CSI-based human sensing using model-based approaches: a survey
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Abstract
Currently, human sensing draws much attention in the field of ubiquitous computing, and human sensing based on WiFi CSI (channel state information) becomes a hot research topic due to the easy deployment and availability of WiFi devices. Although various human sensing applications based on the CSI signal model are emerging, the model-based approach has not been studied thoroughly. This paper provides a comprehensive survey of the latest model-based human sensing methods and their applications. First, the CSI signal and framework of model-based human sensing methods are introduced. Then, related models and fundamental signal preprocessing techniques are described. Next, typical human sensing applications are investigated, and the crucial characteristics are summarized. Finally, the advantages, limitations, and future research trends of model-based human sensing methods are concluded in this paper.

Keywords: channel state information; human sensing; model-based approach; Fresnel model; AoA model; phase calibration

1. Introduction
In the last few years, pervasive computing applications have drawn much attention in ubiquitous computing. With the various sensing devices, both the environment state and the specific target can be monitored. Currently, a variety of applications have been developed to achieve pervasive sensing. Among these applications, this paper is interested in sensing human targets and identifying user state. Compared with some applications that require users to wear some sensors or devices, the device-free pattern is more popular due to the convenient deployment and monitoring procedure. Therefore, this paper focuses on the device-free pattern. According to existing studies, many types of signals can be utilized to achieve device-free human sensing, such as sound (Wang et al., 2016; Wang et al., 2019, 2019), light (Li et al., 2017; Ma et al., 2017; Yang et al., 2017), radio frequency (RF; Adib et al., 2015; Zhao et al., 2016; Cianca et al., 2017; Zhao et al., 2018), etc. The methods based on sound and light signals play an essential role in device-free human sensing and provide useful guidance for RF-based human sensing. Due to the ability to traverse through walls (Adib & Katabi, 2013), RF-based methods are widely applied to human sensing. For example, RF-Capture (Adib et al., 2015), RF-Pose (Zhao et al., 2018), and RF-Action (Li et al., 2019) are proposed to utilize RF signals to achieve device-free human sensing in through-the-wall scenarios. Furthermore, Body-Compass (Yue et al., 2020) realizes accurate sleep posture monitoring based on the RF reflection.

As a kind of RF signal, WiFi signal has drawn much attention recently due to the advantage of simple deployment and wide availability of WiFi devices. Therefore, WiFi signal-based human sensing applications are increasingly emerging (He et al., 2020), such as human localization and tracking (Shi et al., 2018), human vital signs detection (Liu et al., 2018), human behavior...
recognition (Chowdhury et al., 2017; Ahmed et al., 2020), and crowd activity inference (Venkatnarayan et al., 2018). In general, the WiFi device can provide us with two signals, namely RSS (received signal strength) and CSI (channel state information). The former is a measurement of signal power at the receiving end, which can be used to evaluate signal attenuation and recognize human behavior (Gu et al., 2016). However, the multipath fading and temporal dynamics may degrade the performance of RSS dramatically in a complex multipath scenario (Yang et al., 2013). Better than RSS, CSI describes the characteristics of physical layer, which can not only overcome the influence of multipath fading but also provide more suitable amplitude and phase information for human sensing (Chen et al., 2017). Therefore, CSI-based sensing approaches have received more attention in recent years (Ma et al., 2019). According to existing studies, the CSI-based human sensing approaches can be classified into two categories based on the recognition technique, including pattern-based approaches and model-based approaches (Wu et al., 2017; Wang et al., 2019; Ahmed et al., 2020). The pattern-based approaches are most common in the field of human sensing and can achieve satisfactory performance. This kind of approach recognizes human behaviors through the variation pattern of wireless signals caused by human actions. Therefore, the pattern-based application usually requires a large amount of CSI data to train a suitable classifier for recognition (Wu et al., 2017). For example, WiHACS built a multiclass SVM (support vector machine) classifier to recognize different human behaviors (Chowdhury et al., 2017). In contrast, the model-based approach identifies human behavior through a physical model. Based on signal propagation regularity, the physical model of CSI is constructed to describe a specific relationship between the signal space and the physical space mathematically (Wu et al., 2017). Compared to the pattern-based approach, the model-based approach can describe the mathematical relationship between human movements and CSI dynamics, achieving better performance on fine-grained applications (Wang et al., 2018). The performance superiority is verified by Wu et al. (2017) through a case of human respiration detection. Therefore, the model-based application has been increasingly emerging in recent years.

Although some useful CSI physical models have been proposed for human sensing in recent years, there is no comprehensive investigation for these applications and models specifically. This paper provides a comprehensive overview of existing typical models applied to CSI-based human sensing approaches, including the AoA (Angle of Arrival) model, the Fresnel model, etc. The AoA model generally utilizes the incident signals’ angles to deduce human activities (Chen et al., 2017), while the Fresnel model usually detects human activities according to the amplitude and phase changes of CSI caused by human crossing the Fresnel zones (Zhang et al., 2017). Besides, these models’ key characteristics are analysed in detail to illustrate the pros and cons of different models and provide some insights for future studies. Furthermore, this paper investigates the latest model-based applications, including human localization and tracking, human daily behavior recognition, and human respiration detection. These typical applications and their crucial features are summarized in Tables 2–4. To our best knowledge, this paper may be the first survey that provides a thorough summary of existing typical models and corresponding CSI-based human sensing applications. This paper is expected to provide some useful information for the study of model-based CSI human sensing.

The rest of this paper is organized as follows. In Section 2, this paper briefly introduces the concept of CSI and the critical idea of CSI-based human sensing. Also, this paper further describes the basic framework of the model-based human sensing approach. In Section 3, this paper introduces the wireless signal processing approaches used in model-based applications, the principles of typical models, and the application of these models to human sensing. In Section 4, this paper investigates the latest model-based studies and summarizes the crucial characteristics. In Section 5, this paper introduces the advantages of model-based approaches and discusses some significant challenges and future research trends. Finally, a conclusion is given for this survey in Section 6.

2. Channel State Information and Framework of a Sensing System

This section mainly introduces the characteristics of CSI. Also, the application of pattern-based methods and model-based methods to detect human activities is introduced. Moreover, this section provides a general framework of the model-based approach according to related studies.

2.1. Channel state information

CSI is a metric describing the channel properties of a wireless transmission link, which can be obtained by OFDM (Orthogonal Frequency-Division Multiplexing) subcarriers according to the IEEE 802.11n standards (IEEE802.11n, 2009). Precisely, CSI consists of a set of complex values. Let $\text{CSI}_i$ represent the CSI stream corresponding to the $i$th OFDM subcarrier, and it can be described as follows:

$$\text{CSI}_i = |\text{CSI}_i| e^{i\angle\text{CSI}_i},$$

where $|\text{CSI}_i|$ and $\angle\text{CSI}_i$ represent the amplitude and phase, respectively. Most of the existing studies distinguish different human activities exploiting the amplitude and phase information of CSI as features.

As shown in Fig. 1, wireless signals are transmitted through multiple propagation paths from a transmitter to a receiver. When a person stands or moves in the scenario, the propagation of wireless signals will be blocked by the human body. As a result, some significant changes exhibit in the received signals. CSI is usually used to describe these changes in received signals. Different human activities generally lead to distinct changes in amplitude and phase of CSI, resulting in different CSI patterns. Based on this fact, the pattern-based approach first collects a large amount of CSI data. The collected data are then used to train a classifier that relates the predefined activities to different CSI patterns (Chen et al., 2017). Finally, a predefined activity can be recognized once the test data are input into the classifier. Rather than relying on classifiers trained by a lot of CSI data, the model-based approach usually deduces human activities by building models to capture the mathematical relationship among CSI, the rule of wireless signal propagation, and human activities (Wu et al., 2017). Unlike the pattern-based approach, the model-based approach can deduce other activities besides the predefined activities, requiring no significant training effort.

2.2. The framework of model-based approaches

Generally, the framework of a CSI model-based human sensing system comprises three components, including CSI data collection, signal preprocessing, and the model to deduce human activities, as shown in Fig. 2. The first step is the signal
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Figure 1: The propagation paths of a wireless signal.

Figure 2: The framework of model-based human sensing.

Collection. CSI data can be collected by different devices, such as the COTS (Commercial-Off-The-Shelf) NIC (network interface card) [including Intel 5300 NIC (Halperin et al., 2010), Atheros AR9590 (Sun et al., 2015), Broadcom chips (Gringoli et al., 2019), and so on], Internet of Things devices (Atif et al., 2020; Hernandez & Bulut, 2020), etc. Most existing applications utilize COTS NICs (Ahmed et al., 2020), especially Intel 5300 NIC (Ma et al., 2019; Wang et al., 2019). However, raw CSI data usually contain much noise caused by ambient factors and hardware devices, which cannot be used directly. Therefore, the signal preprocessing step is necessary to eliminate the noise. Specifically, the phase noise and outliers are usually removed by utilizing phase calibration methods and some filters (Zheng et al., 2019). Afterward, an appropriate physical model needs to be developed to depict the CSI signal propagation and correlate the CSI variations with user activities mathematically. Therefore, the human is accordingly sensed by the physical model once the changes of CSI are measured (Wu et al., 2017). However, the procedure of human sensing in related applications is different. For simple human activities, some applications utilize the parameters calculated by models to determine the user’s location or activities directly, as shown in the right part of the third component of Fig. 2. For complex activities, most applications first utilize a physical model to extract CSI features. Then, a classifier trained on these features is exploited to accomplish human activity recognition, which is shown in the left part of the third component of Fig. 2.

According to the framework, models can not only be utilized to deduce human activities directly but also be applied to...
Table 1: A survey of models used in existing studies.

| Model                   | Reference                                                                 | Description                                                                 |
|-------------------------|---------------------------------------------------------------------------|-----------------------------------------------------------------------------|
| AoA model               | (Xiong & Jamieson, 2013; Kotaru et al., 2015; Sun et al., 2015; Li et al., 2016; Zhu et al., 2016; Qian et al., 2018; Zheng et al., 2019; Chen et al., 2020) | Estimating the angle of the received signal reflected by the target          |
| Fresnel model           | (Wang et al., 2016; Wang et al., 2016; Wu et al., 2016; Wang et al., 2017; Wang et al., 2017; Wu et al., 2017; Zhang et al., 2017; Zheng et al., 2017; Yang et al., 2018; Zeng et al., 2018; Ren et al., 2019; Zhang et al., 2020) | Correlating the changes of both amplitude and phase with the target’s movements |
| Fresnel penetration model | (Wang et al., 2017)                                                        | Correlating the Fresnel phase difference of different subcarriers with the target’s location |
| Fresnel diffraction model | (Zhang et al., 2018; Zhang et al., 2019)                                   | Correlating the diffraction gain with human movements                       |
| Interacting model       | (Wang et al., 2019)                                                        | Depicting the propagation of wireless signals through the human body        |
| Wi-HD model             | (Xin et al., 2018)                                                         | Estimating the range of sensing coverage for human activities in different granularity |
| CSI-mobility model      | (Qian et al., 2017)                                                        | Quantifying the relationship between the movement speeds of human body parts and specific human activity |
| CSI-speed model         | (Wang et al., 2019)                                                        | Correlating the changes in the CSI ratio of two antennas with human movements |
| CSI-activity model      | (Wang et al., 2019)                                                        | Quantifying the relationship between the movement and CSI dynamics          |
| CSI-quotient model      | (Zeng et al., 2019)                                                        | Correlating the diffraction gain with human movements                       |
| Blind source separation model | (Wu et al., 2020)                                                    | Separating the mixed signals caused by multuser respiration without knowing how signals are mixed |

3. Wireless Signal Processing and Typical CSI Models

The wireless signal processing of model-based approaches mainly consists of two steps, namely signal preprocessing and model building. The signal preprocessing eliminates noises and outliers. The model building constructs physical models to correlate CSI changes to human movements mathematically. This section first introduces some preprocessing methods, including the CSI phase calibration and data denoising. Then, some typical models proposed in existing studies are described, including their essential characteristics and human sensing applications.

3.1. Signal preprocessing

The CSI data collected by COTS network cards usually contain considerable phase noise and outliers. Signal preprocessing is a necessary step to eliminate the influence of noise and outliers.

Phase noise generally comes from two aspects: random factors and hardware device imperfection. Specifically, the change of the wireless channel can cause a random phase offset in CSI measurement. Besides, imperfect synchronization between the sender and receiver also results in some phase errors, including SFO (sampling frequency offset), STO (symbol timing offset), CFO (carrier frequency offset), and CPR (carrier phase offset) (Tadayon et al., 2019). CSI-based human sensing applications utilize different phase calibration and sanitization methods to eliminate the effects of phase errors. For example, SpotFi (Kotaru et al., 2015) and Widar2.0 (Qian et al., 2018) utilize a linear fitting method to eliminate the effects of STO and SFO. Furthermore, BreathTrack (Zhang et al., 2019) uses the hardware (including cables and splitters) correction to calibrate the time-invariant phase errors. The software correction based on the phase difference of CSI between transceivers is leveraged to remove the time-varying phase errors, such as CFO and SFO.

Besides phase errors, some random noises caused by complex multipath propagation of wireless signals and equipment imperfection exist in raw CSI measurements. Various methods are utilized to remove the noise of CSI, such as low-pass filters, discrete wavelet transform (DWT; Zhu et al., 2016), and principal component analysis (PCA; Wang et al., 2015). Among these methods, the low-pass filter, such as the Butterworth filter and Elliptic filter, is the most common denoising method in many CSI-based human sensing applications (Wang et al., 2019). The low-pass filter sets a cutoff frequency as a threshold. Then, signals above this threshold are filtered, and signals below this threshold are passed. Many model-based human sensing applications utilize a low-pass filter to remove noise, such as WIPIN (Wang et al., 2019), Widar (Qian et al., 2017), etc. After handled by the signal preprocessing step, the CSI data can be further processed to build models.

3.2. Models used in human sensing

The key to model-based human sensing is to build a proper model that correlates CSI measurements with human body movements. Some typical models are reviewed in this section and summarized in Table 1. Moreover, this section describes the essential characteristics of these models and provides the basic principle of applying these models to human sensing.

The model in this paper refers to a physical model that describes the law of CSI signal variation. Parameters of the model are calculated using physical law instead of data training. According to Table 1, the AoA model and Fresnel model are the two most popular models. AoA models are generally applied to human localization and tracking, while Fresnel models are usually employed to achieve human respiration detection based on the models’ sensitivity to tiny movements. Apart from these two models, some other models are proposed and applied to different human sensing applications. The models summarized in Table 1 will be briefly introduced.

AoA model mainly relies on the angle at which the incident signal reaches the antennas to deduce human locations and activities. As shown in Fig. 3, M antennas are arranged in a line, forming an antenna array. The incident signal from one propagation path arrives at these antennas at the same angle (i.e., AoA). Most of the applications adopt the MUSIC (MUltiple SIgnal Classification) algorithm to estimate the AoA, such as ArrayTrack (Xiong & Jamieson, 2013), etc. This algorithm estimates AoA...
Incident signals arrive at the antenna array. $\theta$ represents the AoA of the incident signal, and $d$ means the distance between adjacent antennas.

Figure 3: Incident signals arrive at the antenna array. $\theta$ represents the AoA of the incident signal, and $d$ means the distance between adjacent antennas.

The AoA spectrum can be obtained according to the orthogonality of signal and noise. However, the traditional MUSIC algorithm requires more sensors than paths. Some applications utilize a custom device with multiple antennas as the AP to solve this limitation, such as ArrayTrack (Xiong & Jamieson, 2013). Besides, some applications expand the number of sensors by multiplying the number of antennas by the number of subcarriers, such as SpotFi (Kotaru et al., 2015), MaTrack (Li et al., 2016), etc. Exploiting the AoA from one or multiple receivers, some applications calculate human location based on triangulation, such as MaTrack (Li et al., 2016), etc. Furthermore, the AoA generally corresponds to a sharp peak in the spatial spectrum. Whenever the human body blocks the incident signal, the peak will drop significantly. Based on this fact, some applications also utilize the AoA model to achieve behavior recognition, such as WiDraw (Sun et al., 2015), WiseFi (Zhu et al., 2016), etc.

The Fresnel model mainly consists of a set of Fresnel zones (Zhang et al., 2017). Fresnel zone refers to a series of concentric ellipsoids, as shown in Fig. 4. The two foci (i.e. $P_1$ and $P_2$ shown in Fig. 4) of the concentric ellipsoids function as the transmitter and receiver when the Fresnel zone is applied to radio propagation research. The innermost ellipse is defined as the first Fresnel zone (FFZ), and the second Fresnel zone corresponds to the elliptical annuli between the first and second ellipses. Similarly, the $n$th Fresnel zone corresponds to the elliptical annuli between the $(n-1)$th and $n$th ellipses. When human locates in Fresnel zones, the wireless signal is sensitive to human movements. And the middle of the Fresnel zone is the best position for sensing. Meanwhile, the boundaries between any two adjacent Fresnel zones are defined as Fresnel boundaries, and the $n$th Fresnel boundary corresponds to the boundary between the $n$th and $(n+1)$th Fresnel zones. Once human moves across Fresnel boundaries, the amplitude and phase of wireless signal will change correspondingly (Zhang et al., 2017). The phase change can be calculated according to the changes in reflected path length caused by human movements. By analysing the phase changes, researchers can deduce the human location based on mathematical calculations and construct a classifier to recognize human behavior, such as LiFS (Wang et al., 2016), iGest (Ren et al., 2019), etc. Furthermore, the measurement of wireless signals in Fresnel zones reaches a centimeter-level resolution. Thus, fine-grained human sensing applications (such as respiration detection) can achieve excellent performance by using a model based on Fresnel zones, such as TinySense (Wang et al., 2017), FullBreathe (Zeng et al., 2018), etc.

The Fresnel model also has some variants. For instance, Fresnel penetration model (FPM; Wang et al., 2017) describes the mathematical relationship between the Fresnel phase difference of a pair of subcarriers and human location. Moreover, according to the law of signal propagation in the FFZ, Fresnel diffraction model (FDM; Zhang et al., 2019) quantifies the relationship between the diffraction gain and the human body movements. The human sensing method based on the Fresnel model may draw more attention in future research due to its excellent performance for both coarse-grained and fine-grained applications.

Besides, some other models are also proposed in existing studies for specific applications. The interacting model (Wang et al., 2019) describes wireless signals propagation through the human body. Based on the fact that wireless signals propagate differently in bone, fat, and skin, interacting models are applied to human identification. The Wi-HD model (Xin et al., 2018) validates that different sensing coverage is suitable for activity detection with different granularity in the indoor scenario, which provides a useful guide for transceivers’ deployment. Furthermore, the CSI-speed model and the CSI-activity model (Wang et al., 2015) are applied to human behavior recognition, respectively correlating human movement speeds with CSI dynamics.
mathematically or a specific human activity. The CSI-mobility model (Qian et al., 2017) describes the mathematical relationship between CSI power and human velocity (both speed and direction) and location, enabling a direct calculation of human location and moving velocity. Moreover, the CSI-ratio model (Zeng et al., 2019) utilizes the channel quotient between two antennas as the metric to achieve human sensing, which correlates human movements with the changes of the CSI ratio mathematically. This model can reduce the impacts of amplitude noise and phase offset on CSI measurements. The CSI-quotient model (Wu et al., 2020) utilizes the channel quotient between two antennas to eliminate CSI amplitude noise and phase offset. Also, the CSI-quotient model quantifies the correlation between CSI dynamics and object displacement to track finger motions. Besides, a blind source separation (BSS) model (Zeng et al., 2020) is proposed to separate the mixed reflection signal and achieve multiuser respiration sensing.

In summary, the above models can deduce human activities directly and extract complex features for classifier training. Therefore, model-based approaches are increasingly popular in the field of CSI-based human sensing.

### 4. Model-Based Sensing Applications

Due to the robustness for avoiding environmental influences and the sensibility to tiny movements, the model-based approaches have been widely applied to different CSI-based human sensing applications. This section summarizes these applications and divides them into three categories: human localization and tracking, human daily behavior recognition, and human respiration detection. Furthermore, this section provides a brief introduction to these applications and points out their pros and cons, respectively.

#### 4.1. Human localization and tracking

Human localization and tracking are always hot applications in the field of human sensing. Existing CSI-based human localization and tracking applications utilizing the model-based approaches are summarized in Table 2.

| Reference | Application | Users/locations/APs | Preprocessing | Models | Experimental results |
|-----------|-------------|---------------------|---------------|--------|----------------------|
| ArrayTrack (Xiong & Jamieson, 2013) | Indoor localization | 6 APs, 41 clients | Spatial smoothing; AP phase calibration | AoA model | Three APs: median error is 75 cm (static) |
| SpotFi (Kotaru et al., 2015) | Localization | 55 target locations | CSI smoothing; ToF sanitization | AoA model | |
| MaTrack (Li et al., 2016) | Indoor localization | Two APs, one target | Merging useless paths | AoA model | |
| LiFS (Wang et al., 2016) | Localization | 4 APs, 1 user, 212 test locations in all scenarios | Removing subcarriers affected by multipath and hardware noise | FFZ model; FFM | Home: median error of 0.6 m |
| Widar (Qian et al., 2017) | Tracking | Two APs, five volunteers | Passband filtering; PCA; STFT | CSI-mobility model | |
| MFDL (Wang et al., 2017) | Localization | Three APs, five volunteers | Phase offset calibration | FPM | |
| Widar2.0 (Qian et al., 2018) | Tracking | One AP, six volunteers | Eliminating phase noises | AoA; ToF; DFS | Localization: average error is 0.75 m (single link), 0.63 m (two link) |
| OpArray (Zheng et al., 2019) | Indoor localization | More than 2 APs, 75 reference points | Phase sanitization | AoA model | |
| RoArray (Gong & Liu, 2019) | Indoor localization | 6 APs, total 300 test locations | MUSIC-based phase calibration | AoA; ToA; ToF | 80th percentile error 1.0 m |
| AngLoc (Chen et al., 2020) | Indoor localization | 1 AP, 70 training locations, 30 testing locations | Power-based tap filtering program; phase calibration | ToA; AoA; ToF | Mean error is 1.18 m (lab scenario) |

In summary, the above models can deduce human activities directly and extract complex features for classifier training. Therefore, model-based approaches are increasingly popular in the field of CSI-based human sensing.
expanding the number of sensors to the product of the number of antennas and subcarriers. The phase shift between any two subcarriers from the same antenna is introduced by time of flight (ToF). Therefore, the improved MUSIC algorithm can estimate the AoA and the ToF of each propagation path. These two systems can be implemented on the COTS WiFi NICs (each is equipped with only three antennas), exhibiting more convenience than ArrayTrack. Furthermore, OpArray (Zheng et al., 2019) utilizes a novel spatial smoothing technique to improve the traditional MUSIC algorithm. Even though there are only two antennas, the AoA can be estimated to deduce human location. Moreover, OpArray provides a critical insight that the estimation accuracy of AoA is influenced by the orientation of the receiver, which helps us to improve the accuracy of AoA estimation.

In contrast, RoArray (Gong & Liu, 2019) obtains a more sharp and robust AoA spectrum utilizing the sparsity of signals rather than the orthogonality of signal and noise. Better than the above applications, RoArray can locate a target more accurately in an indoor scenario with low signal-to-noise ratio. Besides, Widar2.0 (Qian et al., 2018) utilizes the SAGE (Space Alternating Generalized Expectation maximization) algorithm to jointly estimate multiple parameters of a localization model, including AoA, ToF, Doppler frequency shift (DFS), and attenuation. Widar2.0 estimates these parameters by multiple iterations and constructs a localization model to calculate the target’s current location. The critical advantage of Widar2.0 is that it can deduce human trajectory accurately with only one pair of transceivers. However, Widar2.0 may not work well when the paths between humans and transceivers are non-line of sight. Moreover, AngLoc (Chen et al., 2020) achieves more accurate AoA estimation than SpotFi by combing the AoA-based method and the fingerprinting-based method.

In addition to the AoA model, some other models are also applied to human localization and tracking. LiFS (Wang et al., 2016) utilizes the Fresnel zone model and power fading model (PFM) to estimate the signal fading caused by human presence. Then, the human location can be deduced by analysing the signal fading. Furthermore, Multicarrier FPM based Device-free Localization (MFDL) (Wang et al., 2017) proposes a 2D multicarrier FPM to estimate human location. The basic idea of MFDL is shown in Fig. 6. First, MFDL utilizes CSI phase information to find the gaps between two pairs of Fresnel zones generated by two orthogonal transceivers (i.e. the blue ellipse rings, where human locates, in Fig. 6). Then, human location can be determined by finding the intersection of the two blue circles. Besides, Widar (Qian et al., 2017) extracts the path length change rates (PLCR) from collected CSI data and utilizes the CSI-mobility model to convert PLCR to human location and moving velocity mathematically.

In summary, the model-based method estimates the target’s location through the mathematical relationship between the target’s location and the received signals. Therefore, model-based localization systems are more robust to environmental changes than those pattern-based systems. However, multiuser localization is still a challenging problem for model-based methods. Also, reducing the deployment of transceivers may become a research topic in model-based human localization applications.

4.2 Human daily behavior recognition

Human daily behavior recognition is an important research field in human sensing applications, and some typical studies on CSI-based daily behavior recognition are summarized in Table 3. According to Table 3, some applications recognize human behaviors only utilizing the model-based approach, while some...
Table 3: A summary of studies on human daily behavior recognition.

| Reference          | Activities                                      | Users       | Preprocessing                  | Method                                      | Experimental results                                                                 |
|--------------------|-------------------------------------------------|-------------|-------------------------------|---------------------------------------------|--------------------------------------------------------------------------------------|
| WiDraw (Sun et al., 2019) | Hand trajectory                                | 10 volunteers | Signal filtering             | AOA model                                  | The tracking median error is lower than 5 cm. The mean recognition accuracy is 91%. |
| CARM (Wang et al., 2019) | Running, walking, falling, etc.                | 25 volunteers | PCA-based denoising           | CSI-speed model; HMM                        | The average accuracy is greater than 96%.                                             |
| WiDir (Wu et al., 2016) | Walking direction                               | Five volunteers | Savitzky–Golay filter       | Fresnel model                              | The median error is less than 10 degrees. Localization median errors: LoS: 1.1 m; NLoS: 1.8 m; through-one-wall: 2.5 m; Recognition: LoS: 89.1%; NLoS: 82.5%; through-one-wall: 74.3%. |
| WiseFi (Zhu et al., 2016) | User's location; five different activities      | Three volunteers | DWT-based denoising           | AOA model                                  | The average accuracy is greater than 90%.                                               |
| WiID (Zheng et al., 2017) | Human identity                                 | 10 users     | PCA; DWT                     | Fresnel model; SVM                         | Identification accuracy:                                                              |
| WiPIN (Wang et al., 2019) | Human identity                                 | 30 users     | Butterworth filter; IFFT-FFT | Interacting model                          | Accuracy: 100% (2 persons); 92% (30 persons).                                         |
| Zhang et al. (Zhang et al., 2019) | Push-up, sit-up, walkout                        | 11 volunteers | Savitzky–Golay filter       | FDM; CNN                                   | Both precision and recall for activity recognition of above 95%.                        |
| iGest (Ren et al., 2019) | Push, pull, etc.                                | Four volunteers | Savitzky–Golay filter       | Fresnel model; Decision tree; HMM           | Basic-gesture recognition: 91%. Complex-gesture recognition: above 85%.                  |
| Wi-Run (Liu et al., 2019) | Number of steps                                 | Five volunteers | Hampel filter;              | CSI-step model                             | Accuracies range from a single runner’s 93.18% to five runners’ 81.47% on average.     |
| WiDIGR (Zhang et al., 2020) | Gait recognition                                | 3-6 users    | Savitzky–Golay filter       | Fresnel model; Band-pass filter; FCA        | From 78.28% (a group of 6 people) to 92.83% (a group of 3 people).                      |
| Que-Fi (Zhang et al., 2020) | Queue number identification                     | Four users    | Sliding window filter; phase sanitation | SVM; CNN                                   | 95% (static); 96.67% (dynamic).                                                         |
| FingerDraw (Wu et al., 2020) | Finger motion tracking                          | 20 volunteers | Savitzky–Golay filter       | Fresnel model; CSI-quotient model; Median tracking accuracy: 1.27 cm; Average recognition accuracy: 93%. |

utilize both the model-based approach and the pattern-based approach, such as CSI based human Activity Recognition and Monitoring (CARM) (Wang et al., 2015), etc.

For some complicated human behaviors, such as pull, push, falling, and so on, many applications first utilize models to extract features describing mathematical relationships between human motion and CSI. Then, these extracted features are put into common or special classifiers to recognize human behaviors. CARM (Wang et al., 2015) proposes a CSI-speed model to obtain human movement features and then trains an Hidden Markov Model (HMM) classifier to recognize human behaviors. WiID (Zheng et al., 2017) first utilizes a 2D Fresnel zone model to obtain the information of human moving direction and distance and then feeds the information into a trained SVM to recognize human behaviors. Furthermore, the system proposed by Zhang et al. utilizes the FDM to extract motion features and uses the convolutional neural network (CNN) as a classifier to distinguish human behaviors (Zhang et al., 2019). Moreover, iGest (Ren et al., 2019) leverages the Fresnel model to extract human gesture features and utilizes classifiers of decision tree and HMM to recognize common gestures and complicated gestures, respectively. Besides, WiPIN (Wang et al., 2019) proposes an interacting model to describe the relationship between human biologic features and received signals and trains a one-against-all SVM to identify one target from all persons. Furthermore, WiDIGR (Zhang et al., 2020) utilizes the 2D Fresnel zones to eliminate the effects of walking directions on the signal spectrogram. Then, it trains an SVM classifier with the direction-independent signal spectrogram to achieve gait recognition.

For simple activities, such as hand’s trajectory, walking direction, and so on, some applications can achieve human behavior recognition only utilizing the model-based approach. WiDraw (Sun et al., 2019) utilizes the AoA model to recognize a user’s hand trajectories. The basic idea is that the sharp peak corresponding to AoA in the spectrum will rapidly drop once wireless signals are blocked by hands, which is shown in Fig. 7.

Similarly, WiseFi (Zhu et al., 2016) deduces human locations and some simple behaviors based on the AoA spectrum. Furthermore, WiDir (Wu et al., 2016) utilizes a Fresnel zone model to analyze the CSI phase information and further determines human walking direction and distance. Besides, Wi-Run (Liu et al., 2019) proposes runner CSI-step estimation models that can transform the time series of CSI measurement to power distribution in the frequency domain and then relates the frequency to human velocity mathematically. As shown in Fig. 8, the number of steps can be estimated by identifying the peaks in the time–frequency diagram. Based on the fact that the CSI amplitude will change once targets cross the Fresnel boundaries, Que-Fi (Zhang et al., 2020) is proposed to identify the number of people in a queue. This system utilizes the CNN-based method...
and Fresnel model-based method to count the number of targets in static and dynamic scenarios, respectively. Que-Fi can achieve better accuracy than the traditional SVM-based method. Moreover, based on the changes of the CSI phase, FingerDraw (Wu et al., 2020) combines the Fresnel model and CSI-quotient model to map the CSI quotient to finger motions, thereby tracking finger trajectory.

According to the above description, some applications can recognize simple human activities using only the model-based approach. However, for complex activities, most applications need to combine the model-based approach with the pattern-based approach, such as CARM (Wang et al., 2015), WiPIN (Wang et al., 2019), etc. The reason is that it is difficult to construct a model to describe the mathematical relationships between complex movements of body parts and CSI directly. Therefore, most above applications first utilize a model to extract complex features, such as the movement speed of different body parts (Wang et al., 2015), and then train a classifier based on the extracted features to recognize complex activities. Better than using only the model-based approach or the pattern-based approach, the combination of these two approaches can recognize complex human activities and improve the robustness to the environmental changes. Therefore, it may become a hot research field for CSI-based human sensing in the future.

4.3. Human respiration detection

Human respiration detection plays an important role in the field of human sensing. Table 4 summarizes the existing studies on CSI-based human respiration detection using model-based approaches. According to this table, the Fresnel model is the most popular approach.

Due to the sensitivity to tiny movements, methods based on the Fresnel model have drawn more attention to human respiration detection. Wang et al. (2016) treat the user as a varying-size semicylinder to simulate the chest movement when the user breathes, as shown in Fig. 9. Based on the Fresnel zone model, the chest movement is converted to phase change to describe the relationship between human respiration and received signals. Also, the impacts of human location and body orientation on received signals are investigated.

Moreover, Zhang et al. (2018) build human respiration as the movements of both chest and back. Also, they utilize an FDM to detect the respiration. Besides, Wu et al. (2017) illustrate the advantages of the Fresnel model-based method in human respiration by comparing it to pattern-based methods. Based on the properties of the Fresnel zone, FullBreathe (Zeng et al., 2018) is designed to detect human respiration at all locations using just one pair of transceivers. This system can achieve a detectability ratio of 100% in multiple scenarios. Furthermore, FarSense (Zeng et al., 2019) proposes a CSI-ratio model. This model quantifies the relationship between the change of the CSI ratio from two antennas and human movement. Based on the CSI-ratio model, FarSense can still detect human respiration when the user is far from transceivers. The basic idea is shown in Fig. 10. When a human breathes, the dynamic length of the signal propagation path will increase or decrease with the movements of the human chest. Meanwhile, corresponding to human inhalation or exhalation, the CSI ratio will rotate along a circular arc clockwise or counterclockwise. According to the changes of the CSI ratio, human respiration can be sensed.

As it is difficult to separate the effects of different users on received signals, multiuser respiration detection is a challenging application. However, the Fresnel model contributes to this application. According to the property of the Fresnel zone, the best sensing location and the worst sensing location are in the middle and the boundary, respectively. As shown in Fig. 11, TinySense (Wang et al., 2017) deploys multiple transceivers. The
Table 4: A summary of human respiration detection applications.

| Reference          | Application                                 | Users          | Preprocessing | Model         | Experimental results                                                                 |
|--------------------|---------------------------------------------|----------------|---------------|---------------|----------------------------------------------------------------------------------------|
| Wang et al. (2016) | Respiration detection, different orientation | Nine volunteers| Hampel filter; Fresnel model | Detection performance can be affected by the location and body orientation of the user. |
| Wu et al. (2017)   | Respiration detection                       | One user       | None          | Fresnel model | The median error is 0.09 bpm, 0.15 bpm, 0.06 bpm. More than 80% accuracy               |
| TinySense (2017)   | Multiuser respiration detection.            | Two users      | Wavelet filter; Fresnel model |                                                          |
| Yang et al. (2018) | Multiuser respiration detection, apnea      | Five volunteers| mean filter; | Fresnel model | Mean absolute error of 0.5 bpm ∼ 1 bpm.                                                 |
| FullBreathe (2019) | Respiration detection, full location coverage| Eight volunteers| Savitzky-Golay filter; Fresnel model | The detectability ratio is 100%.                                                        |
| Zhang et al. (2018)| Respiration sensing                         | Eight volunteers| z-score       | FDM           | The accuracy is higher than 98%.                                                       |
| FarSense (2019)    | Respiration sensing, long distance up to 8 m | 12 volunteers  | Savitzky-Golay filter | CSI-ratio model | The overall detection rate of 100%. Mean error of 0.73 bpm (four persons).          |
| MultiSense (2020)  | Multiperson respiration sensing             | 21 volunteers  | None          | BSS model     |                                                                                       |

Figure 9: (a) The movement of the human chest during respiration. (b) A semicylinder model for respiration.

Figure 10: The influence of human respiration on CSI-ratio model. The changes of dynamic path length caused by human chest movements lead to the CSI ratio rotating along a circle arc (labeled in blue). A clockwise rotation corresponds to inhalation, while a counterclockwise rotation corresponds to exhalation.

respiration of up to four users can be detected by changing the deployment of transceivers. Similarly, Yang et al. (2018) also utilize the Fresnel zones produced by multiple pairs of transceivers to achieve multiuser respiration detection. Besides, MultiSense (Zeng et al., 2020) proposes a BSS model to describe the problem of separating mixed signals caused by multiperson respiration. Utilizing independent component analysis, the researchers separate mixed signals successfully. Therefore, MultiSense achieves accurate respiration monitoring for four users simultaneously.

According to the survey of the above applications, the method based on Fresnel models can achieve more accurate respiration detection than the pattern-based approaches (Wu et al., 2017). Also, it can detect multiple users’ respiration simultaneously (Wang et al., 2017). Therefore, the method based on Fresnel
models has excellent potential for future human respiration detection.

5. Advantages, Limitations, and Future Research Trends

In this section, we analyse the advantages of model-based methods in the field of human sensing. This section interprets the reason why the model-based approach is suitable for these applications. Also, this section summarizes the advantages of the model-based method compared with the pattern-based method. Besides, the challenges and future trends of the model-based approach are provided.

It is well known that pattern-based methods rely on pattern establishments and numerous data to recognize human activities. These methods fail to obtain a theoretical description of the relationship between CSI measurements and human movements. By contrast, the model-based methods achieve human sensing solely relying on physical models that quantify the relationships between CSI fluctuations and different human activities. Therefore, the model-based methods have many advantages, including using fewer data and exhibiting more robustness for the environment and user (Wu et al., 2017). Besides, the model-based methods can capture tiny human motion, which can work very well for some fine-grained applications, such as human respiration detection (Wang et al., 2016).

However, some limitations exist in the model-based and CSI-based human sensing methods. First, although the model-based methods are robust to environmental changes, they cannot always achieve significant performance. For example, the model-based methods may not perform as well as pattern-based methods for some coarse-grained applications. Second, it is challenging to establish mathematical relationships between CSI changes and some complex human activities. Third, the model-based methods may not work well in non-line-of-sight scenarios due to the effect of the wall or other occlusion on the signal propagation. For instance, WiseFi (Zhu et al., 2016) can only achieve a median recognition accuracy of 74.3% in a through-one-wall scenario.

According to the limitations of existing studies and requirements of CSI-based human sensing applications, this paper provides some insights for future research of the model-based method. First, more accurate models describing the mathematical relationship between CSI changes and different human activities are required for specific application scenarios. Establishing a suitable model and obtaining the model parameters will become fundamental for model-based approaches. Second, multiuser sensing and non-line-of-sight sensing are common requirements for many application scenarios, which will draw more attention in the future. Third, the combination of model-based methods and pattern-based methods is beneficial for CSI-based human sensing, and it will become more and more popular in this application field.

6. Conclusion

WIFI CSI signal depicts the state of a communication link. The obstruction in the communication path changes CSI parameters, which can be leveraged to infer the target motion. Based on the principle, CSI signal communication models are constructed based on the variation of CSI to recognize human activities. This paper presents a comprehensive survey of the latest model-based human sensing methods. Specifically, this paper summarizes the state-of-the-art CSI-based models, such as the AoA model, the Fresnel model, etc. Compared with other surveys on CSI sensing applications, it is the first research work that performs a thorough analysis of the CSI model for human behavior recognition. According to analysis results, the model-based methods achieve satisfactory recognition performance and show great potential for CSI-based human sensing. Also, the CSI model describes the mathematical relationship between CSI dynamics and human movements, which improves the recognition performance and benefits a variety of applications, especially the fine-grained applications such as tracking and respiration. Despite the limitation of model design and signal propagation, the sensing application using the CSI model will increasingly emerge.

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Conflict of interest statement

None declared.
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