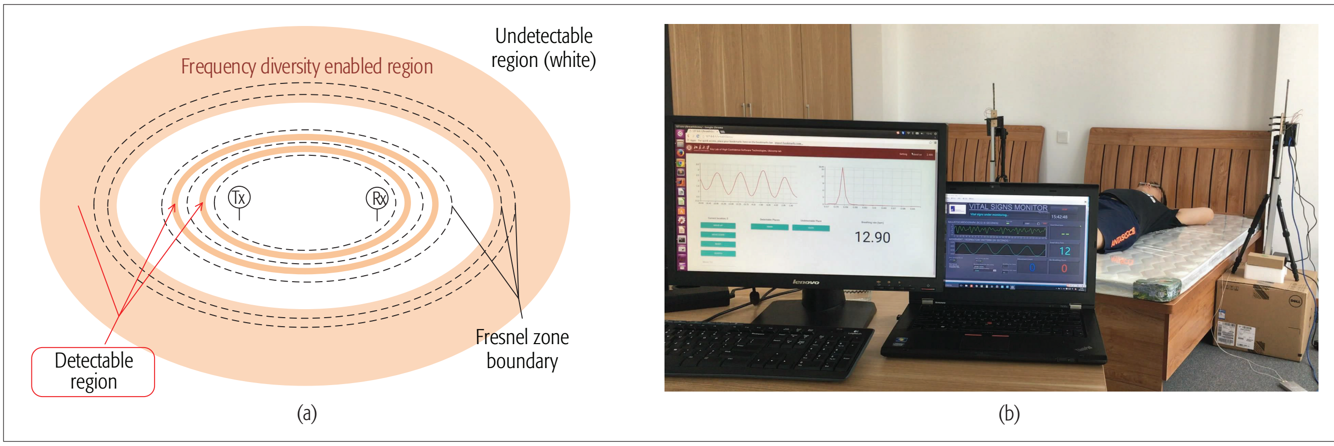

Figure 3. a) Respiration detection map for multi-subcarrier Fresnel zones; b) experiment settings for respiration detection.

Conclusion

Today's device-free WiFi CSI-based human behavior recognition works are either pattern-based or model-based, or a combination of both. While the pattern-based approaches are straightforward and effective for many sensing applications, they are observation- and empirical-study-based, and usually require a deep case-by-case investigation and intensive training for a specific application. Although they have been very popular and successful in this field, pattern-based approaches are trial and error by nature, having the bottleneck of predicting the sensing limit and understanding what complexity of human behaviors is recognizable, especially for continuous and fine-grained human sensing tasks.

Model-based approaches aim to fundamentally understand the governing law on how a human's motion/location/orientation impacts the received signals in the environments, and mathematically depict the direct relationship between the received signals and the sensing target. For this reason, model-based approaches not only have the potential to solve more complex and fine-grained human behavior recognition problems, but also could guide us in understanding the sensing limits (e.g., sensing area, fineness of behavior, accuracy bound) and the rationale behind it in the real world as well. Among all the efforts, the Fresnel zone model seems to be the most general one. It not only shows its effectiveness in supporting both coarse-grained and fine-grained human behavior recognition applications, but also helps us to understand how radio waves propagate in real-world environments and what is the possible sensing limit with WiFi CSI measurements. With those attributes, we believe that the Fresnel zone model has the potential to revolutionize the RF-based human sensing field and enable more real-world applications, which were not possible without the model.

However, there is still a lot of research that needs to be done in order to fully understand the properties of the Fresnel zone model in the multipath-rich indoor environments, especially with multiple moving objects. It also should be noted that there is no single model which can solve all the problems. With those points in mind, while we strongly encourage researchers in the WiFi human sensing field to join us in developing new models and improving the existing models due to their obvious advantages, we envision that combining the model-based approaches with the pattern-based approaches would still be the most effective way for WiFi CSI-based human behavior recognition in the coming years.

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