Wi-Fi Radar: Recognizing Human Behavior with Commodity Wi-Fi

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ABSTRACT

Wi-Fi, which enables convenient wireless access to Internet services, has become integral to our modern lives. With widely-deployed Wi-Fi infrastructure, modern people can enjoy a variety of online services such as web browsing, online shopping, social interaction, and e-commerce almost at any time and any place. Traditionally, the most significant functionality of Wi-Fi is to enable high-throughput data communication between terminal devices and the Internet. However, beyond that, we observe that a novel type of system based on commodity Wi-Fi is increasingly attracting intense academic interest. Without hardware modification and redeployment, researchers are exploiting channel state information output by commodity Wi-Fi and transforming existing Wi-Fi systems into radar-like ones that can recognize human behavior along with data communication. This fancy functionality is tremendously expanding the boundaries of Wi-Fi to a new realm and triggering revolutionary applications in the context of the Internet of Things. In this article, we provide a guide to and introduce the impressive landscape of this new realm.

INTRODUCTION

Nowadays, Wi-Fi is widely used in our daily lives whether in private residential houses or public places such as libraries and offices. It provides users with convenient wireless access to online services such as information retrieval, social networking, and electronic commerce. Compared to other communication technologies, Wi-Fi holds the advantages of providing online services with higher data rates, greater mobility, and broader coverage. It is these positive properties that make Wi-Fi an attractive option with the explosive growth of mobile data traffic, and it is widely deployed in urban cities.

Technically, Wi-Fi refers to a wireless RF communication technology based on a family of standard protocols (e.g., IEEE 802.11 a/b/g/n/ac). It enables wireless data transfer between end devices and Internet infrastructure with high data rates. With the prosperity of the Internet of Things (IoT), connections between humans, objects, and the Internet are increasing more than ever before. A variety of IoT services have sprung up and brought about a sharp increase of data traffic. For example, location-based services (LBS), including mobile advertising, service recommendation, and weather alert, are appealing in most shopping malls, smart cities, and other scenarios. All of these indicate that Wi-Fi shall play a crucial role in the era of IoT.

However, this is far from the whole story of Wi-Fi and IoT. The advances in Wi-Fi physical (PHY) layer technologies have enabled users to get access to low-level information that portrays detailed characteristics of signal propagation through multipath, without hardware modifications or redeployment. A superior example of Wi-Fi PHY information is channel state information (CSI), which describes channel fading with amplitude and phase responses in fine granularity. The ever-increasing pervasiveness of Wi-Fi signals and growing fine-grained accessible PHY information not only open up new possibilities with Wi-Fi but also motivate researchers to pioneer a new realm beyond communication. In this article, we introduce such a pioneering area in which commodity Wi-Fi devices are transformed into radar-like systems that can sense and recognize human behavior by analyzing their motion states or gesture/activity types. *Informally, this kind of sensing system via Wi-Fi signals that achieves similar functions as radars is referred to as Wi-Fi radar in this article*. The significance of human behavior is two-fold. On one hand, it enables researchers to obtain better understanding of human behavioral patterns. On the other hand, recognizing human behavior has a wide range of applications in our lives, such as user authentication, healthcare for the elderly, location-based services, and human-device interaction, as shown in Fig. 1.

As is well known, radar is a kind of RF system that utilizes radio waves to sense, monitor, and track moving objects. With sophisticated hardware and high precision, radar is usually applied in certain specialized areas such as meteorology, the military, and traffic engineering. Similarly, *Wi-Fi radar* can also monitor targets' motions, and recognize human gestures and activities, but with lower precision and coarser granularity. Thus, a question naturally arises: *since radars have exceeding performance, what is the motivation behind designing Wi-Fi radar?* The reasons are mainly twofold. For one thing, the requirements of sensing precision, granularity, and range for most IoT services are not as harsh as for radars. Take indoor location-based services (LBS) as an example. The acceptable precision of human motion monitoring is about meter level in typical indoor environ-

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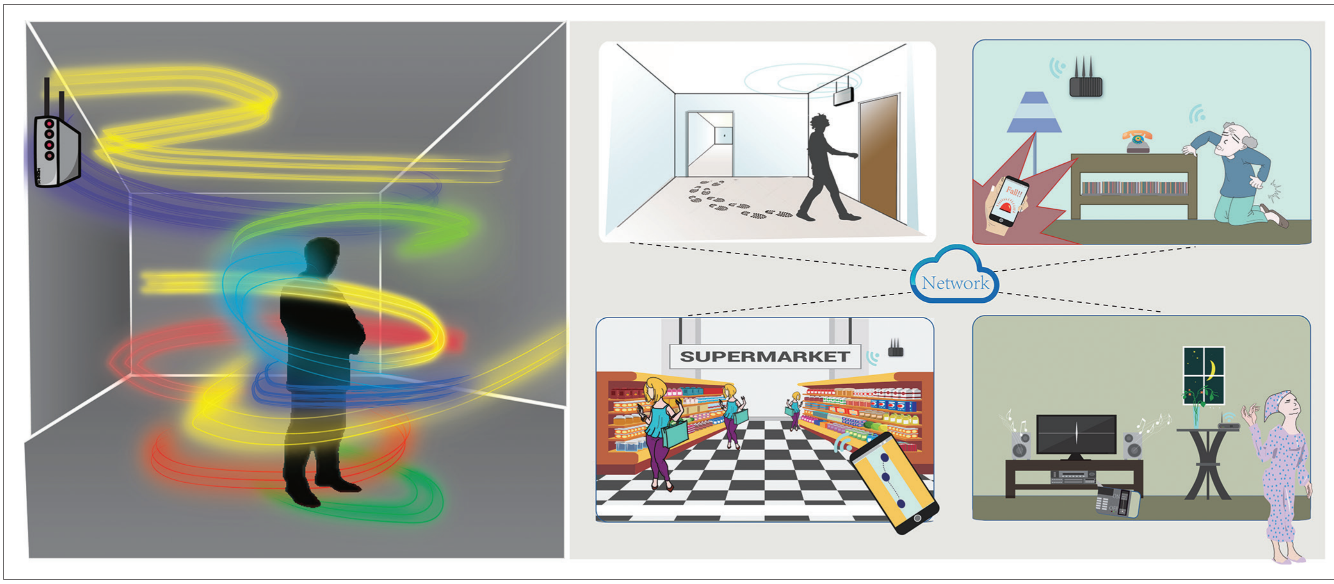

Figure 1. The visualization of Wi-Fi signals and application scenarios of Wi-Fi radar in IoT.

ments such as shopping malls, office spaces, and residential houses. For another thing, radar systems consist of costly and specialized hardware components, which makes them not as pervasive as Wi-Fi. The radar infrastructure and hardware components are rarely deployed in daily environments or embedded in commercial devices. In contrast, Wi-Fi infrastructure is widely deployed as aforementioned, and Wi-Fi Soc is pervasively embedded in various devices such as smartphones, tablets, smart TVs, and the like. Without hardware modification and redeployment, it is rather appealing to perform "secondary development" with commodity Wi-Fi and provide additional services along with communication.

Motivated by the inspiring prospect, researchers have made successive attempts to design Wi-Fi radar with CSI to recognize human behavior. In the remainder of this article, we first give an introduction to the knowledge background of Wi-Fi radar. Following that, an overview of the general design approaches and framework of Wi-Fi radar is presented. After this, a comprehensive survey of the state-of-the-art works in this field is conducted. At last, we put forward our remarks and conclusion.

Background Knowledge

As aforementioned, Wi-Fi radar is built on CSI. Before introducing Wi-Fi radar systems, it is better to give introduction to background knowledge closely related to CSI. In this section, we explain orthogonal frequency-division multiplexing (OFDM), based on which CSI is introduced in the following.

OFDM

OFDM represents a communication technology that transmits signals across orthogonal subcarriers at different frequencies. In OFDM, a wide frequency band is divided into multiple mutually orthogonal narrow subcarriers with different central frequencies. For data transmission, a high-rate bitstream in OFDM is first split into multiple relatively low-rate bitstreams, and then each of them is transmitted over a certain subcarrier independently. It is noted that, due to the orthogonality of subcarriers, bitstreams transmitted over multiple subcarriers simultaneously will not cause interference to each other. As a result, the spacing of subcarriers across the frequency band can be highly tight, which increases the spectrum efficiency to a great extent. In addition, multipath channel is usually frequency-selective, which means signals transmitted over subcarriers experience different levels of fading. Consequently, OFDM possesses better robustness to multipath interference (reflection, scattering, and absorption) than other transmission schemes, and thus is widely used in many wireless systems such as Wi-Fi and LTE.

Concept of CSI

In a Wi-Fi system with IEEE 802.11 a/g/n protocol, signals are transmitted in an OFDM scheme with $K = 48$ subcarriers. Due to the multipath effect, signals arriving at the receiver are not exactly the same as the original version from the transmitter. The differences are reflected in amplitude attenuation and phase shift. To accurately quantify such a channel fading effect, CSI is brought in originally for the sake of adapting transmission rate and optimizing throughput. Mathematically, for a system with M transmitting and N receiving antennas, each CSI sample at an instant is a collection of $M \times N$ complex vector $\mathbf{H} = [H(f_1), H(f_2), ..., H(f_k)]$, which describes the channel response at each subcarrier. Correspondingly, each element $H(f_k)$ in $\mathbf{H}$ represents the amplitude and phase response of the kth OFDM subcarrier that correlates the transmitted signal $X(f_k)$ and received signal $Y(f_k)$ in the frequency domain by $Y(f_k) = H(f_k)X(f_k)$. From the definition, it is obvious that due to OFDM, CSI can portray the propagation channel with a subcarrier-level granularity in the frequency domain and convey richer information compared to the summation of them (i.e., received signal strength indicator, RSSI). Figuratively speaking, CSI is to RSSI what a rainbow is to a sunbeam, where components of different frequencies are separated as shown in Fig. 2.

Properties of CSI

As aforementioned, CSI contains amplitude and phase response of the signal propagation channel at each subcarrier. In what follows, we shall drill down further and analyze the properties of CSI from the amplitude and phase perspectives. We expect that the analysis will shed light on principles of Wi-Fi radar.

Amplitude: By definition, the amplitude of CSI can easily be obtained by calculating the modulus of its every element (e.g., $||H(f_k)||$ for $H(f_k)$). The physical meaning of CSI amplitude is that it quantifies signal power attenuation after multipath fading. In this sense, it is similar to another signal indicator, RSSI. However, CSI amplitude has shown several favorable merits compared to other indicators:

- Frequency diversity. As mentioned above, CSI depicts channel response in each narrow subcarrier. Due to frequency-selective fading, signal streams on different subcarriers go through diverse multipath fading, which results in uncorrelated CSI values across subcarriers.
- Temporal stability. Since CSI amplitude is essentially a set of attenuation coefficients of a channel, it is rather robust to interference coming from transeceivers such as power adaptation, as long as there are no changes to the channel itself.
- Fine-grained granularity. Instead of measuring a channel with a composite value like RSSI, CSI decomposes a whole channel measurement into subcarriers and estimates the frequency response of each subcarrier, which obtains a finer-grained description of the channel in the frequency domain.

Phase: Phase is the information contained in CSI that is the counterpart to amplitude. Similarly, in order to extract phase information from CSI, we only need to calculate the angle of each complex element $\angle H(f_k)$. Theoretically, the phase of CSI has similar properties to amplitude. Nevertheless, the case is more complex for phase in practice. From another perspective, phase $\hat{\phi}_f$ extracted from CSI is composed of four different parts, that is, ϕ_f for genuine channel response phase, $2\pi f_f \Delta t$ for phase shift caused by clock offset, β for phase shift induced by carrier frequency offset, and Z_f for measurement noise. Since it is difficult to measure accurate clock and carrier frequency offsets on commodity devices, the phase extracted from raw CSI data is reported to be randomly distributed. Due to the randomness, the physical meaning of CSI phase is blurred, which means phase has rarely been utilized in previous work. Recently, some methods have been proposed to calibrate raw phase and treat calibrated phase as a new feature, but are still not accurate enough for modeling.

An Overview of a Wi-Fi Radar System

Wi-Fi radar has been informally defined in the introduction. However, the fundamental principles and general architecture of Wi-Fi radar remain unclear. In this section, we give more detail about the above aspects.

Human Behavior Recognition

Human behavior refers to the array of every physical action and observable emotion associated with individuals, and covers a wide range of specific contents. In the context of Wi-Fi sensing, present work toward behavior recognition can be classified mainly into three categories, namely, gesture recognition, activity monitoring, and motion tracking. Although it is difficult to give a precise definition to each category, there are notable differences among them from the perspectives of granularity and continuity. Intuitively, gestures only involve a certain part of the human body, such as finger, hand, arm, and even lip, and are of relatively short duration. In contrast, activities cover more body parts and consist of a sequence of physical actions. Human motion describes continuous physical movement of a whole body or just a certain part. And most of the time, motion tracking outputs human position and direction with high precision in real time.

In fact, there are already some methods for behavior recognition, mainly including sensor-based and camera-based ones. Then what are the benefits of Wi-Fi radar that make it worthy of intense attention from researchers? Obviously, due to the pervasiveness of Wi-Fi infrastructure and devices, Wi-Fi radar has lower hardware cost than these two approaches since they both need additional devices. In addition, compared to a sensor-based approach, Wi-Fi radar works in a device-free way without requiring users to wear any sensors. This is more comfortable and convenient, especially in certain circumstances such as showering. In comparison with the camera-based approach, Wi-Fi radar is not dependent on line of sight (LOS) and light conditions.

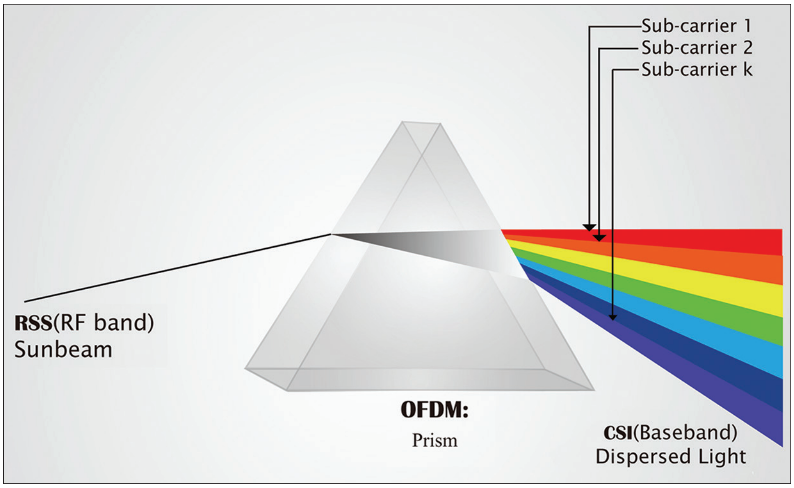

Figure 2. Illustration of the relationship between CSI and RSSI.

Why Is CSI Feasible and Better?

As demonstrated above, CSI has several intrinsic advantages for communication purposes. But it is still unrevealed to readers why CSI is capable of capturing human behavior and better to utilize for designing Wi-Fi radar. As we all know, signals sent by a transmitter travel through multiple propagation paths and experience reflection and scattering before arriving at a receiver. Human behavior (e.g., gestures and activities) is bound to cause significant changes to the propagation channel of signals by altering the multipath. Since CSI quantifies the channel fading effect in amplitude attenuation and phase shift, it is sensitive to

Category	Layer	Resolution	Frequency diversity	Behavior sensitivity	Hardware accessibility
RSSI	MAC	Time domain: packet level Frequency domain: N/A	No	Low	Handy access
CSI	Physical	Time domain: multipath cluster Frequency domain: subcarrier level	Yes	High	Wi-Fi NIC

Table 1. The comparison between RSSI and CSI in human behavior recognition.

any changes of channel state, and thus is capable of capturing human behavior. Moreover, compared to other Wi-Fi indicators such as RSSI, a favorable point of CSI is that it depicts channel state with finer-grained frequency resolution and equivalently higher time resolution to distinguish multipath components as demonstrated by previous research [1]. In other words, it indicates that CSI possesses higher sensitivity to human behavior and is more powerful in uncovering behavior. The comparison between CSI and RSSI can be seen in Table 1.

General Approaches and Framework

In general, Wi-Fi radar systems in present works can be divided into two main streams according to their design approaches. One of them is the data-driven approach, which highly relies on collecting a large amount of data and adopts a training-learning scheme in a supervised or unsupervised way. The rationale lies in the fact that behavior causes changes to multipath and thus results in distinguishable patterns in CSI. By mining the patterns with machine learning techniques, it is possible to recognize behavior. However, without deterministic one-to-one mapping between CSI data and behavior, this approach can only recognize a set of predefined behavior in a certain system and is limited to application in gesture and activity recognition. The other one is the model-based approach. In this approach, deterministic models are built based on physical principles and correlate CSI with behavior with one-to-one mapping. Different from the data-driven approach, it can monitor human behavior continuously with little system training effort. However, due to the great challenge in modeling, there are only a few works that conduct such attempts. Based on the above, we can give a general framework of Wi-Fi radar, as shown in Fig. 3, which mainly consists of three layers: the hardware/infrastructure layer, the data processing layer, and the application layer. In the following, we give details about the above two main approaches.

How Is This Field Evolving?

To the best of our knowledge, [2] is the first work that makes use of CSI to replace RSSI for more accurate rate adaptation and higher throughput in data transmission. In this work, measurements have been conducted to verify the merits of CSI in temporal stability and frequency diversity. Inspired by the reported advantages, researchers have started to explore applying CSI in other areas beyond communication. Wu *et al.* [3] explicitly came up with CSI-based fine-grained indoor localization with commodity devices for the first time. The insights are two-fold, high spatial discrimination and resilience to transmission variation, brought about by CSI. Later, Han *et al.* [4] introduced CSI into the area of human behavior recognition by designing a fall detection system with CSI. The rationale of CSI-based behavior recognition is that CSI is a fine-grained feature sensitive to body movements. Within this area, Wang *et al.* [5] first proposed a model to estimate human walking speed and further utilize the model to recognize activities. Recently, Wang *et al.* [6] brought in a Fresnel model, a well-known physical model, to shed light on fundamental principles and push the limit of high-precision activity recognition with CSI.

A Survey of the State of the Art

As a novel and promising technology, Wi-Fi radar exhibits its attractiveness in various interesting applications. It is these applications that tremendously expand the boundaries of Wi-Fi functionalities and reshape our conventional knowledge of Wi-Fi. In order to demonstrate this clearly, we conduct a thorough survey of the state-of-the-art Wi-Fi radar systems and categorize them into two main streams according to their design approaches: data-driven and model-based.

The Data-Driven Approach

The underlying principle of the data-driven approach has been introduced earlier with a high-level idea about this approach. In this section, we shall introduce in detail the general architecture and state-of-the-art applications of Wi-Fi radar built on this approach.

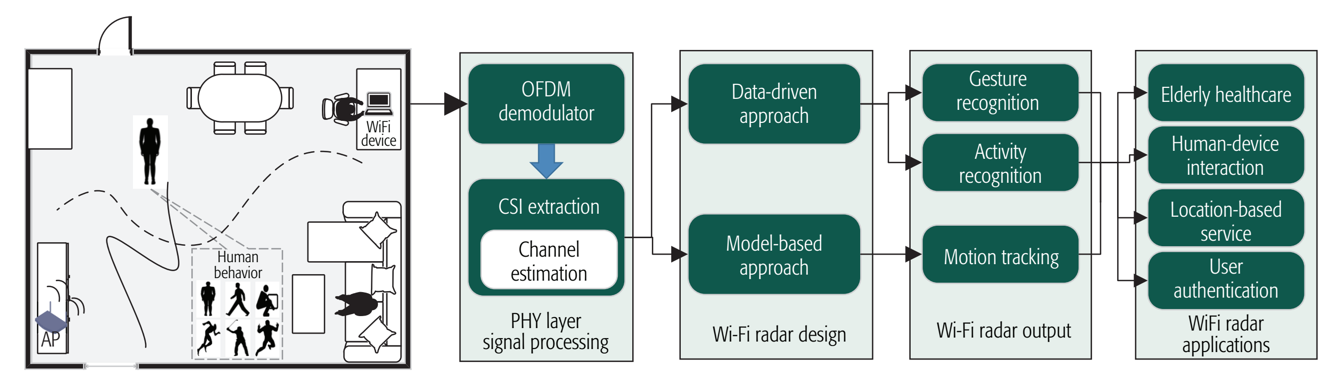

Figure 3. The general framework of a Wi-Fi radar system.

System Architecture: Even though the data-driven approach enables diverse Wi-Fi radar for specific purposes, a general architecture can be abstracted from these systems, as shown in Fig. 4. In general, the system architecture of a data-driven Wi-Fi radar consists of three stages, including data preprocessing, feature extraction and selection, and model training and testing, after CSI data is extracted from commodity Wi-Fi devices. The data flow in the architecture of Wi-Fi radar goes through nearly the same routine in other machine learning applications. However, considering the underlying physical meaning of CSI, there are some unique insights to be utilized in the system design, which are introduced in the following. To clean data in the first stage, researchers usually start by analyzing the properties of signals of interest in the time and frequency domains. Based on the results of signal analysis, they are able to design an appropriate denoising method to remove unwanted components as much as possible. Although the denoising techniques are customized case by case, there are some widely used methods such as Butterworth filtering and wavelet denoising due to their favorable properties [7]. Another important step in the preprocessing stage is behavior detection, which extracts signal segments corresponding to behavior events and discards the useless signals in a CSI sequence. This is essentially a signal detection problem in which energy-based hypothesis testing is frequently used to detect the start and end points of an event. Following data preprocessing, feature extraction and selection are performed on obtained segments. Although features are customized for different systems, they can roughly be classified into time domain, frequency domain, and time-frequency domain. Due to the lack of domain knowledge of the problem, it is common that researchers tend to extract features blindly in a preliminary attempt. Directly utilizing these features to train a machine learning model results in unsatisfactory performance and incurs heavy training overhead in most cases, since some features are noisy and redundant. As a result, a feature selection process is introduced to filter out those features and choose an optimal feature set that can achieve favorable performance and decrease training overhead. The common feature selection methods include correlation-based filtering, PCA, sequential search, and the like. In the last stage, selected features are fed into a certain machine learning model to construct predictive models in the training stage that are used for behavior recognition in the later learning process. The support vector machine (SVM), random forests, and hidden Markov model (HMM) are the common machine learning models in present data-driven Wi-Fi radar.

Applications: As aforementioned, data-driven Wi-Fi radar is mainly applied for human gesture and activity recognition. Within this scope, a number of systems have been developed to recognize a variety of gestures or activities with various granularities. According to our survey, WiFall [4] and E-eyes [8] are the first works that bring CSI in the area of human activities recognition. Nevertheless, they have different focuses. WiFall concentrates on detecting whole-body activities such as falling, walking, and sitting of the elderly in case of emergency. By identifying the unique changes of CSI, the system is able to differentiate three activities with high accuracy. On the other hand, E-eyes focuses on recognizing human daily activities in residential houses such as cooking, brushing, bathing, and watching TV. Compared to WiFall, activities in E-eyes possess higher diversity and complexity. Later works within this scope mainly attempt to design Wi-Fi radar systems to recognize finer-grained activities such as smoking with more sophisticated system design [9]. Another application area of data-driven Wi-Fi radar is gesture recognition. Wang *et al.* [7] first proposed Wihear to recognize minute lip gestures with CSI when someone is speaking. By mapping lip gestures with vowels and consonants, they finally recover what the person has said. However, to prevent external interference from overwhelming signals of interest, Wihear adopts directional antennas and only works in a highly controlled environment. Later research in CSI-based gesture recognition moved toward recognizing gestures with commodity devices in a more realistic environment, covering a variety of applications such as human-computer interaction (HCI) [10], vital signs monitoring [11], keystroke eavesdropping [12], and user authentication [13].

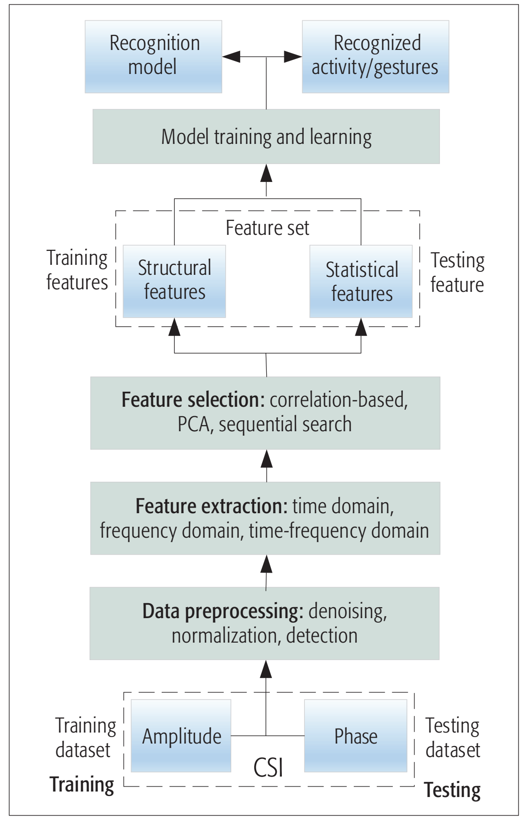

Figure 4. The general architecture of data-driven Wi-Fi radar.

Another important step in the preprocessing stage is behavior detection, which extracts signal segments corresponding to behavior events and discards the rest useless signals in a CSI sequence. This is essentially a signal detection problem in which energy-based hypothesis testing is frequently used to detect the start and end points of an event.

The Model-Based Approach

In addition to the data-driven approach, Wi-Fi radar can also be designed with deterministic physical models and track human motion in real time. Although such Wi-Fi radar systems possess advantages of real-time monitoring and little system training, the critical challenge lies in developing suitable models that correlate CSI with human behavior in a one-to-one mapping. Due to this

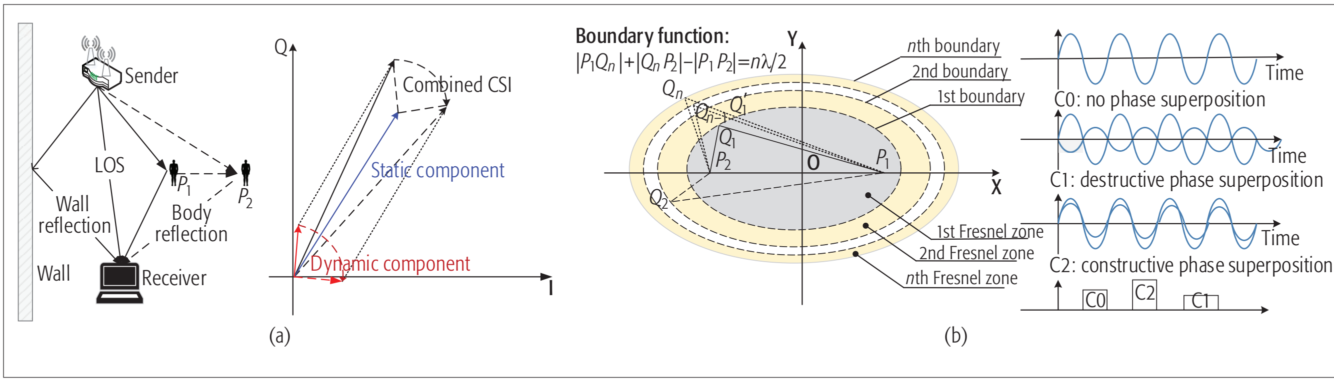

Figure 5. Illustration of a CSI-speed model and a Fresnel zones model: a) visual and phasor representations of the CSI-speed model; b) the Fresnel zone model and corresponding signal superposition.

challenge, only a few works have been conducted in this direction. In the following, we mainly introduce two different models developed to monitor human walking and/or vital signs.

CSI-Speed Model: In CARM [5], the authors propose a CSI-based speed model that estimates the speed of human activities by monitoring the amplitude of CSI. The underlying principle of this model can be demonstrated as follows. In the setting shown on the left side of Fig. 5a, the receiver receives multipath components of transmitted signals, including the LOS component, wall and body reflections, and traveling from different propagation paths. In a static environment, where all the objects are static except the human body, the LOS component and wall reflection are static, and thus result in a constant I-Q vector in the complex plane, as shown in the right part of Fig. 5a. When a person moves from P_1 to P_2, the traveling distance of body reflection changes approximately by $|P_1P_2|$, which consequently induces a phase shift to body reflection. As a result, the composite phase of received signals is to be changed accordingly. In other words, the phase of received signals varies along with walking distance $|P_1P_2|$. Due to the randomness in CSI phase, the authors turn to tracking the variance of CSI amplitude instead of phase in the model, and build up a relationship between CSI amplitude and walking speed.

Fresnel Zones Model: Fresnel zones, named for physicist Augustin-Jean Fresnel, refer to a series of concentric prolate ellipsoidal regions between and around a pair of signal (acoustic or RF) transmitter and receiver (at P_1 and P_2 in Fig. 5b). This model is originally put forward to understand and compute the strength of waves propagating in the space. Referring to Fig. 5b, the innermost ellipse is defined as the first Fresnel zone, the elliptical annuli between the first ellipse and the second one is defined as the second Fresnel zone, and the Nth Fresnel zone corresponds to the elliptical annuli between the $(n - 1)$th and nth ellipses. Correspondingly, the boundary between any two adjacent Fresnel zones (say nth and $(n + 1)$th) is defined as the nth Fresnel boundary. Now assume the transmitter at P_1 is transmitting signals, and the receiver at P_2 only receives the LOS component through P_1P_2, if there are no other objects in the space (free space case). However, when a reflector is located in a position, say Q_1, the received signals are the combination of LOS component via P_1P_2 and multipath component via P_1Q_1 and Q_1P_2. Since these two components possess phase shifts of $2\pi f|P_1P_2|/c$, and $2\pi f(|P_1Q_1| + |Q_1P_2|)/c + \pi$ (c is signal speed, the added π phase shift is caused by reflection), the combination of them depends on their phase difference $\Delta\phi$ (i.e., $2\pi f/c(|P_1Q_1| + |Q_1P_2| - |P_1P_2|) + \pi$). When phase difference $\Delta\phi$ equals $k\pi$ and k is an odd number, indicating that phases of the two components are inverse, both components cancel each other, and the strength of received signals (i.e., CSI amplitude) decreases consequently. On the contrary, if k is an even number, both components reinforce each other, and thus strengthen the strength of received signals. In both cases, the reflector is certain to be located in the Fresnel boundary, which is mathematically determined by the equation shown in Fig. 5b. Moreover, when the reflector is located in a Fresnel zone, the weaken or strengthen effect is in between compared to the case where the reflector is on the corresponding boundary.

According to the above analysis, it is clear that the strength of received signals is highly sensitive to the location of the reflector. In other words, if we treat the human body as a reflector, since any body motion results in variance of CSI amplitude, it is feasible to detect the position and monitor the movement of a human body in real time by analyzing CSI data. Moreover, as the resolution of the Fresnel zone for Wi-Fi signals is centimeter-level, it is possible to achieve fine-grained body motion and activity tracking with this model [14]. Based on this insight, Wang *et al.* first made use of the Fresnel zones model to explain the fundamental principles of CSI-based human activity recognition, and further explored the effect of position and orientation on the performance of vital signs detection [6]. With this model, they also achieved high-precision walking direction estimation in [15].

Remaining Challenges and Open Issues

Wi-Fi radar is a promising technology that stands out for low hardware cost, pervasiveness, and unobtrusiveness. Although researchers have conducted pioneering exploration with notable achievements, there remain several critical challenges and open issues to be handled in order to further advance this area. First, for data-driven Wi-Fi radar, improving the system scalability is a big challenge. Existing systems following this design routine are usually required to be trained and tested in the same environment. It is questionable whether they can maintain high performance when the testing environment is changed even by furniture repositioning or other objects' presence. Second, for existing model-based systems, robustness is a major concern since multipath has a great effect on model performance. When motions or objects out of interest exist, how to remove the induced multipath interference and maintain performance is still a remaining challenge. Moreover, we hold the viewpoint that it is worth trying a combination of both approaches. More specifically, it is desirable to combine the physical meaning of CSI with data mining techniques in designing Wi-Fi radar systems.

Conclusion

In this article, we introduce an emerging and promising technology that transforms commodity Wi-Fi into radar-like systems that can recognize human behavior with channel state information. By surveying the latest works, we summarize the general framework of existing Wi-Fi radar systems, and figure out that the design of these systems mainly follows a data-driven approach or a model-based approach. For each kind of Wi-Fi radar, we give a detailed introduction to the fundamental principles and state-of-the-art applications. We envision that, although Wi-Fi radar still faces critical challenges toward practical use, it has shown a great vision of the future of the Internet of Things.

Acknowledgment

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Wi-Fi radar is a promising technology that stands out by low hardware cost, pervasiveness and unobtrusiveness. Although researchers have conducted pioneering exploration with notable achievements, there still remain several critical challenges and open issues to be handled in order to further advance this area.