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Wireless Sensing for Human Activity: A Survey

Jian Liu, Hongbo Liu, Yingying Chen, Yan Wang, Chen Wang

***Abstract*—With the advancement of wireless technologies and sensing methodologies, many studies have shown the success of re-using wireless signals (e.g., WiFi) to sense human activities and thereby realize a set of emerging applications, ranging from intrusion detection, daily activity recognition, gesture recognition to vital signs monitoring and user identification involving even finer-grained motion sensing. These applications arguably can brace various domains for smart home and office environments, including safety protection, well-being monitoring/management, smart healthcare and smart-appliance interaction. The movements of the human body impact the wireless signal propagation (e.g., reflection, diffraction and scattering), which provide great opportunities to capture human motions by analyzing the received wireless signals. Researchers take the advantage of the existing wireless links among mobile/smart devices (e.g., laptops, smartphones, smart thermostats, smart refrigerators and virtual assistance systems) by either extracting the ready-to-use signal measurements or adopting frequency modulated signals to detect the frequency shift. Due to the low-cost and non-intrusive sensing nature, wireless-based human activity sensing has drawn considerable attention and become a prominent research field over the past decade. In this paper, we survey the existing wireless sensing systems in terms of their basic principles, techniques and system structures. Particularly, we describe how the wireless signals could be utilized to facilitate an array of applications including intrusion detection, room occupancy monitoring, daily activity recognition, gesture recognition, vital signs monitoring, user identification and indoor localization. The future research directions and limitations of using wireless signals for human activity sensing are also discussed.**

I. Introduction

With the rapid development of sensing technology over the past decade, considerable attention has been drawn on human activity recognition to brace a broad range of compelling applications, such as human-computer interactions on smart-home appliances, elder care, well-being management and safety surveillance. To facilitate these applications, active research has been conducted to examine human activities through sensing from different perspectives, including pinpointing target person's positions in an indoor environment, recognizing the regular activities or specific body gestures that the person performed and monitoring his or her vital signs (e.g., breathing rate).

To effectively perform human activity recognition, various sensing technologies, including motion sensors [1], vision-based sensors [2], acoustic-based sensors [3] and pyroelectric infrared (PIR) sensors [4], are deployed to inspect different human activities and gestures. Motion sensor based approaches usually require individuals to wear a specialized device to track body motions, which are not always convenient in practice. The approaches relying on camera or visible light sensors can only work well in the environments under certain light conditions, which could be easily interfered by low illumination condition, smoke, or opaque obstructions. Furthermore, the stability of acoustic-based approaches is vulnerable to ambient noise and surrounding sound interferences, and the sensing range is also limited due to the fast attenuation of acoustic signals. Overall, the aforementioned techniques involve extra overhead in terms of complicated hardware installation and diverse maintenance needs. To overcome the aforementioned limitations, a low-cost and non-intrusive solution is desirable to capture human body movements involved in their daily activities. Recently more and more research work focus on radio frequency (RF) (e.g., WiFi) based techniques to perform human activity sensing. The prevalence of WiFi technology enables almost every electronics in home/office environments such as smart speakers (e.g., Amazon Echo, Apple HomePod), smart TV, smart thermostat, and home security system interconnected wirelessly. WiFi signals can usually reach tens of meters of coverage in indoor environments, and the wireless links among these smart devices provides rich web of reflected rays that spread every indoor corner. The presence of people and related body motion will have considerable impact on wireless signals and result in significant changes in both amplitude and phase of the received signals, which can be utilized to capture human body movements involved in their daily activities.

To quantify the changes of the received WiFi signal, researchers could measure the physical layer properties over wireless channel such as the received signal strength Indicator (RSSI) and channel state information (CSI), which are readily available on many commercial network interface cards (e.g., Intel 5300 NIC [96] and Atheros 9580 NIC [97]) with modified driver software. To pursue more precise sensing, some researchers manipulate the transmitting wireless signals on universal software radio peripheral (USRP) defined radio platform, such as Frequency Modulated Carrier Wave (FMCW), to detect the signal's frequency shift caused by the human motions [28]. Moreover, the Doppler effect is exploited to

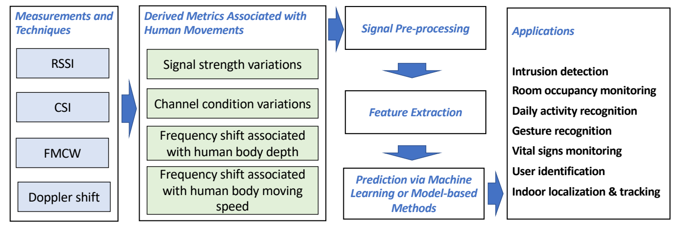

Fig. 1. Typical workflow of human activity sensing via wireless signal.

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TABLE I. APPLICATIONS OF WIFI SENSING FOR HUMAN ACTIVITY.

Section #	Applications	Main Techniques			
		RSSI	CSI	FMCW	Doppler shift
Section III	Intrusion detection	[5], [5]–[7]	[7]–[9], [9]–[11]	—	—
	Room occupancy monitoring	[12]–[14]	[15], [16]	—	—
Section IV	Daily activity recognition	[17], [17]–[20]	[21]–[27]	[28]	[29], [30]
	Gesture recognition	[31]–[33]	[34]–[41]	[42]–[44]	[45]
Section V	Vital signs monitoring	[46]–[48]	[49]–[54]	[55]–[57]	[58]–[66]
Section VI	User identification	—	[67]–[71]	—	—
	Indoor localization & tracking	[72]–[74], [74]–[83]	[84]–[91]	[55]–[57]	[28], [92]–[95]

measure the signal's frequency shift associated with body motions [45], which also needs the support of USRP platforms to control the transmission and receiving of wireless signals. We will elaborate these techniques in details in Section II.

Given the WiFi sensing techniques, a broad range of emerging applications could be supported to improve the quality of people's lives. In this paper, we investigate the state-of-the-art WiFi sensing studies on human activity and related applications. We broadly divide these applications into four categories: *intrusion detection & occupancy monitoring*, *activity & gesture recognition*, *vital signs monitoring* and *user identification & localization*. Specifically, *intrusion detection & occupancy* involves the detecting any abnormality (i.e., human intrusion of a room) and room occupancy monitoring (i.e., crowd estimation). *Activity & gesture recognition* ranges from daily in-home activity (e.g., walking, cooking and washing dishes) recognition to relatively smaller body gestures (e.g., arm/hand/finger/head motions) recognition. *Vital signs monitoring* refers to detecting breathing and heart rates associated with minute human body vibrations, and *user identification & localization* is using the WiFi-based location fingerprints for indoor localization and the unique user-specific activity behavior for further identity verification. The related work for each application category will be introduced together with their main techniques, which are summarized in Table I. Figure 1 shows the typical workflow of the existing human activity sensing systems using wireless signals. Specifically, the sensing systems first extract signal changes associated with human activities based on different sensing methods (e.g., RSSI, CSI, FMCW and Doppler shift). Next a series signal pre-processing procedures (e.g., filtering, denoising and calibration) are adopted to mitigate the impact of interference, ambient noise and system offset. Finally the unique features are extracted and fed into machine learning models to perform human activity detection and recognition.

The remainder of this paper is organized as follows. We first review the four key techniques to perform WiFi sensing in Section II. Next the four categories of WiFi-based human activity sensing applications are introduced. Specifically, the studies on intrusion detection and room occupancy monitoring is presented in Section III; in Section IV, we review the work on regular activity and gesture recognition; we study the work on human vital signs monitoring in Section V; and the work on user identification and indoor localization and tracking will be discussed in Section VI. In Section VII, we discuss the limitations of existing work and the prospects of future WiFi-based human activity sensing. Finally, we conclude the survey of current human activity sensing work leveraging WiFi in Section VIII.

II. TECHNIQUES FOR WIFI SENSING

For both commodity devices and customized hardware, there are many physical layer properties that can be extracted over wireless channel to facilitate human activity sensing. In this section, we identify four common WiFi sensing techniques based on different physical layer properties, including Received signal strength indicator (RSSI), channel state information (CSI), frequency shift for frequency modulated carrier wave (FMCW), and Doppler shift, as summarized in Table II.

A. Techniques Using Commodity Hardware

Received Signal Strength Indicator (RSSI). Received signals are available in most WiFi devices, which indicate the path loss of wireless signals with respect to a certain distance, and can be derived following Log-normal Distance Path Loss (LDPL) model [100]:

$$P(d) = P(d_0) + 10\gamma \log \frac{d}{d_0} + X_\delta, \tag{1}$$

where $P(d)$ denotes RSSI measurement indicating the path loss at distance d measured in Decibel (dB), $P(d_0)$ is the path loss at the reference distance d_0, γ is the path loss exponent, and X_δ is a zero-mean normal noise caused by flat fading.

As one of the most representative RSS-based applications, the success of utilizing RSSI to estimate the positions of target users with carry-on WiFi devices has been demonstrated for a long time [72]. It has also been noticed that the existence of human body within the wireless sensing area would cause signal attenuation, leading to the variation of RSSI measurements. Thus, RSSI has been widely deployed for human activity sensing in recent years, for example, device-free indoor localization [82], [83], [101], room crowd density estimation [12], [14], and breathing rate monitoring [46]–[48]. Although RSSI is easily obtained in any commodity WiFi devices without additional hardware, it can only detect limited types of human activities due to the coarse-grained channel state information (i.e, single path loss value per packet). Furthermore, It has been shown that the stability of the RSSI is not guaranteed even in a static indoor environment [102], making it unreliable in many application scenarios.

Channel State Information (CSI). To achieve accurate and reliable human activity sensing, it is essential to capture more fine-grained CSI, which represents the combined effect of, for example, scattering, fading, and power decay with distance. Since wireless signals could travel through almost any corner in an indoor environment, the presence or movement of a human body would alter the propagation of wireless signals, resulting in the small changes in multiple reflected rays as

TABLE II. MAIN TECHNIQUE COMPARISON.

Techniques	Derived Metric	Granularity	Additional Hardware	Existing Sensing Work
RSSI-based	Wireless signal strength	Coarse-grained	No	[5], [5]–[7], [12]–[14], [17], [17]–[20], [31]–[33], [46]–[48], [72]–[74], [74]–[83]
CSI-based	Channel conditions/properties of wireless links	Fine-grained	No	[7]–[9], [9]–[11], [15], [16], [21]–[27], [34]–[41], [49]–[54], [67]–[71], [84]–[91]
FMCW-based	Frequency shift associated with human body depth	Fine-grained	Yes	[28], [42]–[44], [55]–[57] [29], [30], [45], [98], [99]
Doppler Shift-based	Frequency shift associated with human body moving speed	Fine-grained	Yes	[28]–[30], [45], [58]–[66], [92]–[95]

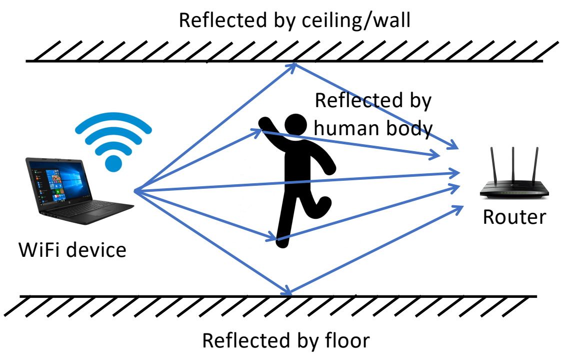

Fig. 2. Illustration of the multipath effect of wireless signals.

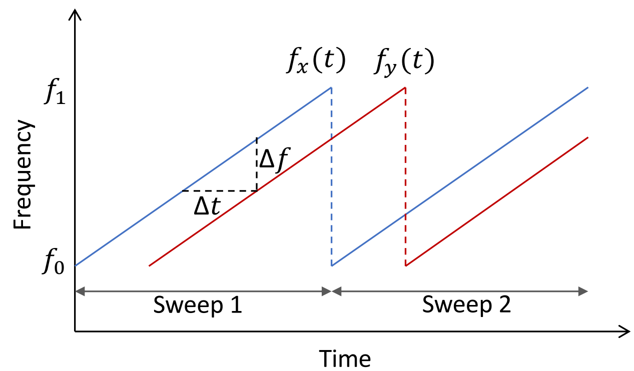

Fig. 3. Illustration of FMCW operation.

shown in Figure 2. All these multi-path rays contribute to the measurable CSI values and could be used to detect and track the human body movements. In contrast to RSSI, CSI consists of a set of a complex values, including both amplitude and phase information, for multiple orthogonal frequency-division multiplexing (OFDM) subcarriers.Each subcarrier with slightly different center frequency experiences different multi-path fading effects, and all the subcarriers together depict the wireless channel in a fine-grained manner. For instance, IEEE 802.11n standard can render the CSI measurements for 52 and 128 subcarriers with $20MHz$ and $40MHz$ bandwidth for each subcarrier, respectively, and the emerging 802.11ac standard supports even wider bandwidth. CSI essentially allows fine-grained channel estimation, and is expressed as:

$$H = [H_1, H_2, ..., H_i, ..., H_N]^T, i \in [1, N], \tag{2}$$

where N is the number of subcarriers, and H_i can be represented as:

$$H_i = |H_i| e^{j \sin(\angle H_i)}, \tag{3}$$

where $|H_i|$ is the CSI amplitude at the i_{th} subcarrier, and $\angle H_i$ denotes its phase. Similar to RSSI, CSI measurements can be obtained at any devices with off-the-shelf WiFi interfaces (e.g., Intel 5300 NIC [96] and Atheors 9580 NIC [97]) with modified driver. Now it has been widely adopted by more and more researchers to perform human activity sensing, such as human intrusion detection, walking speed/direction estimation and human activity recognition [21], [22].

B. Techniques Using Customized Hardware

Frequency Modulated Carrier Wave (FMCW). The human activities can also be captured based on radio reflections off her body, specifically by estimating the time it takes the wireless signal to travel from the transmitter to the reflecting human body and back to the receiver. However, it would be hard to measure the time of flight (ToF) directly since wireless signals travel very fast, specifically at the speed of light. Thus, FMCW which maps differences in time to the shifts of carrier frequency is deployed to measure ToF of radio signals. As shown in Figure 3, the carrier frequency of the transmitting wireless signal $f_x(t)$ is repeatedly swept across a specific bandwidth. After reflected from the human body, it will introduce a frequency shift Δf with the slope k (i.e., swept bandwidth divided by the sweep time) to the received signal $f_y(t)$, and the time-shift (i.e., Δt) with respect to the transmitting signal can be derived based on such frequency shift as follows:

$$\Delta t = \frac{\Delta f}{k}. \tag{4}$$

Compared to measuring the ToF directly, it is much easier to measure the frequency shift Δf to obtain the Δt. Then the round-trip distance of wireless signals (i.e., $d = c \cdot \Delta f$, and c is the speed of light) can be obtained to describe the distance of the human body relative to the transmitter and receiver. It is important to note that, in contrast to off-the-shelf WiFi that uses OFDM, FMCW technique relies on specialized device (e.g., USRP) to generate the signal that sweeps the frequency across time.

A number of wireless sensing systems leveraging FMCW technique have been developed to track different human activities. For instance, the researchers utilize FMCW signals generated by USRP software radio with directional antennas to capture human figure through a wall [103], track user's 3D motion [28], estimate gait velocity and stride length [104], detect vital signs [56], monitor sleep and insomnia [105], and recognize people emotions [106].

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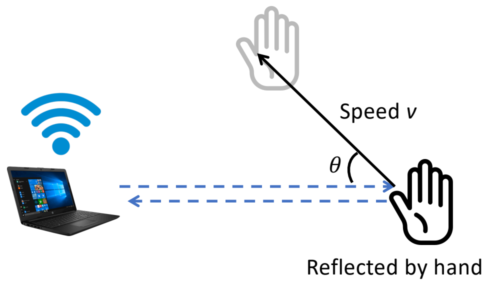

Fig. 4. Illustration of Doppler shift when a hand is moving towards a WiFi device.

Doppler Shift. Doppler shift effects is another physical layer property of wireless signals that can be used to perform human activity sensing. Specifically, it measures the frequency change of the received wireless signal as the transmitter and the receiver move to each other. If we consider the received wireless signal reflected from the human body as the signal emitted from the wireless transmitter, any movements of the human body would result in a Doppler shift. Specifically, positive frequency change (i.e., Doppler shift) is produced if the person moves towards the receiver, while negative frequency change occurs if the person departs from the receiver. As shown in Figure 4, when an object (e.g., hand) moves at the speed v along the direction θ with respect to the receiver, it will result in a Doppler shift [107] as:

$$\Delta f = \frac{2v\cos(\theta)}{c} f, \tag{5}$$

where c is the speed of light and f is the center frequency of wireless signal. Leveraging Doppler shift effects, some WiFi sensing systems are developed based on software defined radio device (e.g., USRP N210) to detect walking [30], [98], running [29] and human body/hand gestures [45], [99].

III. Intrusion Detection & Room Occupancy Monitoring

In this section, we introduce the existing studies on the room-level human activity sensing with WiFi signals, including human intrusion detection and room occupancy monitoring. We particularly focus on RSSI-based and CSI-based methods leveraging the commodity devices.

A. Human Intrusion Detection

As an important security issue, human intrusion detection has drawn considerable attention in recent years. Traditional methods mainly rely on cameras (e.g., closed-circuit television (CCTV) or Internet protocol (IP) cameras [108], [109]) or dedicated sensors (e.g., acoustic sensor [3] or infrared (IR) sensor [4]) to perform intrusion detection. However, camera-based approaches are difficult to detect an intrusion event under low illumination condition or without LoS view, while the sensor-based approaches usually require complex hardware installation and diverse maintenance needs. To reduce the implementation/maintenance overhead, researchers take advantage of existing WiFi infrastructure to perform intrusion detection. The RSSI-based and CSI-based intrusion detection methods are investigated.

RSSI-based Detection. RSSI-based methods primarily infer intruders through detecting human disturbances to RSSI measurements in WiFi networks. When an intruder enters the sensing area, WiFi links would be disrupted due to the presence or body motions of the intruder, resulting in the RSSI changes of radio signals. Inspired by such phenomenon, the concept of device-free passive detection using WiFi was first proposed in [5], which facilitates intrusion detection leveraging time-series analysis on the RSSI readings like the moving average and moving variance techniques. Following the work [5], Ikeda et al. [110], [111] leverage a threshold of RSSI fluctuation width, the difference between the RSSI when event occurs and the average of RSSI observed in advance in static state, to identify intrusion. Other than the work [110], Moussa and Youssef [6] later present an alternative algorithm, based on the maximum likelihood estimator (MLE), to achieve better detection performance in real environments. RASID [7] develops a non-parametric statistical anomaly detection technique with adaptive environment-dependent profile updating to achieve accurate and robust intrusion detection. In contrast to the aforementioned techniques, RASID has significantly lower overhead than MLE technique while maintaining comparable detection performance. In addition, RASID is more robust to temporal changes of training profiles as compared to other existing intrusion detection systems.

CSI-based Detection. Due to the fine-grained wireless channel measurement, CSI recently becomes a popular and powerful tool for intrusion detection system design. Nishimori *et al.* [112] measure the influences of antenna arrangement on radio signal propagation in indoor environments, and then utilize the channel matrix in MIMO channels to detect intrusion. Hong *et al.* [113] further extract eigenvectors to achieve intrusion detection with higher accuracy. Moreover, Honma *et al.* [114] propose the antenna arrangements for the MIMO interference to provide better intrusion detection performance. FIMD [115] realizes device-free motion detection by leveraging the eigenvalues of a CSI-based correlation matrix in a given time period. Pilot [8] leverages the correlation of CSI over time to monitor abnormal appearance and further locate the entity. Moreover, PADS [9] and DeMan [116] further extract the maximum eigenvalues of the covariance matrix from successive full CSI information, including both amplitude and phase, to enhance detection performance. Ding *et al.* [10] explore phase difference between adjacent antenna pairs for passive device-free motion detection. Additionally, OmniPHD [11] achieves the omnidirectional sensing coverage for passive human detection in typical multipath-rich indoor scenarios. The aforementioned studies mainly rely on the characteristic from matrix of CSI amplitude, phase or phase difference to detect the sudden changes associated with human intrusion. Compare to RSSI-based methods, CSI-based method can achieve more accurate and reliable intrusion detection performance.

B. Room Occupancy Monitoring

Room occupancy monitoring plays a critical role in serving various purposes including public area surveillance, energy saving (e.g., controlling lights and air-flow rate) and hotspot

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TABLE III. A COMPARISON OF EXISTING ROOM OCCUPANCY MONITORING STUDIES.

Work	Technique	Frequency Band	Number of People	Accuracy
Nakatsuka et al. [12]	RSSI	2.4GHz	23-29	N/A
Yuan et al. [13]	RSSI	2.4GHz	10	94%
Xu et al. [14]	RSSI	2.13GHz	4	86%
Xi *et al.* [16]	CSI	2.4GHz, 5GHz	4	83%
Guo et al. [15]	CSI	2.4GHz	6	98% estimation errors are less than 2 persons in indoor environment

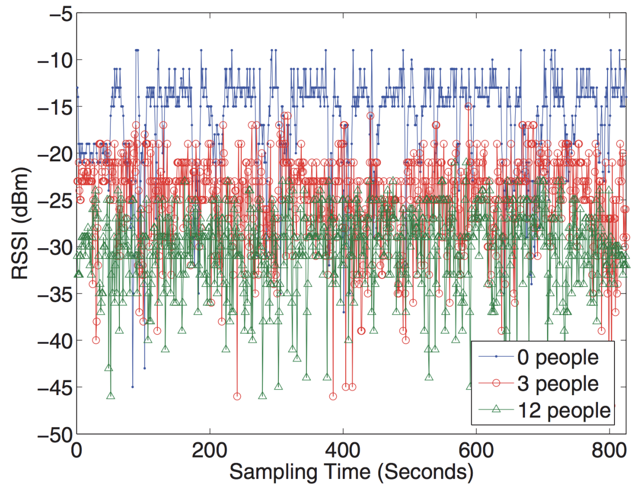
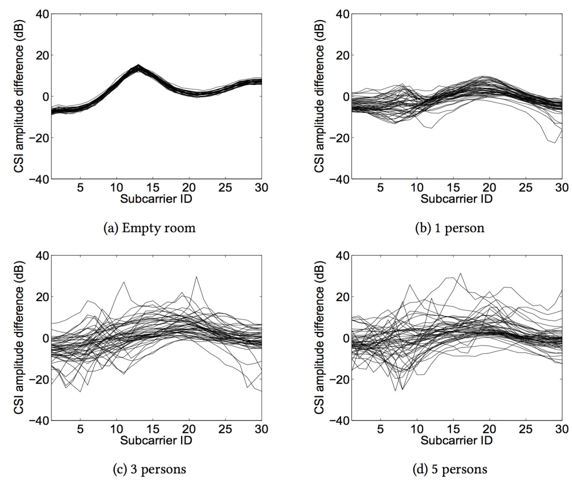


Fig. 5. RSSI readings when there are different number of people in a room when people are not moving around [13].



(a) Empty room (b) 1 person (c) 3 persons (d) 5 persons

Fig. 6. CSI amplitude difference between two antennas under different number of subjects in a room [15].

tracking in multi-functional room management, etc. Existing studies [117], [118] mainly rely on surveillance camera to inspect human flow, but the high deployment costs and privacy concerns prevent them to be deployed in large-scale. Moreover, some other studies infer people density based on the number of detected devices. For instance, the number of connected mobile devices via Bluetooth [119] and microphone/speaker pair [120] are estimated to derive the people density. However, the aforementioned approaches require the users to carry the mobile devices running with specific applications, making them not always applicable in practice. Differently, device-free approaches rely on existing WiFi infrastructure to perform room occupancy monitoring without requiring people to carry additional devices. Specifically, we will investigate both RSSI-based and CSI-based methods as follows. A comparison of these solutions for room occupancy monitoring is summarized in Table III.

RSSI-based Approaches. It is well known that RSSI changes when a subject approaches the LoS of a wireless link [5], [19]. Existing studies [12]–[14] also verified more subjects in a room will make an even greater impact on the surrounding wireless environment. To facilitate room occupancy monitoring, the researchers empirically conclude that: (1) When no subject in the area of interest, the RSSI values stay at a stable level; (2) When some subjects enter the sensing zone, the RSSI reading of some RF links would decrease dramatically; and (3) The more the number of subjects, the more the radio links are affected, resulting in significant drops on RSSI readings. Figure 5 shows the collected RSSI readings from a specific wireless link when there are different number of people (i.e., 0, 3 and 12) in a room, indicating the aforementioned relationship between people density and RSSI readings. A set of studies [12]–[14] conduct a large scale deployment of wireless sensors in indoor environments and infer the number of moving people leveraging RSSI from multiple wireless links. However, these approaches need a large number of wireless nodes or devices to create dense RF links, resulting in extremely high cost and complex maintenance efforts.

CSI-based Approaches. Similar to RSSI-based solutions, the variation of CSI measurements can also be extracted to infer the number of walking people in an indoor environment. As mentioned before, CSI provides more fine-grained channel information (i.e., both amplitude and phase information) with multiple subcarriers. Figure 6 shows the impact of different number of subjects (i.e., no person, 1 person, 3 persons and 5 persons) on CSI amplitude differences across 30 subcarriers [15]. It is obvious to find that more people could induce a higher CSI variance over WiFi links. Inspired by this observation, Xi *et al.* [16] theoretically studied the relationship between the number of moving people and the variation of wireless CSI. A stable monotonic function is formulated to characterize the relationship between the crowd number and various features of CSI (i.e., Percentage of nonzero Elements (PEM) in the dilated CSI matrix). In addition, Guo *et al.* [15] propose a comprehensive human flow management system leveraging existing WiFi traffic to estimate crowd counting, people density, walking speed and direction. Different from the previous studies [16], [69], the proposed system adopts a robust semi-supervised learning approach for estimation of the number of participants, which can be easily extended to a new environment. They also propose to utilize CSI variance

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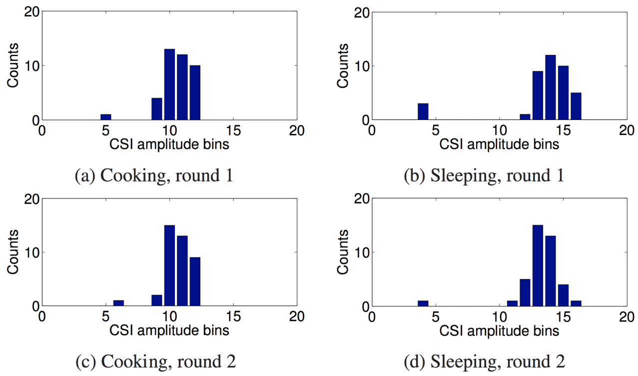
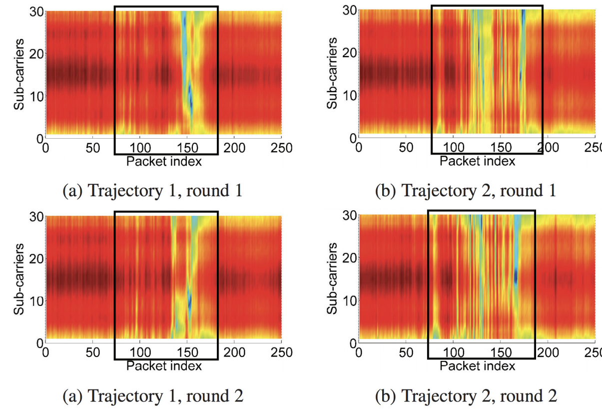


(a) Cooking, round 1 (b) Sleeping, round 1
(c) Cooking, round 2 (d) Sleeping, round 2

Fig. 7. Histogram of CSI amplitudes on a particular subcarrier when a person is cooking and sleeping, respectively [21].



(a) Trajectory 1, round 1 (b) Trajectory 2, round 1
(a) Trajectory 1, round 2 (b) Trajectory 2, round 2

Fig. 8. Similar CSI amplitude time series pattern for same walking trajectory [21].

histogram to estimate human density distribution within a specific region.

IV. Activity & Gesture Recognition

Human activity recognition is the key technology to support a broad array of applications including human-computer interaction (HCI), elder care, well-being management and security monitoring fields, etc. Traditionally, it mainly relies on dedicated sensors, such as wearable devices [121] or cameras [122]. However, wearable-based methods require users' active participation (e.g., wearing sensor devices) and have limited sensing capability, while camera-based approaches usually raise privacy concerns, making them inapplicable in personal areas. Compared to traditional human activity recognition approaches, RF-based solutions are device-free without incurring potential privacy issues (i.e., capturing unnecessary and sensitive information). Generally, human activity can be divided into two main categories, regular activities (e.g., daily activity and abnormal body motion) and gestures (e.g., hand/finger gesture and head motion). We will discuss the related research on human activity recognition with respect to the above two categories.

A. Activity Recognition

Regular activity refers to the daily in-home activity (e.g., walking, sitting, cooking and watching television). By tracking a sequence of such meaningful activities of a person, it is possible to suggest a healthier daily routine change towards health improvement. Additionally, it also benefits many other domains such as elder-care, latchkey child safety, etc. Specifically, four types of WiFi-based regular activity recognition approaches are reviewed as follows.

RSSI-based Recognition. Wireless signals are easily affected by surrounding body movement that associated with human activities, resulting in a special fluctuation pattern on RSSI. Each specific activity has its particular way to be conducted by human, it is thus possible to induce a unique RSSI fingerprint on the RF-signals, which can be captured by nearby wireless receivers. Sigg *et al.* [17], [18] propose a device-free human activity recognition system by leveraging the fluctuation of RSSI of WiFi signal caused by human movements. Specifically, Sigg *et al.* [17] extract 17 empirical features (e.g. highest signal peak and median signal strength) from RSS signal and utilize k nearest neighborhood (KNN) classifier to recognize four regular activities (i.e., lying, standing, walking and crawling). To further improve the environmental sensing generosity of RSSI-based system, Sigg *et al.* [18] focus on the detection of static and dynamic activities of single individuals by using active or passive systems and further recognize four regular activities (i.e., lying, standing, walking and crawling). Particularly, the active system employs dedicated transmitter hardware as a part of the system while the passive system solely uses ambient FM radio. In addition, radio tomographic imaging (RTI) [19] is also an effective way to perform RSS-based device-free motion tracking, which deploys a wireless sensor network around the interesting area and uses the raw RSS measurements to image the moving targets. Wilson and Patwari also proposed vRTI [20], an extension of the RTI technique, by leveraging the motion-induced variance of RSS measurements for better activity recognition.

CSI-based Recognition. Due to the low-resolution and limited sensing capability of RSSI measurements, it is difficult to achieve fine-grained activity recognition. Therefore, recent studies propose to exploit CSI measurements for better recognition performance. Wang *et al.* [21] propose the first work, E-eyes, to explore using fine-grained CSI to recognize daily activities. Particularly, E-eyes seeks to utilize the relationship between location and activity characteristics to develop a location-oriented activity identification system to distinguish a set of in-place (e.g., cooking, washing dishes, bathing, studying, eating and sleeping) and walking activities (i.e., walking from one room to another) with only a single WiFi access point. For instance, the authors showed the similarity levels of the CSI amplitude distribution for the same and different in-place activity (i.e., cooking in a kitchen and sleeping on a bed) respectively at a particular subcarrier in Figure 7. When cooking, the histogram of CSI amplitude mainly ranges from 9 to 12, whereas the histogram while sleeping mainly ranges from 11 to 16. Furthermore, regarding the large-scale body movements (i.e., walking), CSI measurements exhibit similar changing patterns for the same trajectory, whereas the changes of CSI measurements over time are different for different

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trajectories, which is shown in Figure 8. This observation validates that the CSI measurement from WiFi signals is dominated by the specific in-place activity or unique path of the walking activity, and it thus is a good alternative for recognizing regular daily activities. However, the aforementioned system (i.e., [21]) is based on empirical study, and lacks the theoretical support explaining the relationship between CSI measurements and human activities. Therefore, Wang *et al.* [22], [23] propose a human activity recognition system, named CARM, which builds CSI-speed model and CSI-activity model to quantify the correlation between the movement speeds of different human body parts and a specific human activity. The proposed system can work in both trained and untrained environments, in which a large set of daily activities (e.g., walking, running, opening refrigerator, falling and boxing) are evaluated.

In addition to recognizing human daily activities, abnormal human motion detection (e.g., falling down) is also important, especially for timely elder-care. WiFall [24] is the first CSI-based fall detection system. In order to achieve reliable fall detection, WiFall constructs the radio propagation model to analyze the time variability and special diversity of CSI and trains a support vector machine(SVM) classifier to differentiate fall from other human motions (i.e., walk, sit and stand up). To further enhance the performance of CSI-based fall detection system, Zhang *et al.* [25] propose Anti-Fall that uses both the phase and amplitude of CSI readings to accurately detect the fall from other fall-like activities. Moreover, Wang *et al.* [26] find that the CSI phase difference over two antennas is more sensitive to fall action. Also, they find the unique sharp decline pattern of fall action in the time-frequency domain and first propose to utilize the frequency-based features to detect fall accurately. Similarly, Palipana *et al.* [27] propose FallDeFi that extracts time-frequency features in CSI using the conventional Short-Time Fourier Transform (STFT) to achieve accurate fall detection. To ensure the fall detection system resilient to environmental changes, the authors [27] also devise a sequential forward selection algorithm to single out the robust features.

FMCW-based Recognition. In addition to the aforementioned RSSI and CSI based approaches that can leverage off-the-shelf wireless devices, there are also some existing work relying on USRP platform to facilitate activity recognition. These methods precisely modulate the transmitting wireless signals to sweep across a certain frequency band (e.g., FMCW radio) and then derive Δt measurements based on the reflected signals. Due to the super-heterodyne based architecture of FMCW radio, the Δt measurements delivers good sensitivity and stability on activity recognition. WiTrack [28] is one of the precursory FMCW-based activity recognition system, which leverages the radio signals reflected off human body to track the 3D motion of the user. By leveraging the T shape directional antenna array, WiTrack can localize the center of a human body in a 3D domain. It can also coarsely track body parts, such as identifying the direction of a pointing hand with a median of 11.2°. Additionally, WiTrack can distinguish a fall action from other activities (e.g., standing, walking, sitting on a chair and sitting on the floor) by monitoring the absolute Z-axis value and the change in elevation as shown in Figure 9.

Doppler-based Recognition. Human activity recognition can also be achieved by leveraging Doppler effects [29], [30], which capture the minute changes in the WiFi signals caused by human motion such as running [29], walking forward and backward [30]. Chetty *et al.* [29] build a passive WiFi radar running on USRP platform to measure the Doppler shifts caused by the human activities through the wall. Adib *et al.* [30] later improve the through-the-wall system by using MIMO interference nulling to eliminate the flash effect of Doppler shifts and render more accurate recognition performance. Additionally, Okamoto *et al.* [123] use the temporal phase shift obtained from the moving target in addition to MIMO interference to measure the relative velocity between the target and the antenna. Okamoto *et al.* [124] further utilize bistatic radar model based on MIMO scheme to classify various human activities and track multiple targets. Later work [125], [126] build antenna array to measure the Doppler Shifts caused by the daily movement of elder people (i.e., falling down on the floor after standing, sitting on the chair after standing).

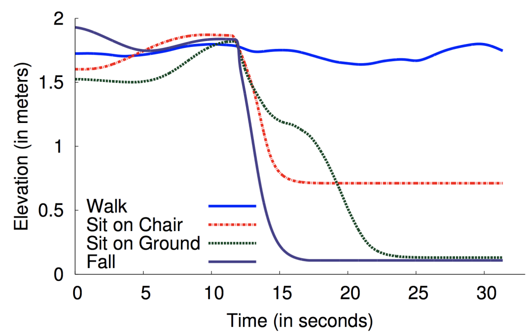

Fig. 9. WiTrack automatically detects falls by monitoring the absolute value and the change in elevation [28].

B. Gesture Recognition

Human gestures such as arm/hand movements, head motion and even finger motion are important interaction interfaces to smart Internet of Things (IoT) and mobile devices. In this section, we review four main WiFi-based gesture recognition technologies (i.e., RSSI, CSI, FMCW, and Doppler shift). The existing gesture recognition systems are summarized in Table IV.

RSSI-based Recognition. Early gesture recognition systems mainly rely on RSSI extracted from off-the-shelf devices to identify different hand gestures. Sigg [31] examine the fluctuation in RSSI from the mobile phone to identify 11 different hand gestures, but the recognition accuracy is as low as 51.0%. To eliminate the environmental effects of RSSI, Melgarejo et al. [32] take advantage of directional antennas and short-range wireless propagation properties and achieve higher recognition accuracy with 25 hand gestures. The proposed gesture recognition system has been successfully applied to gesture-based electronic activation from wheelchair and gesture-based control of car infotainment system. Abdelnasser et al. [33] devise WiGest that further improves the recognition accuracy of 8 hand gestures to 96%. The wavelet techniques are adopted to eliminate the environmental interferences and ambient noises from the RSSI measurements. Also, WiGest requires no training efforts and works well in none-line-of-sight scenario. However, due to the coarse granularity and the

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TABLE IV. A COMPARISON OF WIFI-BASED GESTURE RECOGNITION WORKS.

Work	Technique	Gesture	Accuracy
Sigg [31]	RSSI	11 hand gestures	51%
Melgarejo et al. [32]	RSSI	25 hand gestures	92%
Abdenasser et al. [33]	RSSI	8 hand gestures	96%
Nandakumar et al. [34]	RSSI, CSI	4 arm gestures	91%
WiG [127]	CSI	4 arm gestures	92%
Virmani et al. [35]	CSI	6 arm gestures	91.4%
WiDraw [128]	CSI	Hand trajectory for drawing letters, words, and sentences	91%
Li et al. [36]	CSI	9 finger gestures	90.4%
SignFi [37]	CSI	276 head, arm, hand and finger gestures	94.81%
WiCatch [38]	CSI	9 two-hand gestures	95%
Ali et al. [39]	CSI	Keystroke recognition	93.5%
Fang et al. [41]	CSI	5 hand and mouth gestures	86.3%
Wang et al. [40]	CSI	9 mouse movements	91%
Adib [42]	FMCW	Hand gestures of multiple people simultaneously	95%
Soli [43]	FMCW	4 hand gestures	92.1%
WiSee [45]	Doppler shift	9 arm/leg involved gestures	94%

high sensitivity of RSSI to environmental changes, RSSI-based gesture recognition systems have no ability to capture more fine-grained gestures (e.g., finger gestures, keystrokes, mouth movements).

CSI-based Recognition. To further improve the recognition accuracy and capture more subtle motion, the fine-grained CSI information becomes prevalent for gesture recognition [34]–[41]. Nandakumar et al. [34] propose to leverage both RSSI and CSI information to recognize arm movements, and it can achieve 91.0% accuracy with respect to four arm gestures (i.e., right, left, push, pull). In comparison, WiG [127] is an arm gesture recognition system solely relying on CSI. The recognition accuracy of WiG is up to 92% in line-of-sight scenario and 88% average accuracy in none-line-of-sight scenario. However, both the above two systems [34], [127] work effectively only under consistent setup (i.e., stand at the same position with same orientation) during training and testing phases. To combat such limitation, Virmani et al. [35] propose WiAG to recognize user's arm gestures with different positions and orientations, which largely improve the practical usability. The key idea behind WiAG is to convert the training samples to the virtual samples for all gestures in all possible configurations through the proposed gesture translation function. In addition to the regular hand gesture recognition, WiDraw [128] can continuously track the hand's trajectory to enable in-air drawing by using the Angle-of-Arrival (AoA) estimation with CSI.

Instead of tracking the whole hand, Li et al. [36] proposes WiFinger to recognize 9 finger gestures of American Sign Language with the accuracy as high as 90.4%. WiFinger enables continuously input text in off-the-shelf WiFi environment to facilitate human-computer interaction. SignFi [37] further exploits CSI measurements to recognize sign language involving the head, arm, hand, and finger gestures. The system extends the recognizing ability to 276 sign gestures by using Convolutional Neural Network (CNN). Moreover, WiCatch [38] is developed to detect two-hand gestures by constructing the virtual antenna array based on CSIM samples in time domain.

To push the limit of more subtle gestures recognition, Ali et al. [39] propose a CSI-based keystroke recognition system, named WiKey, which can capture more fine-grained variations in CSI values to recognize different keystrokes. Moreover, Fang et al. [41] propose HeadScan to recognize the head and mouth gestures including eating, drinking, coughing and speaking. However, the usability of HeanScan is restricted by using a wearable WiFi system instead of off-the-shelf WiFi device to capture the head gestures. In contrast, Wang et al. [40] leverage off-the-shelf WiFi to recognize the mouth movements by using partial multi-path effects derived from the CSI measurements.

FMCW-based Recognition. In addition to WiFi-based gesture recognition systems, FMCW radar have also been applied to gesture recognition [42]–[44]. FMCW radar takes up to 1.79 GHz bandwidth compared to 20 MHz bandwidth of WiFi devices, so it can achieve much higher time resolution on gesture recognition. Adib et al. [42] propose the first multi-person gesture tracking system with FMCW radar, which is able to recognize the hand gestures of multiple people simultaneously. In addition, due to the high-resolution and great robustness of FMCW radar, FMCW-based gesture recognition systems are on their way to commercialization. In 2016, Google proposes a public project Soli [43] aiming to develop a robust, high-resolution gesture recognition system for human-computer interaction based on FMCW radar. NVIDIA also develops a short-range FMCW radar-based system for sensing hand gestures for intelligent driver assistance systems [44].

Doppler-based Recognition. As a Doppler-based gesture recognition system, WiSee [45] successfully recognize 9 arm/leg involved gestures based on the unique Doppler shifts profile extracted from wireless signals as shown in Figure 10. Due to the different relative body movements to the wireless radar sensor, we can observe unique positive and negative Doppler shift pattern of these arm/leg gestures. A proof-of-concept prototype using USRP-N210s is evaluated in both office and apartment environment, and the experimental results indicate WiSee can achieve the average recognition accuracy as high as 94%.

V. VITAL SIGNS MONITORING

Vital signs (i.e., breathing and heart rates) and biometric statistics are important indicators for evaluating one's sleep quality, stress level and health conditions. Traditional approaches, such as camera-based (e.g., DistancePPG [129]) and sensor-based (e.g., Geophone [130], [131]) methods, could accurately track vital signs. However, these approaches either need to work under bright lighting condition or require complex installation and maintenance efforts. Differently, RF-based approaches become more appealing due to their low-cost, contact-free, easy-to-deploy properties. Leveraging the main

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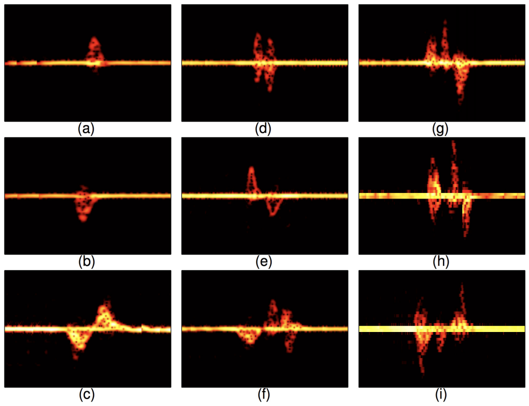

Fig. 10. Unique positive and negative Doppler shifts corresponding to each gesture [45].

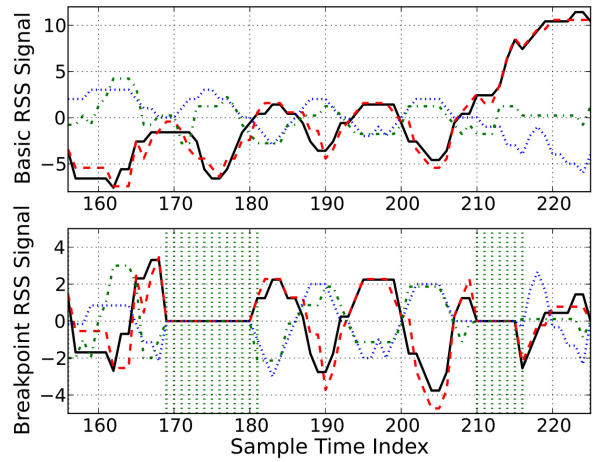

Fig. 11. Mean-removed RSS signal for the basic and breakpoint methods [47].

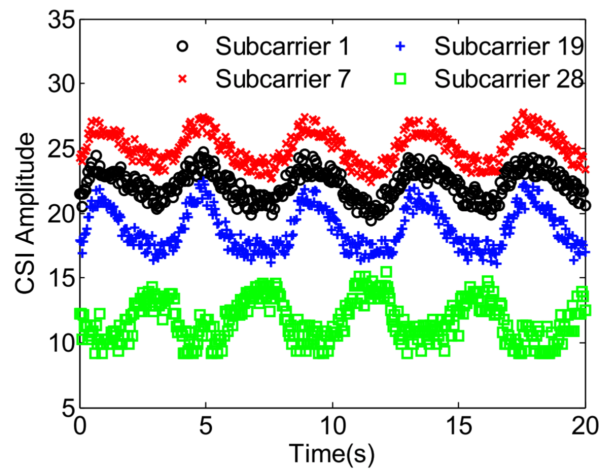

Fig. 12. CSI amplitude measurements of four subcarriers when a person is in asleep [51].

techniques discussed in Section II, four different vital sign monitoring system, RSSI-based, CSI-based Dopper-based and FMCW-based, are reviewed as follows.

RSSI-based Recognition. Many existing studies observed that even the minute body movements associated with breathing and heartbeat would impact the wireless channel, resulting in the fluctuated RSSI readings. Inspired by such observation, Kaltiokallio, Ossi Johannes *et al.* [46] measure RSSI from 16 frequency channels in IEEE 802.15.4 wireless sensor network to detect the user's breathing rate. Consider the interferences from other body motions, N. Patwari *et al.* [47] defined "breakpoints" to indicate the sudden changes of RSSI signal caused by the user's motion interference (e.g., a person rolls over in bed or moves a foot) and apply appropriate mean removal to ensure the breathing rate estimation more robust to motion interference. Figure 11 compares the RSSI signals of four links obtained from basic method (top) and breakpoint method (bottom). The green-dot areas are the estimated breakpoints, showing the breathing rate estimation with breakpoint method is more robust to motion interferences. However, the above approaches usually require additional wireless network infrastructure with high-density placement of sensor nodes. BreathTaking [132] model the breathing signals as sinusoidal waveforms and apply the maximum likelihood estimation (MLE) to estimate the breathing rate based on the RSSI measurements collected on around 20 wireless links. Additionally, UbiBreath [48] can achieve accurate estimation of user's breathing rate with the error less than 1 breaths per minute (bpm) and also detect apnea with more than 96% accuracy.

CSI-based Recognition. Due to the low granularity, RSSI-based approaches usually rely on redundant dimensions (i.e., multiple wireless links from various devices) to capture minute movement related to vital signs. Toward accurate vital sign estimation with less complex infrastructure, many studies turn to CSI signals for detecting subdued actions. Liu *el al.* [49], [50] re-use existing WiFi network to track the breathing and heartbeat concurrently without requiring dedicated/wearable sensors or additional wireless infrastructure. Figure 12 shows the CSI amplitude of four subcarriers extracted from a laptop 3-meter-apart away from a sleeping person. The proposed device-free approach has the potential to be widely deployed in home and many other non-clinical environments. BodyScan [51] can recognize a diverse set of human activities while estimating the user's breathing rate, by analyzing the CSI captured by two designed wearable devices on the user's hip and wrist. WiCare [52] utilizes CSI of WiFi signals to monitor breathing rate with the coexistence of some micro-motions (e.g., reading, writing, using the phone). Specifically, WiCare is able to distinguish micro-motions of a specific individual from his/her breathing based on the fact that breathing results in the CSI fluctuation with a much narrower frequency band compared to micro-motions. PhaseBeat [53] leverages CSI phase differences between two receiving antennas on WiFi devices [133] to monitor breathing rate and heart rate in real time. Along with this direction, Wang *et al.* [54] further verify the feasible condition (e.g., user's relative location and orientation) to perform breathing estimation with extensive experimental studies. The proposed system employs Fresnel zone model to explore the feasibility of breathing rate detection based on one's breathing depth, location and orientation.

FMCW-based Recognition. Doppler-based vital sign recognition approaches present good performance under some

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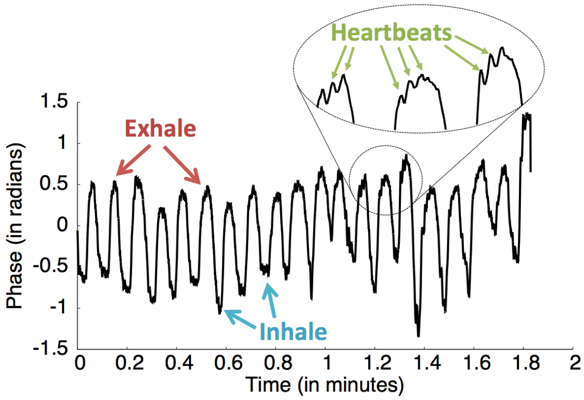

Fig. 13. FMCW phase changes due to breathing and hearbeat [56].

specific circumstances, however, it does not have a good way to eliminate the influence of moving objects in the front or behind the target. Since FMCW radar can separate the radio signal reflections from different objects, Anitori et al. [55] propose to detect breathing and heartbeat leveraging 9.6 GHz FMCW radar signal. Vital-Radio [56] uses FMCW radar to separate the reflections from different objects as different buckets depending on the distance between these objects and the device. The system could differentiate multiple users and track their vital signs simultaneously. As shown in Figure 13, breathing causes the variation on FMCW radar signal phase, where peaks and valleys correspond to exhale and inhale periods, respectively. Moreover, heartbeats are modulated on the top of the breathing motion. Zhang at al. [57] demonstrate that for the FMCW-based approach, the breathing signal's harmonics may overwhelm the heartbeat signal, making the latter invisible in the spectral analysis sign. Therefore, they propose to suppress unnecessary periodic fluctuation component with a projection matrix.

Doppler-based Recognition. Doppler radar is notable on low-power, cost-effective and robust on longer distance, low visibility, and through-wall detections [134]. SleepMinder [58] implements a radio-frequency Doppler radar system to capture physiological movements in the form of phase modulation. Passive radar system [59] extract breathing rate based on micro Doppler derived from cross ambiguity function (CAF) [135]. Another critical issue of Doppler-based approaches is that the noise produced by random body movement influence the monitoring accuracy. Figure 14 shows the difference of received Doppler radar signals with and without occlusion scenario. Salmi, Jussi, Olli Luukkonen, and Visa Koivunen. [60] show that nonlinear (arctan, or phase) demodulation combined with proper offset estimation could give good performance only if the radar presents close tA set ofo user's chest. Several following studies [61]–[63] introduce signal demodulation methods and mutually injection-locked SIL radars to cancel the influence of random body movement. WiSpiro [64] exploit 2.4 GHz Doppler radar to capture the breath volume based on phase-motion demodulation algorithm, which eliminate the impact from body movement. Other than CW Doppler radar, Zhao, Heng *et al.* [65] employ digital-IF Doppler radar [66] to further improve the performance on vital sign recognition with its high sensitivity and low power design.

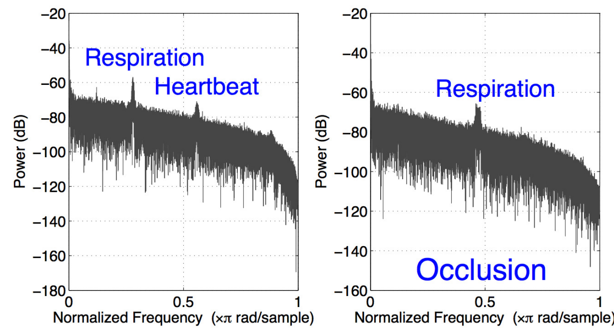

Fig. 14. Received signal when doppler radar beams to human heart location without and with occlusion scenario [64].

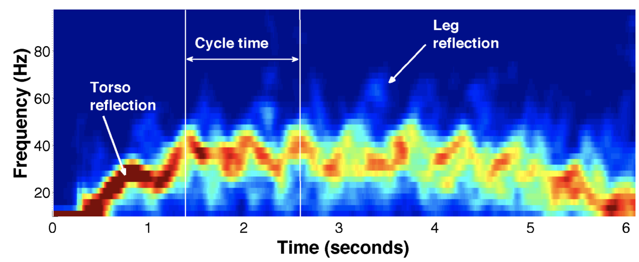

Fig. 15. CSI Spectrogram with human walking [69].

VI. User Identification & Localization

Due to the inherent behavioral and physiological differences existed among different people, researchers have demonstrated the possibility to perform user authentication by characterizing the wireless signal affected by human activities. Such device-free approaches are low-cost and easy-to-deploy leveraging the prevalent WiFi signals made available by IoT devices (i.e., smart refrigerator, smart TV and thermostat, etc.), and the privacy of users are also preserved. Additionally, localizing users or devices in an indoor space, such as an office building or a mall, has attracted significant attention in the past decades. In this section, we will review the related work on user identification as well as indoor localization using WiFi signals.

A. User Identification

WiFi-based user identification approaches primarily rely on CSI to capture the unique physiological and behavioral characteristics inherited from people's daily activities (e.g., human gait pattern) to discriminate people. We review the CSI-based approaches as follows. These approaches are also summarized in Table V.

CSI-based. Existing studies [67]–[69] perform user identification by capturing the unique walking gait pattern based on the CSI measurements. Specifically, Zhang *et al.* [67] extract 10 representative features from CSI variations caused by human walking to uniquely identify each individual among a group of 2 to 6 people. Zeng *et al.* [68] propose to identify a person's steps and walking gait for user identification leveraging the CSI amplitude features, but it requires the human subject to walk along a path with a distance of 1 meter parallel to the LoS

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TABLE V. A COMPARISON OF WIFI-BASED USER IDENTIFICATION WORKS.

Work	Technique	Frequency Band	Accuracy	Activity	Distance
Zhang et al. [67]	CSI	2.4GHz/5GHz	93% for 2 subject, 77% for 6 subject	Human walking	2m
Zeng et al. [68]	CSI	2.4GHz	92% for 2 subject, 80% for 6 subject	Steps and walking gait	2-3m
Wang et al. [69]	CSI	5GHz	79.28% for top-1, 89.52% for top-2, 93.05% for top-3	Movement speed of different body parts	6m
WFID [70]	CSI	N/A	91.9% for 9 subjects, 93.1% for 6 subjects	Standing, marching and walking	3.6m
Shi et al. [71]	CSI	5GHz	94% for walking, 91% for stationary activities	Walking and stationary activities	10m

path between the WiFi transmitter and receiver. Additionally, Wang *et al.* [69] examine the moving speed changes of different body parts, e.g., torso and legs, from the spectrogram, as shown in Figure 15 and correlates the movement speed of different body parts with WiFi spectrogram, which are exploited to recognize the gaits from different users at a distance of more than 6 meters to the LoS path. However, these approaches are limited to walking people either following well-designed paths (e.g., clear LoS path between the WiFi devices) or moving near the WiFi transceivers. Moreover, WFID [70] performs device-free user authentication via characterizing the uniqueness of subcarrier-amplitude frequency (SAF) from CSI measurements when the users are standing, marching, and walking. Different from the aforementioned approaches based on walking activities, Shi *et al.* [71] examine the WiFi signals and extracts unique physiological and behavioral characteristics inherited from people's in-home or in-office activities including both walking activities (e.g., waking between rooms) and stationary activities (e.g., operating appliances) to differentiate each individual person. The authors exploit the unique variation patterns on both amplitude and relative phase of CSI caused by people's daily activities. A deep learning based model is developed to perform both activity recognition and user authentication, and thereby facilitate many applications in both corporate offices and residential areas.

B. Indoor Localization & Tracking

Beside human motions, the locations of people also have significant impacts on wireless signal propagation in an indoor environment. Therefore, the physical properties of wireless signals can be used to infer the locations. There are a large body of work in the field of indoor localization and tracking. In this paper, we described a subset of the work that provide localization and tracking in term os adopted sensing techniques (i.e., RSSI-based, CSI-based and FMCW-based).

RSSI-based. Banhl and Padmanabhan [72] introduces RADAR, a radio-frequency (RF) based system, which uses RSSI measurements to model the relationship between signal strength and distance and further track the people inside a building. To improve the accuracy, Guvenc et al. [73] and Paul [74] propose to use Kalman filter algorithm to the propagation model of RSSI-based localization system. In addition, some other approaches (e.g., [74]–[76]) are developed to combine RSS measurements with the measurements of other sensors (e.g., GPS [75], [76], infra-red (IR) motion sensor [74]) to enhance the stability of indoor localization. Since RSSI is too sensitive to the small environmental changes, it is critical to ensure the robustness of RSSI-based localization system. A differential RSSI-based approach [77] is proposed to model the shadowed links and utilizes the particle filter to realize location estimation robustly. A dynamic distance reference

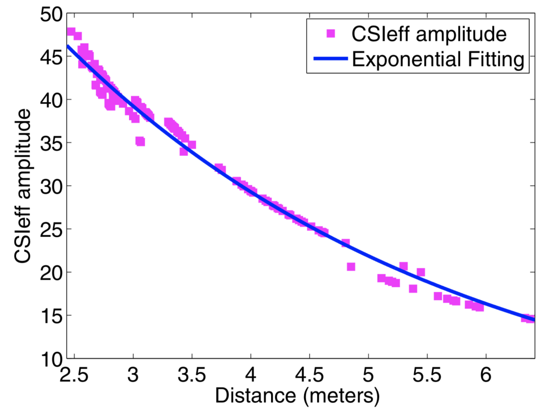

Fig. 16. Relation between effective CSI readings and distance [84].

anchor method is proposed in [78] to alleviate environmental effects. The proposed system computes the dynamic correction coefficient for each distance reference anchor node based on each RSSI measurement, and a continuous feedback is provided to reflect the environmental changes for robust location estimation. Xie *et al.* [79] present a K-Nearest-Neighbor (KNN) scheme based on spearman distance to eliminate the multi-path attenuation in RSSI-based localization system. Hong *et al.* [136] rely on Support Vector Machine (SVM) to detect eigenvector changes of RSS measurements and further improve the localization accuracy. To enhance the efficiency of RSSI-based system, Barsocchi *et al.* [80] propose a virtual calibration technique for wireless signal propagation model, which does not require the human intervention during training phase. Xiong and Jamieson [81] propose ArrayTrack, which requires no calibration beforehand to achieve high localization accuracy using RSSI. Unlike aforementioned approaches which only localize the single person, Bocca et al. [82] and Nannuru et al. [83] utilize Radio-frequency (RF) tomography of RSSI measurements to achieve multi-user localization in indoor environments.

CSI-based. CSI-based indoor localization, first proposed by Wu *et al.* [84], [85] and Sen *et al.* [86], is emerging to replace RSSI, due to its fine-grained channel information and high robustness. Wu *et al.* [84], [85] re-defined the indoor propagation model based on a modified free space path loss propagation model to capture the relationship between the effective CSI readings (i.e., *CSIeff* in Figure 16) and distance. Figure 16 illustrates the approximated relationship between *CSIeff* and distance according to the refined propagation model. Through exponential fitting, a CSI-distance model can be built to enable indoor localization. Similarly, Sen *et al.* [86] model the channel response and demonstrate that the localization accuracy using CSI can achieve the granularity of 1m x 1m boxes. Furthermore, Sen *et al.* [87] propose to effectively

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reduce the impact of multipath reflections by applying CSI information to indoor localization system. Different from the aforementioned localization systems involving multiple access points (APs), SAIL [88] is proposed to capture the user's location accurately with only a single WiFi AP. Additionally, Wang *et al.* [89], [90] propose to use deep learning techniques to facilitate indoor localization. Specifically, the weights in the deep network replace the raw CSI measurements to represent the location fingerprints.

FMCW-based. The first FMCW-based localization system, proposed by Vossiek *et al.* [92], uses three FMCW radars to achieve object tracking in 3-D space. In contrast to the work that relies on a wireless signal channel for localization, Feger *et al.* [93] and Gierlich *et al.* [94] propose to apply multiple-input multiple-output (MIMO) technique to FWCW system for high-precision location estimation. Recently, WiTrack [28] further leverages the MIMO FMCW technique to obtain the Δt measurements to track single moving person and the related motion of different body parts. To enhance the performance of WiTrack, Adib *et al.* proposed WiTrack2.0 [95] that not only achieves multiple moving people tracking but also localizes multiple static people through the TOF measurements of FMCW signals. Evaluation of WiTrack2.0 shows that it can localize up to five people simultaneously with a median accuracy of 11.7 *cm*.

VII. Limitations and Discussions

Although the aforementioned research studies have demonstrated the powerful capability of WiFi-based sensing systems on serving a broad array of applications, there still exist limitations and open problems that need further exploration in the future.

Impact of Environmental Changes. For many RSSI or CSI-based sensing systems that need to build training profiles (e.g., activity recognition [21], gesture recognition [127] and indoor localization [72], [86]), the profiles can be easily altered by environmental changes (e.g., furniture movements, closing a door), which could lead to the inconsistency between incoming testing instance (e.g., activity, gesture and location) and the profiles. As a result, the system usually needs a huge amount of extra efforts to re-train the profiles, which requires unacceptable labor cost and system downtime. To mitigate the impacts of environmental changes, existing studies [22], [23] build CSI-speed model and CSI-activity model to quantify the correlation between the movement speeds of different body parts and a specific activity, but it may affect the sensitivity of the proposed system on detecting human activities. Furthermore, AutoFi [91] develops a novel contaminant removal module and applies feature-preserving autoencoder [137] to intelligently calibrate the Wi-Fi profiles. It estimates the CSI changes caused by the environment changes and then eliminates these contaminants with a linear regression module with the autoencoder, making the profile features adaptive to the new environment. More efforts, such as intelligent profile calibration with multiple WiFi links and advanced data filtering/machine learning techniques, would be helpful in future work.

Impact of User's Location and Orientation. In addition to the environmental changes, the user's location and orientation also have critical impact on the performance of WiFi-based sensing systems. For the human involved activities, the differences on users' location and orientation could induce different variation pattern of RSSI or CSI measurements. Thus, existing systems usually require the user to keep the same location and orientation during both the training and testing phases. Some research studies attempt to overcome such limitations. For example, existing work WiAG [35] proposed a translation function that can generate virtual samples of a given gesture in any desired configuration (i.e., location and orientation) based on the real samples of the same gesture under another known configuration. Yet WiAG needs additional efforts to derive a few parameters (i.e, gesture shape and speed) by asking the user to hold a smartphone while performing gestures, making it less practical for some application scenarios. A more efficient and convenient solution is to build a rigorous theoretical model, which is independent to the user's location and orientation, to map the relationship between WiFi measurements and the human involved action/activity.

Multi-user Activity Sensing. Existing FMCW-based solution WiTrack2.0 [42] can track the hand gestures of multiple people simultaneously leveraging a directional antenna array. Vital-Radio [56] can differentiate multiple users and track their vital signs simultaneously through differentiating the reflections from different subjects. The CSI-based approach [49], [50] could use the frequency difference of multiple users' breathing rates to track them simultaneously. However, most of the RSSI and CSI based sensing approaches can only handle single-person case as it is challenging to distinguish the movements of multiple people from WiFi signal measurements. A promising way would be isolating concurrent activities of different people in separate spaces and perform activity sensing separately, but a complex web of WiFi links in an area is required.

Re-using Real WiFi Traffic. The sensing capability of many existing RSSI or CSI-based sensing systems is usually fulfilled with periodic WiFi traffic at a constant rate. Existing WiFi sensing systems relying on RSSI or CSI measurements need to be running with periodic WiFi traffic at a constant rate to keep continuous and synchronized sensing ability. The researchers usually use *ping* command to generate such traffic to satisfy this requirement. However, real WiFi traffic depends on the real-time demand of users or IoT devices, which cannot be manageable. Moreover, the commercial routers can only broadcast beacon packages with a default constant interval 100*ms* to help keep the network synchronized. Empirical demonstration of re-using such aforementioned real WiFi traffic in various sensing application domains would be necessary. Additionally, FMCW and Doppler-based solutions require well-defined transmitting signals, which might be hard to use on the top of the existing WiFi signals. Further exploration needs to be made along with this direction.

Security & Privacy Considerations. With the rapid advancement of WiFi sensing techniques, it also raises serious security and privacy breaches. Existing work has demonstrated that WiFi signals can be used to snoop keystrokes [39] and infer mobile phone password [138]. Adversaries could also use existing activity sensing systems to spy on the position and activities of others (e.g., neighbors). Thus, when we enjoy the convenience brought by the WiFi sensing technologies, we need to pay more attention to the accompanying security and privacy concerns. There is an urgent need to derive security solutions during the new sensing system design.

VIII. Conclusion

In this work, a survey of recent studies on human activity sensing systems using RF signals (e.g., WiFi) has been provided. We review a broad array of emerging applications associated with human body movements using wireless signals, including intrusion detection, room occupancy monitoring, activity and gesture recognition, vital signs monitoring, identity identification and indoor localization. According to the sensing technique introduced in these studies, we categorize the literature into four major categories: RSSI-based, CSI-based, FMCW-based and Doppler-shift-based. These compelling wireless sensing studies have shown promising performance in various application domains. In addition, we also point out the limitations of the current WiFi-based sensing approaches and show a few challenges that need to be addressed in the future.

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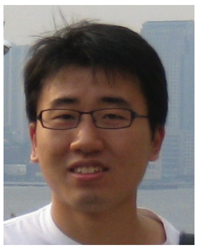

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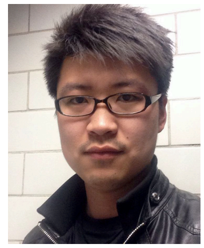

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