Contactless WiFi Sensing and Monitoring for Future Healthcare: Emerging Trends, Challenges and Opportunities

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Contactless WiFi Sensing and Monitoring for Future Healthcare - Emerging Trends, Challenges and Opportunities

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Abstract—WiFi sensing has received recent and significant interest from academia, industry, healthcare professionals, and other caregivers (including family members) as a potential mechanism to monitor our aging population at a distance without deploying devices on users' bodies. In particular, these methods have the potential to detect critical events such as falls, sleep disturbances, wandering behavior, respiratory disorders, and abnormal cardiac activity experienced by vulnerable people. The interest in such WiFi-based sensing systems arises from practical advantages including its ease of operation indoors as well as ready compliance from monitored individuals. Unlike other sensing methods, such as wearables, camera-based imaging, and acoustic-based solutions, WiFi technology is easy to implement and unobtrusive. This paper reviews the current state-of-the-art research on collecting and analyzing channel state information extracted using ubiquitous WiFi signals, describing a range of healthcare applications and identifying a series of open research challenges, including untapped areas of research and related trends. This work aims to provide an overarching view in understanding the technology and discusses its use-cases from a perspective that considers hardware, advanced signal processing, and data acquisition.

Index Terms—WiFi sensing, healthcare detection, machine learning, deep learning

I. INTRODUCTION

Sensing and monitoring systems for human healthcare have become increasingly popular, driven in part through our knowledge economy as well as the significant improvements in our longevity and living standards. In healthcare applications, such systems can provide individuals with the capability of long-term detection of daily activities and variations in vital signs, all in the privacy of our homes. With simple, long-term, and continuous health monitoring in the daily home environment, it is possible to record the signs of illness and physiological deterioration that cannot be detected during a short formal clinical consultation. Such monitoring systems can also be combined with deep learning and can be used to monitor behavior, including emotional states and mental well-being. Such information can be integrated into smart homes to support our daily lives. In this study, we focus on a detailed review which explores the application of WiFi sensing in such

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healthcare applications, demonstrating its relative advantages over other monitoring systems such as sensing methods, such as wearable sensors, camera-based imaging, and acoustic-based solutions.

A. Comparison of WiFi RF sensing and other approaches

Broadly, current sensing and monitoring systems can be divided into those using contact-based sensors, including wearables [1] and contactless systems [2], [3]. Besides wearable devices, the contactless monitoring approaches can be divided into visual based sensing radio frequency (RF) signals based sensing. RF signals at frequencies between 30 kHz & 300 GHz, comprise electromagnetic waves called radio waves (as are widely used in radar systems, including household and commercial behavior recognition [4]). Recently, the carrier frequency range of WiFi signals is from 2.4 GHz to 5.9 GHz, which is covered by radio waves.

Applications of wearable devices cover a wide range of methods, including measurements of heartbeat and respiration rates, oxygen saturation level, electromyographic signals and many others [5], [6]. However, these sensors are expensive, as it is necessary to provide a single device to each person being monitored. Moreover, the successful capture of the health information is dependant on the patient wearing the sensor or keeping it close to the body, which, if forgotten, can have severe consequences in applications such as fall detection. There is also the challenge of the re-usability of wearable equipment, resulting in widespread contact-transmission viruses, such as COVID-19, if not appropriately disinfected. Generally the adoption of the technology is problematic amongst some of the most needy individuals, namely those who are old or disabled.

In contactless sensing methods, camera-based sensing applications have proven their accuracy [7]. However, several disadvantages make it difficult, in some scenarios, to rely on such systems, which includes:

- System complexity and high cost due to computational requirements for multiple cameras to cover areas of activity.
- Privacy concerns due to the capturing and storage of images, which unauthorized users can access in a low-security system.

Compared with wearable sensing technologies, ambient RF sensing has the advantage of reducing the risk of contact transmission infections. Because it is capable of the contactless measurement of vital signatures and macro-health indicators in non-line-of-sight (NLOS) environments. In hospitals, wireless systems can capture the signal signature of vital signs, such as

coughing, shortness of breath, fever, and aches [8]–[10]. Given that these symptoms are closely linked to patient infections, WiFi sensing has the potential to detect illness. The comparison of WiFi sensing and other RF sensing technique is conducted and discussed in Section II-B.

B. Specification of WiFi sensing in healthcare

At present, WiFi sensing research in healthcare is being mostly developed for use in non-hospital environments, driven by two trends: vital sign detection and activity detection (see Fig. 1). Vital sign detection system aims to monitor the movement of the lungs and heart in humans using WiFi signals to recognize the respiration and heartbeat rate, in real-time. For activity detection task, alarms for critical events such as falling, and other specific actions that can cause severe and fatal consequences to human-beings has been studied in academia, and industry [11].

Generally, such systems use WiFi devices alongside intelligent classification algorithms to monitor and predict human subjects' movements. In the same context, WiFi signals are also used to report, over the internet, the activity status and/or vitals of the monitored subjects to the medical specialist and families or carers. Beneficiaries of such valuable real-time data and information are the internet of things (IoT) systems [12]. For example, vital signs detection in a smart home can help IoT systems adjust the temperature, humidity, and other environmental factors automatically to improve the quality of the user's experience [13], [14]. At present, WiFi sensing has been applied in the home. For example, Linksys sells a WiFi router and provides a service called "Linksys Aware," which enables WiFi devices to perceive the signals' vibration around the house. Although there have been numerous research studies conducted in this field, it is difficult to replace wearable and visualized healthcare applications due to their high reliability and efficiency. However, as academia and industry continue to optimize sensing technology, and as it becomes more reliable and accurate for the healthcare monitoring of human beings, we can expect to see changes from the current situation.

C. Contributions

There are a number of surveys of specific WiFi sensing techniques that have been published in recent years, including human activity recognition [15]–[22], human identification [18], [21], localization [18], [21], vital signs [17], [18], [21], [22], and imaging [21] (see Table I). All of the studies mention human activity recognition; few of them explore localization and vitals estimation. The review papers discuss trends that can be related to healthcare (human activity recognition, vitals, localization), which is introduced in Section II-C2, focusing on the technology development, with less detail on the applications in healthcare [18]. In comparison with existing surveys within detailed contents of various techniques and applications, the view of our survey is distinct, which specifically focuses on the analysis of WiFi applications in the healthcare field.

Our paper is structured to discuss the capability of WiFi sensing in healthcare applications, including current achievements and future expectations through a thematic analysis

review, providing a healthcare perspective to researchers. More specifically, the contributions are as follows:

- Provide a detailed overview of the methodologies adopted in developing healthcare monitoring systems.
- Classify healthcare related applications into different categories, and then provide insights for distinct trends.
- Highlight challenges and their potential solutions that require further investigation for generalization of healthcare applications based on WiFi sensing.

The paper is organized as follows: Section II introduces WiFi sensing technical background and development in healthcare range. Section III reviews different techniques applied in WiFi sensing, including signal preprocessing techniques and algorithms. Section IV concludes and analyzes the recent healthcare related applications in different fields, including vitals detection, localization, large-scale and small scale activity recognition. While finally, Section V discusses the technical and ethical challenges based on the recent researches. Then provides future perspectives associated with healthcare WiFi sensing.

II. RELATED WORK OF WiFi SENSING

This section presents the existing research studies focused on the technical background of WiFi monitoring systems with CSI and received signal strength indicator (RSSI) and descriptions of different tracks of WiFi sensing technology. Meanwhile, human activity recognition based on other RF sensing technology is introduced.

A. Technical background of WiFi sensing

With the rapid advances in communication and network technology, it is possible to assume the broad deployment of WiFi devices across society. Multiple-input multiple-output (MIMO) systems using orthogonal frequency division multiplexing (OFDM) technology, which supports the IEEE 802.11n protocol, provide high throughput transmission mode to serve the high data rate requirements. In such a system, disturbance of physical objects is capable of bringing different extent variation of wireless information on different subcarriers, which provided conditions for the generalization of wireless sensing based on WiFi signals. This section, therefore, discusses some of the primary techniques used to perform WiFi sensing.

1) Received Signal Strength Indicator (RSSI): The RSSI technique has been widely used for the localization of individuals. In MIMO systems, the RSSI is represented by the superposition of the strength of all the received signals. Most network devices can perform this task, including network interface cards (NICs), as they are easily accessible. An RSSI-based detection system depends on the magnitude changes of RSSI levels caused by the activity. However, due to multipath fading and time dynamics, its performance under complex conditions is significantly impacted. Early WiFi sensing systems that have been used for commercial localization are primarily dependent on RSSI without fine-grained information. Hence, they cannot be used to recognize complex human behavior [23].
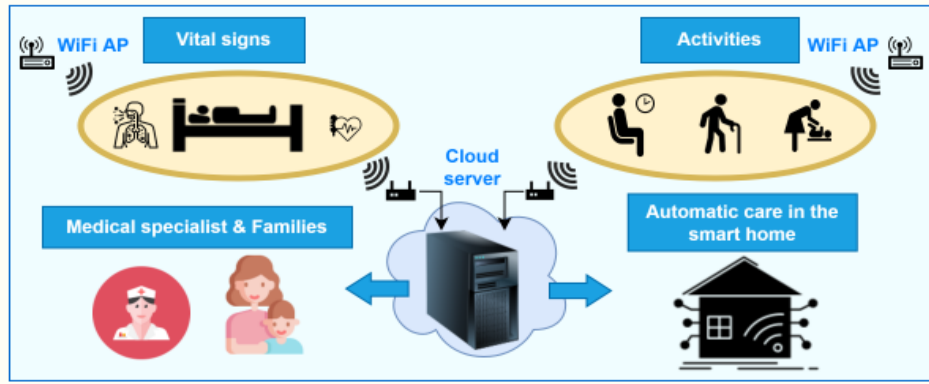
Fig. 1: Recent WiFi research used in healthcare

TABLE I: Related WiFi sensing surveys in specific track

Reference	Application Range	Main topic
[15]	human activity recognition	histogram-based techniques, deep learning methods
[16]	human activity recognition	comparison of human activity recognition methods
[17]	respiration estimation	model-based approaches, pattern-based approaches
[18]	human activity recognition, vitals estimation, localization/tracking, identification	details of various WiFi sensing techniques, applications, challenges and future trends
[19]	human gesture recognition	comparison of WiFi sensing performance
[20]	human activity recognition	through-wall human activity recognition methods
[21]	human activity recognition, imaging, vitals estimation	details of various WiFi sensing techniques
[22]	human activity recognition, vitals estimation, identification	sensing applications in smart home
This paper	human activity recognition, vitals estimation, localization	details of various WiFi sensing techniques, sensing applications in healthcare, technical and ethic challenges, future trends

2) Channel State Information (CSI): CSI is the channel property of the wireless communication link. It represents channel frequency response (CFR) for each subcarrier between transmitter and receiver, which describes the fading factor of the signal on every transmission path, *i.e.* the value of every element in channel gain matrix H (sometimes called channel matrix or channel fading matrix). In WiFi systems, the CSI signals can be obtained from the physical layer on the commercial IEEE 802.11A/G/N wireless network card based on OFDM. For each subcarrier, the WiFi channel is modeled by $\mathbf{y} = H\mathbf{x} + \mathbf{n}$, Where $\mathbf{y}$ stands for the received signal, $\mathbf{x}$ is the transmitted signal, $\mathbf{n}$ is the noise component. The receiver computes the CSI matrix with the pre-defined signal $\mathbf{x}$ and the received signal $\mathbf{y}$. However, in reality, WiFi systems' estimation of CSI is affected by multipath fading. The CSI matrix of a given subcarrier with frequency f and time t can be represented as [24]:

$$H(f,t) = e^{-j2\pi\Delta ft}\left(H_s(f) + \sum_{i=1}^{N_d} a_i(f,t)e^{-j2\pi d_i(t)\lambda}\right) \quad (1)$$

Where $e^{-j2\pi\Delta ft}$ is the random phase shift due to the hardware/software error of the WiFi system; H_s represents the

CSI signals from all the static paths (including the signals in line of sight (LOS) areas and those reflected off the stationary objects). The rest of the expression is the summation of signals from all dynamic paths (including signals reflected from the dynamic objects). N_d is the index of the dynamic path, $a_i(f,t)$ represents the complex attenuation factor and the initial phase of the ith path; $e^{-j2\pi d_i(t)\lambda}$ represents the phase change of ith path; $d_i(t)$ and λ are the length of the ith path and the wavelength of the WiFi signal, respectively. The CSI value can adapt the communication system to the current channel conditions and guarantee high reliability and high rate communication in multi-antenna systems. With MIMO and OFDM technologies, the size of the CSI matrix is constructed in 3 dimensions, with N transmitter antennas, M receiver antennas, and K subcarriers. The CSI packet is transmitted as $N \times M \times K$, with the packet index t (see Fig. 2). The propagation performance of wireless signals through both the direct path and the multiple reflection paths will show the physical space environment, including any object and the human body. Compared to RSSI values, the CSI offers a fine-grained representation of activity. Hence recent device-free WiFi sensing studies favor CSI, instead of RSSI [20].
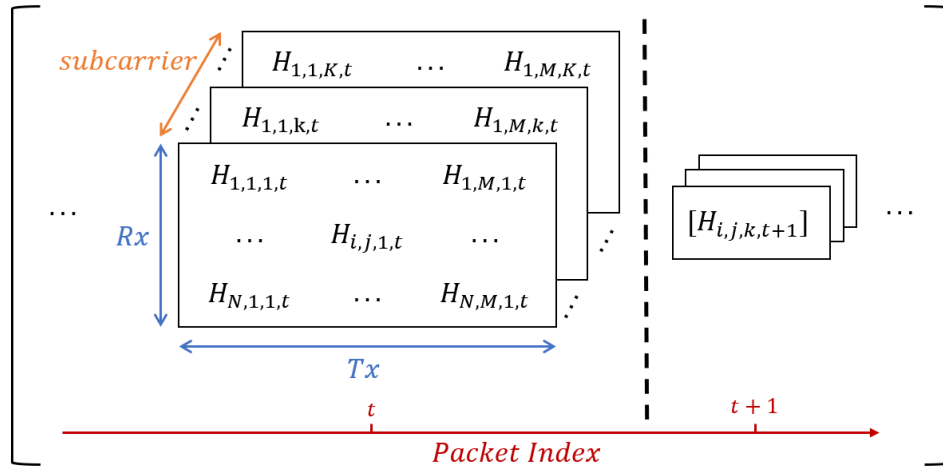
Fig. 2: CSI matrices of MIMO-OFDM channels

B. Comparison with non-WiFi RF sensing

Prior to the wide use of WiFi sensing technology, considerable subject-identification research has been performed with traditional radar systems due to their contactless and privacy-preserving characteristic. For example, frequency-modulated continuous-wave (FMCW) radar equipment was applied in [25]–[27], while in [28], the radar system was proven in its accuracy through 8-meter distance monitoring of breathing and heart rate within 5.46 - 7.25 GHz bandwidth.

In [29], the authors use a MIMO ultra-wide-band (UWB) transceiver system to estimate the speed of human movement with an average accuracy of 96.33%. However, in all cases, there is a high cost to establish a specific testbed. In [30], a system based on SDR using USRP was proposed. The experiment simulated an FMCW system to analyze the phase change status caused by respiration. The achievements of these non-wifi sensing systems are also heavily informed by WiFi sensing due to the similarity of RF signals. However, the key difference between the two methods is that CSI in the WiFi communication system is designed to recover transmitted information but not to explore the physical characteristic of the communication channel. For example, FMCW radar has the capability to consistently and linearly adjust the frequency. Combined with the time of flight (ToF) algorithm, FMCW can accurately estimate the distance information of the objects. WiFi signals are only supposed to transmit within a shallow frequency bandwidth, which is limited to the devices, so it cannot be modulated to do the frequency sweep operation to get the range bins [31]. Nevertheless, a lot of research studies found the potential of this technique and proposed various researches to compensate for the shortages and improve the feasibility in different tasks.

C. The Evolution of WiFi Sensing for healthcare

1) Hardware platform development of WiFi sensing: For the past few years, research studies on CSI measurement from WiFi signals have been emerging for different sensing applications. In a WiFi system, CSI is essentially a data format used to represent the CFR sampling of the sub-carriers granularity in the system's frequency band, obtained from the physical layer of the commercial IEEE 802.11n wireless network card, based on OFDM technology. Based on the WiFi devices, the researchers first developed an open-source CSI tool driver using the Intel 5300 NICs [32]. This CSI tool enables 30 subcarriers in a 20 MHz channel bandwidth for CSI collection from commercial off-the-shelf (COTS) WiFi devices. This driver provides a quick and low-cost method to establish the WiFi sensing platform. In another study, the authors in [33], [34] have implemented their system based on the Qualcomm Atheros NICs offered by [35], which has 114 CSI subcarriers, hence a higher resolution compared to the Intel 5300 CSI tool. In [34], the results of the comparative study have shown that the higher the number of subcarriers, the higher the sensing accuracy. Other sensing devices include the Wi-ESP which has a reduced cost and is smaller in size compared to the previously mentioned COTS WiFi router [36]. Besides NICs, software-defined radio (SDR) platforms are commonly used to measure CSI, such as the universal software radio peripheral (USRP) and the wireless open-access research platform (WARP) [18], [37], [38].

2) WiFi Sensing Applications towards Healthcare: Based on the foundation of the open-source WiFi sensing driver's development demonstrated in Section II-C1, researchers have started to propose several methods and applications based on WiFi sensing. This section provides a general overview of WiFi sensing development trends in healthcare, and more detailed technical analysis is demonstrated in Section IV. Table II shows some popular applications of WiFi sensing in recent years. For the convenience of demonstration, different tasks are separated into two parts, human activity recognition, and vital signs monitoring. In this case, we define the classification and analysis of all active motion based on torso movement as human activity recognition. From another perspective, vital signs are necessary to maintain regular human activity and are therefore not directly controlled by consciousness and torso movement for the vast majority of time. So, we differentiate it from general human activity recognition.

For the human activity recognition applications in healthcare, we divide them into two types: healthcare auxiliary and healthcare recognition, based on the aspects of monitoring requirement of instant and long-term feedback. In case of healthcare auxiliary applications in an indoor environment, the literature covers daily activity recognition [24], [34], [39]–[44], and other specific activity recognition such as falling [45], smoking [46], sedentary behavior [47], pose estimation [48]–[51], keystroke [52] and mouth motion [53]. As for the daily activity types, most papers consider: walking, running (or jogging), sitting, pushing and dragging, jumping, squatting, opening the door, and other actions that people always take in daily life. Through these instant activity monitoring methods, the alarm of dangerous accidents like falling can be transferred to the nearest community hospital and families to take an instant action to prevent delayed medical attention, especially for elderly people [54]. At the same time, these approaches are helpful for a disabled person to improve self-care capability through contactless interactive smart controlling methods of gestures recognition and pose estimation. For another range of the healthcare, recognition approaches, it mainly covers the detection of the diseases through long-term gait monitoring, for paraparesis detection [55] and Parkinson detection [56]. These works train the specific model to learn the gait difference of healthy people and patients for diseases recognition. Nevertheless, because datasets from disabled person are difficult to obtain, relatively few works have been published in this field.

Vital signs estimation belongs to the range of healthcare recognition applications, which is performed by monitoring the motion of the chest and heart. Most papers analyze the respiration rate [50], [57]–[67], some of them detect heartbeats [50], [59], [60], [62], [64], [67], and another paper demonstrates the biometric estimation [68]. The difference between respiration and heartbeat estimation is demonstrated in Section IV-B. From the perspective of potential in healthcare applications, these systems are useful for instant monitoring of vitals in the non-hospital environments and helpful in the detection of long-term chronic diseases' such as arrhythmia, and some respiratory diseases.

Convincing results with regards to WiFi sensing for biometrics estimation is still lacking in the literature compared to radar-based systems [69], [70] which has shown good performance. So using WiFi signals to estimate biometric parameters can be regarded as a potential application waiting for further development.

Further to the previously reported studies, it is crucial to have reliable localization and tracking systems to complement healthcare monitoring ones. For instance, monitoring vitals during sleeping cannot be performed when the person is not in bed [71], as the position of human is essential to the decision making process.

Meanwhile, from the timeline shown in the Table II, we can conclude the emerging trend is that the researchers are expecting specific WiFi sensing applications like diseases detection, biometric estimation, sedentary activity recognition, which have more application value in healthcare. On the other hand, as the types of perceptible activities in the traditional WiFi sensing method are limited, the pose estimation task is proposed

to restore the human skeleton in visualization with only WiFi signals. Combined with the state-of-the-art framework of computer vision-based human activity recognition, it has expected that the performance will be further improved [48], [49].

III. Main Components of Contactless WiFi Sensing

The development of WiFi sensing systems involves two stages, the first is applying signal processing techniques, and the second is the algorithm design. The signal processing stage consists of three sub-stages, i.e., denoising, signal transformation, and feature extraction. The algorithm stage explains modeling-based and learning-based tracks, respectively. A generalized architecture diagram of a typical WiFi sensing system is shown in Fig. 3. Firstly, raw WiFi signals are collected by the receiver devices, where they are denoised, transformed, and features are extracted for the data-mining of CSI signals. Secondly, algorithms are applied to classify/recognize/estimate the results. Each of the stages is detailed in the following subsections. In this section, we review various kinds of technologies and classify them in different stages.
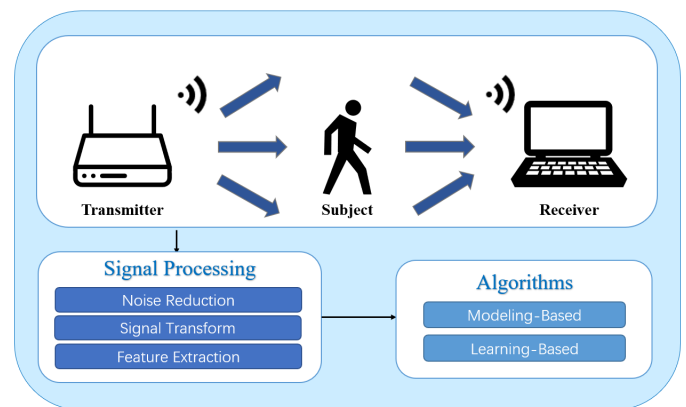

Fig. 3: WiFi Sensing System Architecture

A. Signal Processing Techniques

This stage is concerned with the processing of the collected CSI signals captured during the subject's motion. CSI data is processed by different methods to obtain the nature of the information that is required by the system. The signal processing of WiFi signals constitutes three phases: Noise Reduction, Signal Transformation, and Feature Extraction, to feed noise-free information to the algorithms (see Section III-A1, III-A2 and III-A3)). Table III lists the various methodologies adopted and applied in the literature to process WiFi signals.

1) Noise Reduction: Noise components, like outliers of CSI data, always exist, which impacts the signal and causes a significant reduction in the recognition accuracy of the overall system. Denoising raw data can reduce the redundant computation of invalid information and improve efficiency and accuracy. De-noising is performed in two stages, the first is the removal of outliers, and the second is performing interpolation.

Outlier is the data that stands out from the rest of the data set, leading to suspicion that no random deviations are resulting

TABLE II: General wifi sensing applications since from 2015 to 2020

Year of Publication	Human Activity Recognition	Vitals Signs Monitoring
2015	gestures recognition [72], [73], human motion [74], localization [75], tracking [76], daily activity [24]	respiration [57]
2016	localization [77], tracking [78], location and velocity [79], smoking [80], gait identification [81], mouth motion [53], gestures recognition [82]	sleep vitals monitor [58], respiration and heart rate [59]
2017	falling [45], daily activity [83], smoking [46], location and velocity [84], keystroke [52]	respiration and heart rate [60]
2018	falling [68], dynamic velocity [85], daily activity [34], [39], [40], localization and tracking [86], gesture recognition [68], [87], [88], sedentary behavior [47]	respiration [61], respiration and heart rate [62], biometrics estimation [68]
2019	paraparesis detection [55], localization [33], daily activity [41], Parkinson detection [56], 2D pose estimation [48], gesture recognition [89], [90], pedestrian flow estimation [91]	respiration [63], sleep vitals monitoring [64]
2020	pose estimation [50], driver activity & falling [92], 3D pose estimation [49], gesture [93], [94], daily activity [42]	respiration [65], [66], respiration and heart rate [50], [67]

TABLE III: Signal processing techniques applied in literature for wireless sensing

Reference	Noise Reduction	Signal Transformation	Feature Extraction	Application
WiFall [45]	LOF, MA	N/A	N/A	falling detection
WiHear [53]	N/A	IFFT, DWT	butterworth BPF	mouth motion recognition
Omni-PHD [95]	N/A	N/A	thresholding	human moving detection
Somkey [46]	Hampel filter, interpolation	N/A	thresholding	smoking detection
Widar [79], [84]	N/A	STFT	Butterworth BPF, PCA	localization
PADS [85], [96]	hampel filter	N/A	Combination of Phase Difference and Phase Linear Transform	human moving detection
WiSee [73]	Interpolation	FFT	band pass filter	gesture recognition
Ri-2017 [97]	N/A	N/A	signal separation by ICA	daily objects moving detection
TensorBeat [98]	hampel filter, PBD, SFO, CFO	N/A	thresholding	vitals
CSI-Net [68]	DWT, butterworth LPF	N/A	N/A	human activity recognition
PhaseBeat [67]	DWT, hampel filter	FFT	N/A	vitals

from entirely different mechanisms. In a WiFi system, outliers can be caused by hardware or software errors. Moving average (MA) is a primary method to solve the outliers, which uses statistical methods to average the CSI values in a certain period and connect the average values in the time range. A Hampel filter is also used to remove the outliers, where for each sample of the CSI datasets, the median value of the window consisting of the sample and several surrounding samples is calculated, and then the absolute value of the median is used to estimate the standard deviation of the median of each sample pair. Using the median to replace outliers is less sensitive to noise than using mean and standard deviation [18], [59]. The median filter has the same principle as the Hampel filter, which traverses the signal without outlier detection. LOF is used to find abnormal CSI patterns calculating the local density of the points with respect to k-nearest neighbors [99]. The local density of the selected point will be calculated by reach-ability distance to neighbors and compared with other points.

On the other hand, interpolation processing ensures the continuity of the signal in time and reliability of the experimental data, especially when the data packets are collected at a higher frequency. If packets are lost during communication, the interpolation method would take the average of the nearest two points to replace the unperceived data. Meanwhile, to keep the continuity of the signals, linear interpolation is applied in many proposed systems [46], [68], [73].

2) Signal Transformation: The signal transformation method targets the analysis of CSI signals in the time-frequency domain. In the virtual environment, the wireless signal will be impacted by high and low-frequency noise. Through frequency domain filtering processing, these noise signals can be effectively reduced. At the same time, the signal components of the frequency band required by the systems can be obtained using a band-pass filter and inverse transformation. Fast Fourier transform (FFT) is a standard method applied in the OFDM systems where the CSI is a sample of FFT of channel impulse response (CIR). Short-time Fourier transform (STFT) frames and windows the original signal first, then performs FFT on each frame. These characteristic assists researchers in finding the dominant frequency change in the time domain, which is efficient for real-time sensing. However, when the length of the frame is constant, STFT takes a poor balance of signal restoration in the time and frequency domains. Suppose FFT window length (for CSI signals in the time domain) gets extremely short, it will cause inaccurate frequency analysis with inadequate signal information. Inversely, longer window length

6

brings a lower resolution of signal in the time domain. Discrete wavelet transform (DWT) is utilized to decompose signals on different scales to improve the performance compared with the Fourier transform. Meanwhile, DWT is available in time-frequency analysis to judge the signal frequency changes in the time range, the instantaneous frequency, and amplitude at each moment.

3) Feature Extraction: Feature extraction is the process of obtaining information from the signal, which is the basis of a different algorithm for classification and estimation from the CSI data. Phase difference and phase linear transform are used to find the relationship between the changes in the phase and human activities.

Filtering is adequate for detection of the behavior with constant frequency like heartbeat and respiration, even for the detection of walking, which focuses on filtered high frequency CSI signals out to get cleaner human-related signals, such as the respiration and heartbeat rate [67], [98]. Butterworth filter is widely used because the frequency response curve in the pass-band is flat without fluctuations, while it gradually drops to zero in the stop-band.

Thresholding is used to distinguish valid signals in the time range based on ToF. As shown in equation 1, the ToF value of each path can be estimated by CSI data [78]. Based on the distance of transmission lines, those signals with high ToF value are reflected more times around the environment than others, which is meaningless for systems and can be excluded. Last but not least, signal compression utilizes dimensional decrease methods that generally work in feature extraction, like principal component analysis (PCA) and independent component correlation algorithm (ICA). PCA is a statistical method, transforming a group of potentially correlated variables into a group of linearly uncorrelated variables through orthogonal transformation. This group of variables after conversion is called the principal component. In WiFi sensing, PCA is mainly adopted to integrate the signals from different subcarriers to extract main components of variance (see Fig. 4). ICA is also a method to find the hidden factors of non-Gaussian data, regarded as a powerful method in blind signal analysis. From the previously familiar sample-feature perspective, the prerequisite for using ICA is that implicit factors of independent non-Gaussian distribution generate the sample data.

B. WiFi Sensing Algorithms

The core methodology applied for detection or recognition of activities lies in the algorithm, which is divided into either modeling-based or learning-based. Some examples from the literature are shown in the Table IV.

1) Modeling-Based Algorithm: Modeling-based approaches apply statistical or mathematical models to extract specific features, depending on the tasks. These studies are less dependent on training set and have more robustness compared to the learning-based methods.

ToF and angle of arrival (AoA) models have been frequently applied for indoor tracking and localization. When receiving signals in the same physical path, the delay should be a constant
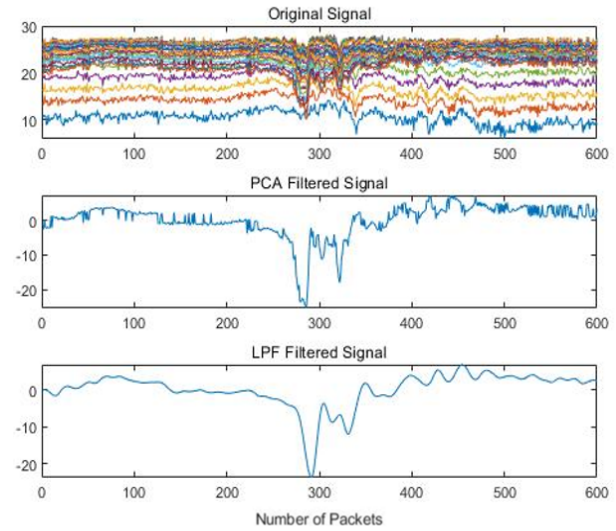

Fig. 4: Example of PCA & LPF process for CSI amplitude signals

value. However, due to the multi-path effect, which reflects the transmitted signal, the value of ToF can be influenced. Power delay profile (PDP) is a common approach to get the value of ToF through inverse fast Fourier transform (IFFT), which is popular in tracking and localization [76]. Meanwhile, AoA makes different antennas show different phase observations. Multiple Signal Classification (MUSIC) performs well on the AoA estimation [75], [78], which correlates phase difference with the distance of multiple antennas to estimate the transmission direction.

The phase difference is required to combine with the Fresnel zones (see Fig. 5). The Fresnel zone is a concentric ellipse with foci between the transmit and receiving antenna horizontally in the WiFi system. [100] designs the related experiments and proves that the motion that happens in the middle of the Fresnel zone is more efficient than happens on the boundary.
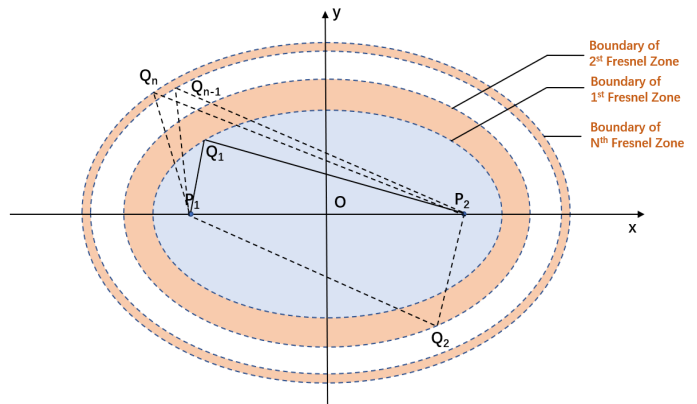

Fig. 5: Geometry of the Fresnel zone

Doppler frequency spectrum (DFS) represents frequency shift influenced from the active motion, which is feasible to extract the velocity of subjects. CSI itself represents the channel frequency response, so it is convenient to do time-frequency analysis of the WiFi signals (see Fig. 6)). The authors of [84]

TABLE IV: Feature extraction and classification techniques applied in the literature for wireless sensing

| Reference	Modeling-based	Learning-based	Application
WiFall [45]	N/A	KNN, One-Class SVM	falling detection
WiHear [53]	MCFS	DTW	mouth motion recognition
Omni-PHD [95]	EMD	N/A	human moving detection
Smokey [46]	Peak Detection	Autocorrelation	smoking detection
Widar [79], [84]	Doppler Shift,PLCR	N/A	localization
PADS [85], [96]	N/A	One-class SVM	human moving detection
WiSee [73]	Doppler Shift	Pattern Mapping	gesture recognition
CSI-Net [68]	N/A	Deep learning network	human activity recognition
PhaseBeat [67]	Peak Detection, Root-MUSIC	N/A	vitals estimation
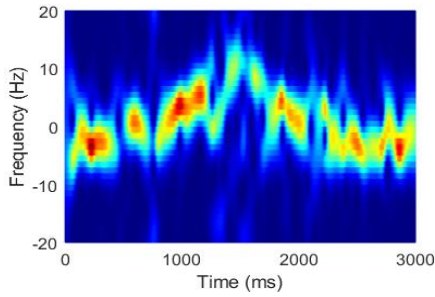
Fig. 6: DFS representing human activity of leaning forward and back

developed an algorithm to correlate static CSI values with active multi-path gradient and utilize the Doppler frequency change to estimate the velocity and location of the humans. Besides, [89] adopts the body velocity profile (BVP) algorithm to apply the earth mover's distance to integrate the multiple spectrum's characteristics to classify the gestures (see Fig. 7). In each BVP, the velocity component is projected onto the normal direction of a physical WiFi link and contributes to the power of the corresponding radial velocity component in the DFS profile. Due to the path length change of the Doppler signal, WiFi equipment in a different position collects distinct CSI signals. This Widar3.0 considers the location of devices and maps DFS value into the BVP. This method reduces the negative influence from the environment and has been tested in unknown locations where signals are collected for the training set.

2) Learning-Based Algorithm: Machine learning-based classification algorithms such as the k-nearest nighbors (KNN) and support vector machines (SVM) are widely used in detection and recognition tasks [101]. Multi-cluster/class feature selection (MCFS) in the WiHear system [53] sets to extract the optimal feature subset and find the correlation feature between different subsets, using a pattern matching algorithm to avoid over-fitting. On the other hand, with the fixed size of the dataset, the classification process of MCFS on the testing set takes 5 seconds, which is much lower than 3 - 5 minutes taken by the SVM algorithm. The Dynamic Time Wrapping (DTW) method calculates the similarity between time series data by extending and shortening the sequences widely used in fingerprint-based learning methods. Similarly, earth mover's distance (EMD)

defines distance measurement, which can measure the distance between two distributions. The function of EMD and DTW is similar in CSI based classification, which both belongs to the range of linear regression. By contrast, DTW focus on estimation in single dimension CSI sequence, and EMD can be used in higher dimensions, like DFS integration shown in Fig. 7.

Besides ML methods, many deep neural network (DNN) frameworks have been widely applied in WiFi sensing. With the rapid development of neural network in recent years in various fields, different DNN structures have been applied in WiFi sensing, for example, convolutional neural network (CNN), long short-term memory (LSTM) and etc. In [41], instead of using long short-term memory (LSTM), an attention-based bi-directional long short-term memory (ABLSTM) neural network is proposed to extract 2-dimensional features from WiFi CSI data, representing human activity. In the results, recognition of six different activities in public places, recorded an accuracy of more than 97.5%. In [40] the author applies the CNN classification algorithm, which records a higher accuracy in comparison with the SVM classifier. Similarly, SignFi [87], and 1D-CNN [55] propose the use of different CNN structures for WiFi sensing. The 1D-CNN performs better than the KNN method (average 4% higher in 1D-CNN), and SignFi improved 2% - 4% accuracy compared to the KNN-DTW method proposed in [82], [102]. Instead of using external neural networks (less than five layers) as alternate nonlinear operators, [68] proposed a novel method to extend the size of CSI input from $30 \times 1 \times 1$ to $6 \times 224 \times 224$ with bi-linear interpolation, which provided an image-like structure for further deep learning. It offers conditions to apply different backbone networks like AlexNet, visual geometry group (VGG) network, inception cluster, etc. The deep learning network framework proved that body perception of CSI sequences for WiFi could accomplish: two body characterization problems of biometrics estimation (including body fat, muscle, water, and bone rate) and identification, two activity recognition: gesture recognition and fall detection. For both traditional ML and DNN methods, the performance suffers from the distribution shift that arises from different circumstances/locations. To avoid the repeated training of the model and fitting new areas, transfer learning methods can be utilized with lower computation resources [88]. Furthermore, the metric learning approach also helps the model generalize to new environments for applications such
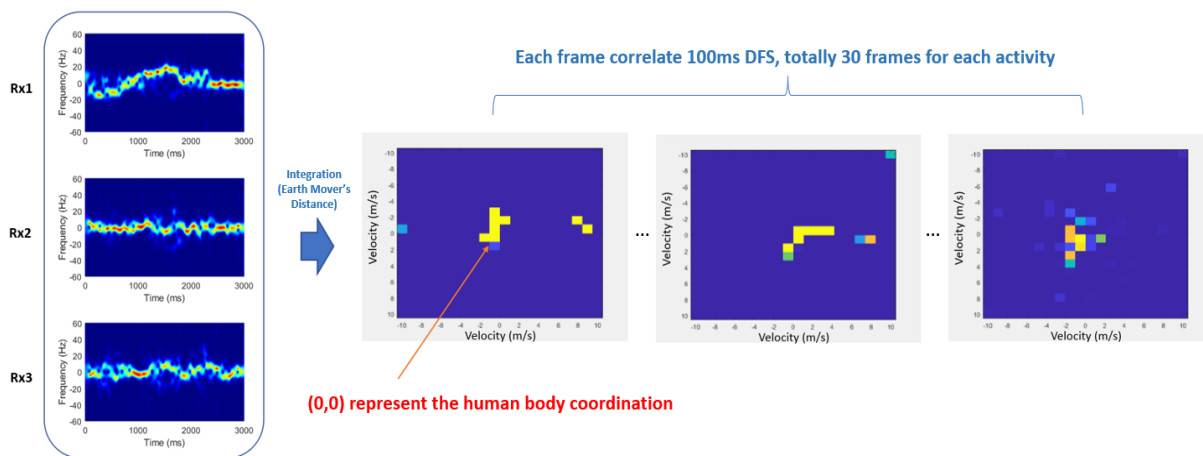
Fig. 7: BVP methodology proposed in [89]

as gesture recognition [90]. Although all above methodologies apply distinct network structures, the central task is the same, which is adopt DNN to match the CSI signal with the artificial label.

Moreover, pose estimation adopts the label from camera-based methods, and proposes a novel DNN structure to match the human skeleton to WiFi CSI data. In the training stage, the skeleton of a human being can be acquired from image processing with cameras. Afterward, the collected WiFi data is labelled and correlated with different patterns of skeleton coordination and trained by a neural network. The authors of [103] proposed a novel network to apply a fully convolutional network (FCN) for estimation of a single person's pose from the collected data and annotations. This work aims to train the specific neural network to map the CSI variance to the human skeletons, and get the fine-grained human skeletons from CSI signals. Furthermore, they developed another structure for multi-persons' pose estimation [48]. Based on a similar theory, [104] proposes a image-based preprocess method to get a CSI-image for CNN framework to estimate the pose. However, in the mentioned 2D human skeleton restoration, there are few discussions of the robustness. Due to the sensitivity of CSI signals, environment has the severe impact on channel information, which means the overfitting issue is inevitable. Because 2D pixels obviously can not map all human activities, especially for NLOS side, with CSI variance. To improve the reliablity, the study of [49] improves the BVP to 3D velocity profile through changing the antennas' height. These ideas create the condition of more applications development with pose estimation.

IV. WiFi Sensing applications for In-home health monitoring

Remote healthcare monitoring systems, based on WiFi sensing, perform two main operations of healthcare recognition and healthcare auxiliary (described in Section II-C). Healthcare recognition applications require the monitoring system to analyse the human health for activity- and vitals-related diseases' detection, through the long-term monitoring of activities and vitals. Healthcare auxiliary applications cover the systems that are capable of providing smart detection services for human beings, which can be further divided into two categories based on the typical tasks. Firstly, healthcare auxiliary depends on the real-time detection of critical events, such as falling and irregular respiration rate, to alert the nearest healthcare center or family member. Then, location and tracking functions are also available in indoor healthcare auxiliary tasks. This section reviews recent WiFi sensing healthcare applications based on the range of supportive applications, and discusses the efficiency and availability of different methods for implementation in an indoor environment. Some applications with technical details are shown in Table V.

A. Healthcare recognition applications

1) Disease detection: At present, chronic disease detection in WiFi sensing is limited to activity recognition without vitals analysis. Due to the action difference of identity, the current detection strategy is to recognize the feature of the disease while volunteers are doing the specific test.

The WiFreeze system [56] proposes a deep learning method to recognize Parkinson's disease based on the walk, sitting–standing and voluntary stopping activities of humans. Freezing of gait (FOG) is an explicit characteristic of Parkinson's disease infection. The authors apply the CSI amplitude for continuous wavelet transform analysis and get the time-frequency spectrograms. For the evaluation stage, they use the dataset of human activities that contains FOG, walking slow, walking fast, sit-stand, voluntary stop. For classification, they applied a revised neural network structure from VGG-18. The result records the FOG detection accuracy of 99.7%. However, the average accuracy of 5 activities is much lower, approximately 85.06%, which is not a good model for human activity recognition and here are several points that needs to be considered:

- Accounting for the phase of the CSI data and not just the amplitude.
- The impact of decomposing wavelets from original signals when using CWT on the overall performance of a real-time system.

TABLE V: WiFi sensing applications of In-home health monitoring

Reference	Applications	Device Type & Number	Antenna Number	Performance
1D-CNN [55]	Lower extremity paraparesis detection	COTS WiFi device (1Rx,1Tx)	NTx=1, NRx=3	Average Accuracy: 99%
Wi-COVID [105]	Breathing shortage detection	COTS WiFi device (Tx), Raspberry PI 4 (Rx) (1Rx,1Tx)	NTx=1, NRx=3	Missing information
WiFreeze [56]	Parkinson's disease	COTS WiFi device (1Rx,1Tx)	NTx=1, NRx=3	Average Accuracy: 99.7%
ESPRIT [106]	Respiration rate	USRP B210 (1Rx,1Tx)	NTx=1, NRx=1	0.15 bpm mean error
WiHealth [59]	Heartbeat and Respiration rate	COTS WiFi device (1Rx,1Tx)	NTx=3, NRx=3	0.6 bpm of heartbeat, 6 bpm of respiration
Tensorbeat [98]	Respiration rate	COTS WiFi device (1Rx,1Tx)	NTx=1, NRx=3	0.19 bpm mean error in LOS, 0.25 & 0.26 bpm in corridor and through-wall scenarios.
PhaseBeat [67]	Heartbeat and Respiration rate	COTS WiFi device (1Rx,1Tx)	NTx=1, NRx=3	1.19 bpm median estimation error of heartbeat; 0.25 bpm mean error of respiration detetion when the sampling rate is 400Hz using directional antennas.
In [50]	Respiration rate	COTS WiFi device	NTx=1, NRx=3	Average Accuracy: 91.2%
CSI-Net [68]	Falling detection; Biometrics estimation	COTS WiFi device (1Rx,1Tx)	NTx=3, NRx=3	Falling detection: 97.73%;
WiSee [73]	Gestures Recognition	USRP N210 (2Rx,2Tx)	NTx=1, NRx=1-5	Average Accuracy: 94%
Widar3.0 [89]	Gestures Recognition	COTS WiFi device (3-6Rx,1Tx)	NTx=1, NRx=3	Average Accuracy: 90.9% (Test Places not included in the training set).
WiFall [45]	Human Activity Detection	COTS WiFi device (1Rx,1Tx)	NTx=3, NRx=3	Average Accuracy: 87%
ABLSTM [41]	Human Activity Detection	COTS WiFi device (1Rx,1Tx)	NTx=1, NRx=3	Average Accuracy: 99%
WiHear [53]	Mouth Detection	COTS WiFi device and USRP N210 (1Rx,1Tx)	NTx=1, NRx=3 for WiFi device; NTx=2, NRx=2 for USRP	WiFi devices have higher accuracy of 91% with single person, 74% with less than three persons.
CARIN [92]	Driving Fatigue Detection	COTS WiFi device (1Rx,1Tx)	Information missing	Average F1 score: 90.9%
DfP [86]	Localization and tracking	COTS WiFi device (3Rx,4Tx)	Information missing	Average mean absolute errors of four environments: 0.92m
Widar2.0 [107]	Localization and tracking	COTS WiFi device (1Rx,1Tx)	Information missing	Average mean absolute errors: 0.75m

- The size of the training and testing datasets for DNN to avoid overfitting the model.

The authors in [55] propose a 1D-CNN algorithm to detect lower extremity paraparesis. The dataset contains the CSI signal of two series of specific motion detection (Barre and Mingazzini methods) for paraparesis detection. The 1D-CNN system achieves an accuracy of 98% for the Barre test and 99% for the Mingazzini test respectively. This work applies a relatively shallow network structure compared to the above WiFreeze system. However, the dataset only contains two classes: typical result and abnormal result based on two test methods. This study would improve if it considers introducing more classes like gender, ages, health status to explore more based on WiFi sensing. Meanwhile, in a realistic environment,

the use of the 1D-CNN and the WiFreeze system cannot prove the reliability of multiple persons. Secondly, the setup details, like Barre and Mingazzini test in [55], should be more straightforward for other researchers to repeat the experiments because WiFi signals can be significantly affected by the environment. Lastly, the discussion of application value is not enough. Parkinson's and paraparesis are chronic diseases that should be detected in the long-term, and it has expected to do the evaluation test using a similar system on the infected groups for intelligent healthcare. Therefore, disease surveillance based on WiFi sensing is a direction with development potential.

2) Vitals detection: Vitals detection of heartbeat and respiration rate belongs to passive healthcare recognition because they both are produced by the tiny and rhythmic vibration of the

heart and chest. This section covers the theory of respiration and heartbeat detection and related issues.

Respiration activity is crucial for the evaluation of sleep quality and the detection of respiratory diseases. One rise and fall of the chest is one breath, which means one inhalation and one exhalation. The regular adult breathing rate is 12 - 20 times per minute, while children and older adults have slightly higher rates. Breathing activity has been considered in several research studies, such as [57], [98]. In [98], the TensorBeat system is proposed to recognize the breathing rate of single and multiple individuals. The performance results of two-person and three-person tests are similar, accounting for 93% accuracy, with the error in both being less than 0.5 bpm. However, the performance is reduced to approximately 62% when number of people increased to five people, highlighting a correlation between number of subjects and the deterioration in the accuracy of breathing rate estimation.

Heartbeat rate is also a significant index of human health. The number of heartbeats per minute of a normal person in a calm state is generally 60 to 100 beats per minute, varying among individuals due to age, gender, or other physiological factors. In [59], [60], heart and respiratory rates are both measured by their proposed system. The errors are recorded for the WiHealth system, in [59], are 0.6 bpm, for the breathing rate, and 6 bpm of heart rate. PhaseBeat [67] proposes a novel task classification method. The authors use the resolution of the feature maps to classify detected results for different tasks, which provides new ideas for future multi-task recognition based on deep learning, and the errors decrease to 0.23 bpm of respiration rate and 0.48 bpm of heartbeat rate. Besides, [67] also provides a comparison test of the omni-directional antenna and directional antenna on vitals detection. In the test, the error of heartbeat rate reduces to 1.19 bpm, which proves the efficiency of a directional antenna. For respiration rate, the error improves from 0.23 bpm to 0.25 bpm, but it is an acceptable performance fluctuation.
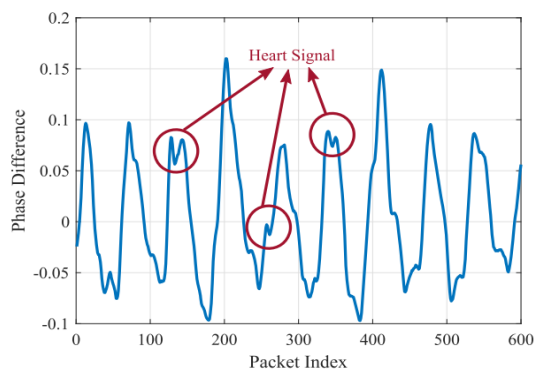

Fig. 8: Heartbeats hidden in the breathing signal [67]

From the comparison of results, we can conclude that the heartbeat is more difficult to sense. In WiFi frequency, 2.4 GHz and 5 GHz are standard, of which wavelengths are 60 mm and 125 mm. The maximum range of human chest motion while breathing is around 10 mm and 24 mm [108], which is far less than the wavelength. Under this condition, the phase of reflected signals will appear a difference (from 60 degrees to

150 degrees for a 5 GHz signal). For heartbeat measurement, it is more difficult because the motion of the heart is hugely less than chest movements, as shown in Fig. 8. Directional antennas should be used if the system requires higher accuracy of heartbeat monitoring.

Secondly, Fresnel zones take a significant impact on this tiny movement of the heart and chest. The Fig. 9 explains how the Fresnel zones influence the respiration detection. When the people are located on the boundary of the Fresnel zone, the variance of phase is brutal to extract compared to the center of two boundaries. Therefore, WiFi based contactless vitals detection can achieve high performance but is severely dependent on the implementation of devices.

B. Healthcare auxiliary applications

This section covers all the classification studies related to the humans' daily activities, as discussed earlier in Section II-C2. Based on the methodologies, we divide the studies into activity detection, pose estimation and localization. At the same time, based on the movement range of human motions, the activity detection is further separated from large-scale and small-scale, because these tasks need to consider the specificity of actions when designing an experiment and the movement range of each activity class in the comparison test should be kept similar. The different scale will influence the experiment design as well, shown as Fig. 10a and Fig. 10b. For instance, compared to the gait recognition experiment, the distance and implementation of gesture detection are much more specific than the position of gait recognition.

1) Large-scale activity recognition: Large-scale recognition methods contain falling detection, daily activity like sitting-standing, gait recognition, human moving detection. Compared with small-scale detection, large-scale recognition is generally more efficient and accessible in applications because the CSI signals can be severely affected by the extensive range motion of limbs and torso. For instance, in the falling detection, due to the instantaneous velocity change of the human torso, part of the channel transmission medium and reflection and scattering conditions of WiFi signals have changed, resulting in the apparent doppler effect on CSI. The WiFall system, presented in [45], processed the amplitude of the collected CSI data to detect falls in an indoor setting. Besides, abnormal activities can contain health-damaged behavior like smoking, especially in some indoor non-smoking areas. Wireless smoking behavior testing can protect smokers' privacy, compared to the current camera-based detection. The WiFi wireless sensing is used in smoking detection [46], and overcomes the blind spot in camera-based detection systems.

2) Small-scale activity recognition: Small-scale activity detection is specific to the tiny movement of humans, including motion of hands and arms, with various kinds of studies. For example, the authors of [94] propose a CSI-based classification method to classify different movements of limbs while walking. Gesture recognition is helpful for disabled people to feasibly control their daily life and contact others in an emergency [110]. WiSee [73] introduces a system that sets out to recognise nine gestures using WiFi sensing (see Fig. 11a) with up
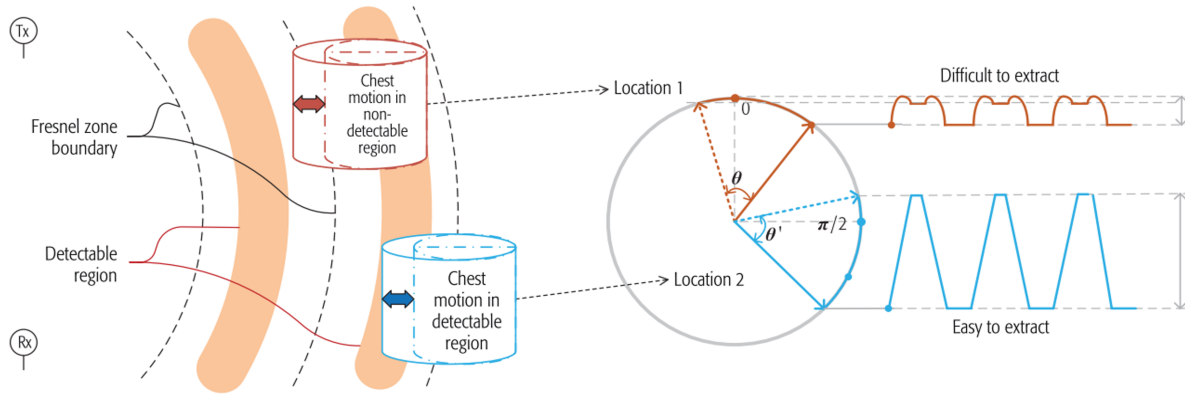
Fig. 9: Phase variety of human respiration detection in Fresnel zone boundary (Location 1) and middle region of Fresnel zone (Location 2) of [17]

(a) Experiment setup of gesture recognition in [90]
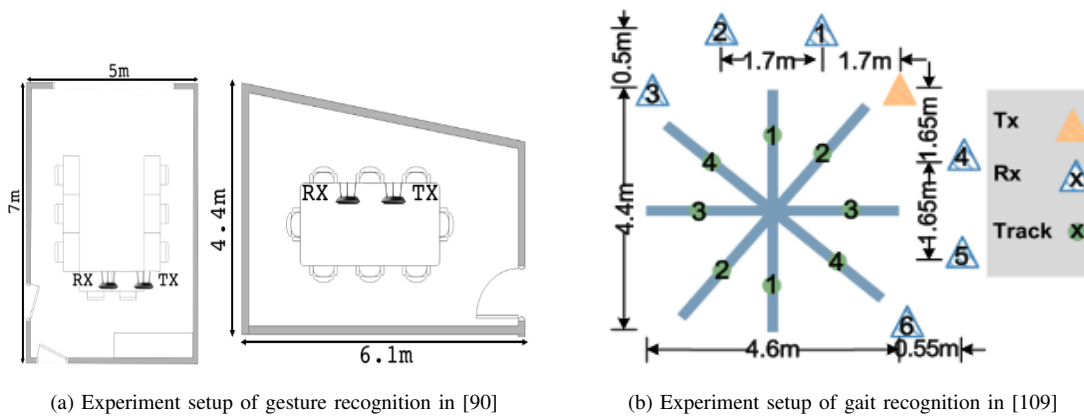
(b) Experiment setup of gait recognition in [109]

Fig. 10: Experiment setup comparison of small-scale gesture detection and large-scale gait recognition

to four people, set up in different scenarios (see Fig. 11b) with an average accuracy of 94%. For the tiny motion of the hands, WiKey proposes a system to recognize stroked words from general keystroke behavior [52], the accuracy achieved was 97.5% of stroke behavior detection and 96.4% of word recognition. However, the test environment has limited the transceiver direction, distance change, moving speed of typing fingers and direction, the keyboard layout, and size of factors that affect system performance, which can be difficult to replicate the work in a real-life scenario. To improve the robustness, [89] is proposed to correlate the CSI data of more than three receivers in different directions and positions. The result shows average accuracy above 85% for all testing locations. Nevertheless, the good performance of the system encourages researchers to design more applications based on WiFi signals.

Mouth movement always represents speaking, eating, and coughing. In the healthcare monitoring system, cough is a significant symptom in patients infected with respiratory diseases, including COVID-19 [111], [112]. Wireless-based activity recognition can be regarded as a suitable method for cough detection. Recently, WiFi sensing has been applied in many other health-related applications, other than cough detection. On this side, [53] presents the WiHear system

for speech recognition using WiFi. The system establishes a mapping dictionary from the pronunciation of vowels to the mouth shapes to recognize a part of different types of pronouncing and even some short words, shown in Fig. 12. The COTS WiFi device can capture sensitive Doppler signals in CSI. Combined with the move of the head during the coughing process, the accuracy of cough sensing would be higher than speaking single words. It is worth mentioning that the system adopts directional antennas for implementation.

3) Fine-grained human pose estimation: In daily life, human body language is extremely various that it is difficult to categorize it with a few fixed variables. Therefore, a system that uses limited data sets for motion classification is difficult to deploy effectively in a non-experimental environment. Pose estimation targets to recover the human skeleton for people to recognize the human actions through the vision, which is clear and intuitive. Compared to the classification studies mentioned above, this fine-grained pose estimation is more competitive and humanized and capable of recovering both large-scale and small-scale activities' pose. A fine-grained [48] system was firstly implemented in WiFi range with the skeleton on the 2D images for users, shown in Fig. 13. This system tests processed human skeletons and achieves 0.66 of mean intersection over union (mIoU) with 1 - 5 persons. [49]
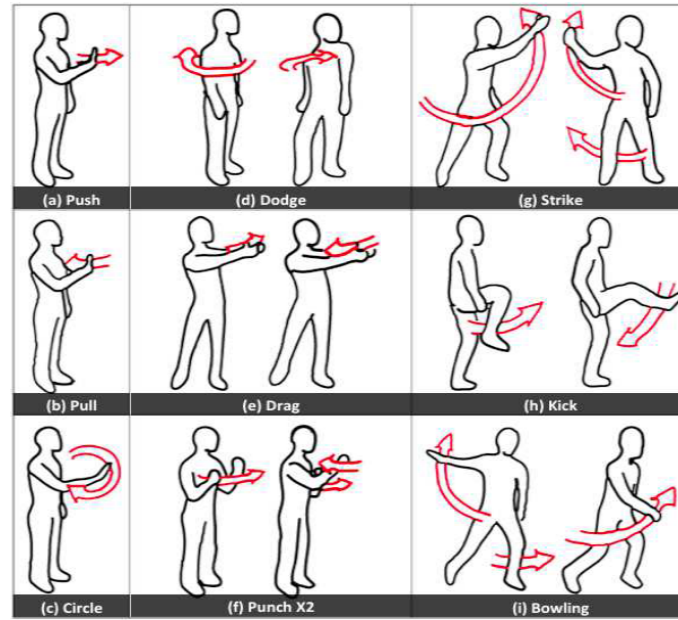
(a) Gestures diagrams
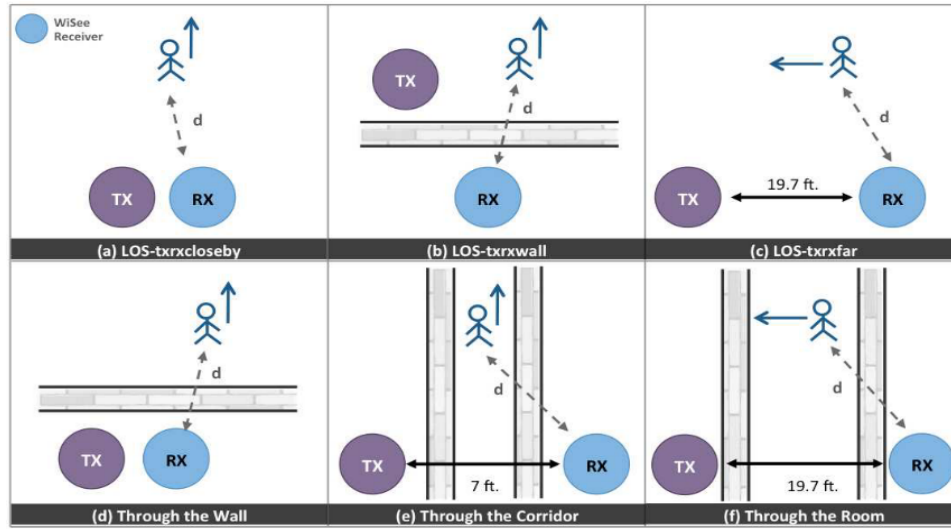
(b) Testbed diagrams

Fig. 11: Nine gestures detected in WiSee System in 11a and scenarios of testbed in Whole-home range in 11b of [73]

proposes a 3D skeleton restoration method using WiFi signals, where the authors used the VICON motion camera system as the ground truth 3D skeleton of the human body, shown in Fig. 14. In this system, the skeleton represents the physical distance instead of the pixels, which further proves that the WiFi signal can perform fine-grained detection. The restored skeleton can assist users in judging the performance of the sensing system and is available for further activity recognition. Also, due to visible skeleton restoration, these works have the exemplary significance regarding the increase of the human activity types without re-training the whole system. However, human skeleton restoration is limited to the overfitting. The training set of 3D restoration works only contains the human skeleton in constant location, which means most predicted skeletons have limited variance.

4) Human Localization: Further to the previously high-lighted studies, WiFi sensing also shows potential in indoor localization and tracking. At present, traditional WiFi localization adopts RSSI signals from mobile devices, which depends multiple access points (AP) with different media access control address value for measurement (at least three devices). CSI based WiFi localization can reduce the required number of AP, and be independent on portable devices. In [113], the authors propose a method with location fingerprint to locate people with RSSI fingerprints using the WiFi COTS devices and mobile phones. In the setup shown in Fig. 15, there are 24 APs in total equipped in a plain floor of 1610 square meter. DeMan [74] regards human breathing as an inherent indicator of the human state and judges the existence of a stationary person by detecting specific signal patterns caused by tiny chest
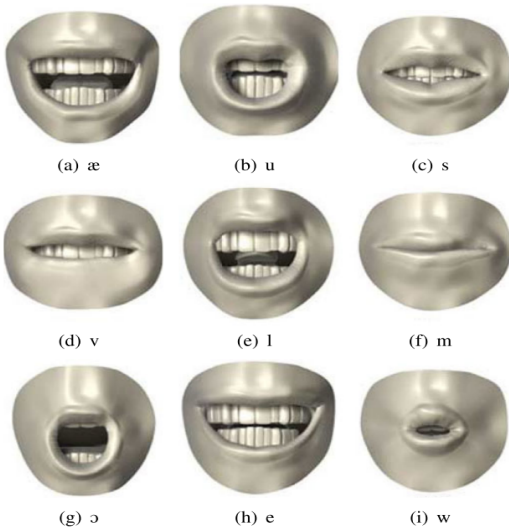
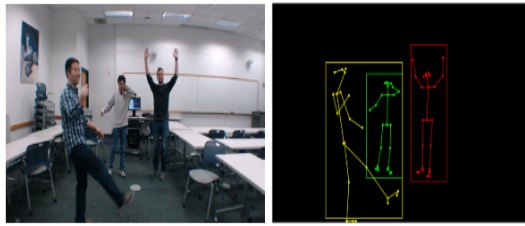Fig. 12: Mouth motion detection in WiHear [53]

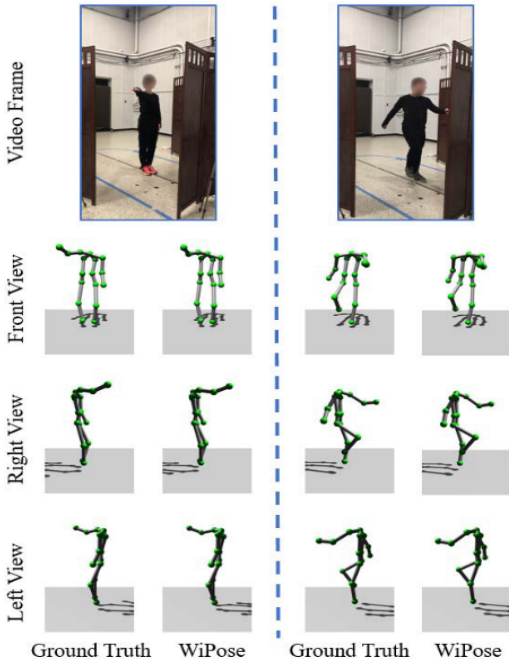Fig. 13: 2D restoration of human pose [48]

Fig. 14: 3D restoration of human pose [49]

Fig. 15: RSSI based localization implementation of [113]

movements. Another work proposed a passive localization indoor system [77] using CSI with an improved Dynamic-MUSIC algorithm. The system gets the AoA value from moving targets to establish the fingerprints of the location (see Fig. 16) and records a median error of approximately 0.6 m, with two pair of devices, which is sufficient for localizing children and disabled persons. In [86], a probabilistic fingerprint-based method is proposed and tested in four environments. Their result demonstrates the system of the Kalman filter for tracking objects at a fixed walking speed, which is available to analyze the movement of monitored people with pose estimation for early symptom detection, with 3 transmitters and four receivers. More specifically, [107] achieves the indoor tracking with one pair of WiFi devices, in general office and corridor, with the average error of 1 meter. In conclusion, contactless WiFi sensing approach can be applied with fewer number of devices compared to RSSI based methods, without portable devices. However, RSSI-based method is more capable to achieve the larger range tracking in cross-rooms environment.

V. CHALLENGES AND FUTURE DIRECTIONS

Due to the popularity and consistent upgrade of WiFi devices, WiFi sensing is the technology with considerable potential. However, the popularisation of technology in healthcare will inevitably encounter not only technical limitations as applications introduced but also ethical problems in Section IV. Specific challenges and future directions are presented and discussed in this section.

A. Challenges of WiFi sensing in healthcare

Section IV has introduced various types of WiFi sensing systems for healthcare that achieved high accuracy in a specific task. However, most of the work is challenging to implement at home simply because the environment is distinct, which means the performance is limited with regards to different scenarios (see the comparison regarding six different factors in Table VI,VII,VIII,IX,X). This section discusses these issues and gives the corresponding technical-level solutions.

1) Robustness: Robustness is essential for the future development of WiFi healthcare sensing, resulting in whether the experiment's repeatability and validity can be guaranteed in different environments. Although most learning-based methods have good experimental results, due to the method itself on the specific data, the performance of such methods in
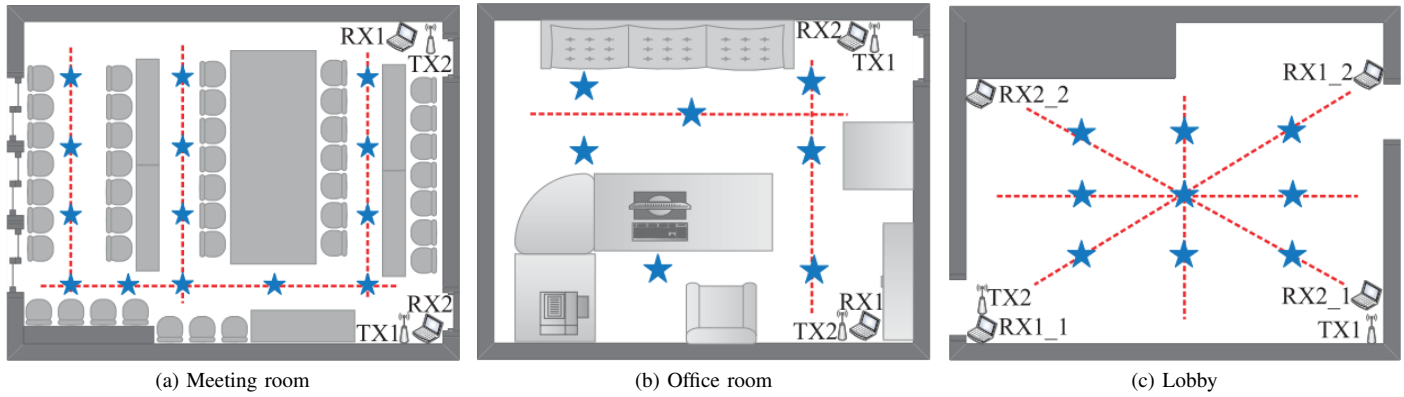
(a) Meeting room (b) Office room (c) Lobby

Fig. 16: CSI based localization system environments of [77]

TABLE VI: Sampling frequency versus WiFi sensing performance

	Smokey [46]	widar2.0 [107]	DfP [86]	PhaseBeat [67]
Sampling frequency	drop 80% (100Hz - 10Hz)	no significant change (time consumption increases from 0.7s to 1.5s)	Increase 20% accuracy (1kHz-10kHz)	no significant change on breathing detection, heart rate error decreases from 3bpm to 1.1bpm

TABLE VII: Performing distance versus WiFi sensing performance

	WiFall [45]	Smokey [46]	Human recognition [81]	WiGest [72]	Widar3.0 [89]	MaTrack [77]	RespiRadio [114]	PhaseBeat [67]
Distance or location	drop 16% (1.5m - 3m)	drop 33% (0.5m - 3m)	drop 45% (2m - 16m)	drop 20% (1m - 19m)	13% maximum difference of 5 locations	drop 20% (1m - 9m)	the error increases from 0.1bpm to 1.2bpm (Tx-Rx: 2m - 10m)	the error increases from 0.27bpm to 0.54bpm (Tx-Rx: 2m - 7m)

TABLE VIII: Performing environments versus WiFi sensing performance

	WiFall [45]	Smokey [46]	SignFi [87]	Widar3.0 [89]	DfP [86]
Environments	9% maximum difference of 3 environments	19.2% maximum difference of 3 environments	3% maximum difference of 3 environments	4.5% maximum difference of 3 environments	0.2m maximum error of 4 environments

unknown scenarios cannot be promised. In the comparison tables, most challenges are related to achieving generalization of sensing methods under different conditions: distance or location, environments, identity difference, and orientation of action. These factors are discussed in the studies and show the limitation behind the overall performance.

Therefore, sensitivity to changes in the physical environment is a double-edged sword, which supports the high performance of detecting specific activity but allows much noise from surroundings to disturb the process. For example, for the methods using DNN and ML for activity recognition, the size of the experimental setup is kept in a limited variance of the noise. For the complex real-world environment, the barriers around the circumstance can take serious adverse effects on the accuracy. For example, estimation of human respiration rate needs to filter out the noise component of other activities. However, even if unconscious human activity is filtered out, conscious rhythmic activity can easily interfere with detection results and other objects' activities.

2) Complicated implementation of setup: Meanwhile, it is also a challenge to set up the WiFi devices while using. In [89], the study involves a robust system for gesture recognition using 3 - 6 receivers with the predetermined location. Objectively, it's not possible for each consumer to set the devices in the same position due to the limited physical spaces or other issues. In addition, sampling frequency's setting has a significant impact on performance as shown in Table VI, which needs experiment validation to achieve a trade-off between low power consumption and high accuracy performance. These problems have hindered the popularisation of the WiFi sensing technique.

3) Multiple Subjects Sensing: The performance of different WiFi sensing systems becomes worse as the number of subjects involved in the experiment increases, as shown in Table X. Majority of works do not mention the multiple human scenarios due to the low angle resolution of WiFi. Although the AoA technique based on MIMO is accurate enough to distinguish the human and count the number of people, it is not enough to distinguish the signal from a different person and get a

15

TABLE IX: Performing environments versus WiFi sensing performance

	Gait recognition [115]	WiKey [52]	WiFinger [82]	SignFi [87]	Widar3.0 [89]	widar2.0 [107]	PhaseBeat [67]
Identity difference	average accuracy drop 24% (2-11)	15% maximum difference of 10 subjects	14% maximum difference of 10 subjects	30% maximum difference of 5 subjects	13% maximum difference of 8 subjects	no significant change	0.2bpm maximum difference of 4 directions

TABLE X: Orientation and Multiple human versus WiFi sensing performance

	WiFall [45]	Widar3.0 [89]			Smokey [46]	PhaseBeat [67]
Orientations	drop 30% (10 - 110 degree)	11% maximum difference of 5 directions		Multiple human senarios	drop 25% (1 - 4)	error increases from 0.25 bpm to 0.7 bpm (2 - 4)

specific result. To improve the resolution of sensing, efficient multiple subjects recognition method must be developed and improved for more practical and real-world setups. Meanwhile, it is challenging to track the person's identity with specific respiration for in-home healthcare analysis in the multiple subjects environment.

4) Performance of WiFi Networking: CSI is collected using NICs, which are primarily used for networking, with stable transmitted frequency. Current drivers of WiFi device is able to increase the frequency to meet the requirement of higher frequency of CSI packets collection that most of the systems rely on, which will produce empty packets for networking. In the case where the empty package takes up more, they will interfere with typical networking tasks. Hence, it is challenging to operate a WiFi device to complete sensing and networking tasks simultaneously.

5) Privacy and Security: Privacy and security are being threatened by WiFi passive sensing technology. In state-of-the-art methodologies, WiFi sensing can be used in the NLOS range for human and object behavior. A well-trained system can be used to recognize the gesture and keystrokes of the human being. Suppose WiFi sensing is used to steal other people's private information due to the portability and generalization of WiFi equipment. In that case, it is difficult for people to recognize privacy-invasion behavior from those who collect that private information. Fortunately, thanks to the limitations of NIC manufacturers on channel information decoding, only a limited number of devices can collect CSI data through open-source drivers. However, with the miniaturization of NICs and the maturity of sensing technology, this issue will be much more concerning in the future.

B. Future Directions of WiFi Sensing in Healthcare

Although WiFi sensing has significant challenges for generalization, there is still great potential for healthcare applications in the real world. To overcome the issues discussed above, the technique is expected to improve in four directions.

1) A unified framework of WiFi sensing: One of the most challenging problems of WiFi sensing robustness is various experimental setup and devices. Although theoretically, all WiFi sensing methods should get the same performance as any type of WiFi device. In practice, even the sampling rate of WiFi can significantly influence the performance (see Table VI). It is necessary to follow a framework from hardware to software of WiFi sensing system for future generalization,

which has a completely unique setup and test standard for different methodologies to assess their performance in the indoor environment. For example, the framework should contain the available sampling frequency, type of antennas and NICs, human location, distance between transmitter and receiver, number of subjects and etc. Based on the framework, extra modules for mobile edge computing can be incorporated in the WiFi sensing systems [93] to accelerate the processing speed and decrease the influence on WiFi networking system.

2) Spatial Sensing for wide applications: WiFi sensing applications can sense ambient information regardless of direction due to the omni-directional antennas of WiFi devices. However, this characteristic is not helpful in some cases. If the WiFi sensing system can monitor the vitals or activities of individuals, for example, only detect the vital signs of people on the fixed bed in the hospital, instead of detecting caregivers. It will be more efficient to analyze the data without massive ambient noise from other directions. Nevertheless, due to CSI data collected from WiFi devices that have low resolution and high sensitivity, it is challenging to separate signals from a specific space. Beamforming technology with an intelligent reflecting surface (IRS) [116] and directional antennas [67] are considered methods to overcome this disadvantage and improve the performance.

With spatial sensing, WiFi sensing of human activities is not limited to residential environments only. For instance, they can be of great use in vehicles to detect drivers' tiredness levels, which is significant for the safety of the driver and the passengers. The authors of [92] have successfully set up the WiFi testbed in a vehicle, and eight human activities from the driver and the passengers were accounted for in the CARIN system, including pushing, pulling, and swiping. The experiment results have shown an average accuracy of 90.0% for more than 3000 real-world activity traces. Also, the vitals detection in-cabin can be more efficient than the detection indoor because the position of people in the traffic tools is constant in most cases. It will not take effort to change sensing area with spatial sensing like directional antennas are others.

3) Joint sensing in Home for Healthcare: Implementation in real-world environments of WiFi sensing is one of the most challenging tasks. Although many model-based algorithms described in Section III-B2 provide the approaches of human action estimation without training, especially in vitals detection and tracking. For activity recognition, most studies still adopt DNN based classification method to get the result with better

performance due to the influence of unexpected human actions.

The trends of joint sensing can be separated into two aspects, the first one is joint training and second one is joint sensing [117]. Joint training will combine the WiFi signals and different types of data from other sources like skeleton key-points from images as ground truth datasets for the training step of the estimation system with WiFi signals. Hence, WiFi signals can be used in other tasks with higher resolution and more functions in human support without label limitation. On the other hand, DNN is available in large size of training and mining the feature from data for multiple human sensing [48].

Joint sensing needs to establish a whole framework of general indoor environments for the users. Due to the restriction of performance versus WiFi devices' setting, as demonstrated in Section V-A, CSI data cannot be used to perform multiple tasks within one type of implementation in complex real-world scenarios. Extensive data analysis has been the trend for the future healthcare [118]. CSI signal can be integrated with data from other sensors to monitor the health status of human beings using artificial intelligence techniques [4], [68]. Cooperative sensing with different sensors will improve the precision with a larger size of precise data. Different kinds of radar sensors (millimeter-wave radar, LIDAR), and other sensors like infrared sensors, cameras, microphones, are able to provide data for users to achieve specific tasks [50], [119], [120]. Joint sensing around the household environment is potential to improve the humanization of the future healthcare monitoring system in the whole-home range.

VI. CONCLUSIONS

Intelligent sensing based on commercial WiFi devices is an emerging trend for next-generation healthcare monitoring with great potential of development, due to the low-cost and popularization of WiFi devices. Meanwhile, WiFi sensing is capable to provide high accuracy contactless monitoring service for the users, unlike other wearable sensors and systems that require intimate contact. This paper presented an extensive review of the recent techniques, open research challenges, and development trends of non-contact WiFi sensing related to healthcare. Different classes of healthcare applications are demonstrated, including large-scale and small-scale activity recognition like falling and gestures, vital signs' detection, and supportive localization. These clinical applications are supportive to reduce the future pressure from the rapidly rising aging population presents numerous societal and economic challenges.

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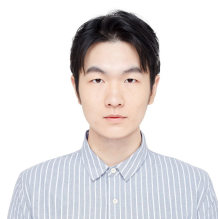
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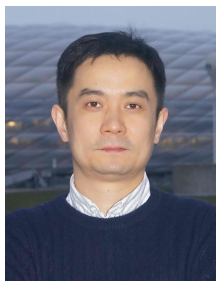
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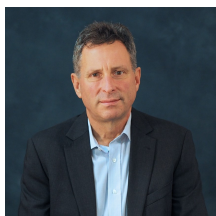
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