IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 8, 2019, accepted September 23, 2019, date of publication October 11, 2019,
date of current version November 5, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2947024

Wiar: A Public Dataset for Wifi-Based Activity Recognition

LINLIN GUO[1,2], LEI WANG[1], CHUANG LIN[2], (Member, IEEE), JIALIN LIU[1], BINGXIAN LU[1], JIAN FANG[1], ZHONGHAO LIU[1], ZEYANG SHAN[1], JINGWEN YANG[1], AND SILU GUO[3]

[1]School of Software Technology, Dalian University of Technology, Dalian 116024, China
[2]Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen 518055, China
[3]Shenzhen Institute, Sun Yat-sen University, Guangzhou 510275, China

Corresponding authors: Lei Wang (lei.wang@dlut.edu.cn) and Chuang Lin (chuang.lin@siat.ac.cn)

This work was supported in part by the Shenzhen Basic Research Grants under Grant JCYJ20170413152804728 and Grant JCYJ20180507182508857, in part by the National Natural Science Foundation of China under Grant 61733002, Grant 61842601, and Grant 61902052, in part by the National Key Research and Development Plan under Grant 2017YFC0821003-2, in part by the Fundamental Research Funds for the Central Universities under Grant DUT19RC(3)003, and in part by the Pioneer Hundred Talents Program of Chinese Academy of Sciences.

ABSTRACT We construct a public dataset for WiFi-based Activity Recognition named WiAR with sixteen activities operated by ten volunteers in three indoor environments. It aims to provide public signal data for researchers to reduce the cost of collected signal data and conveniently evaluate the performance of WiFi-based human activity recognition in different domains. First, we introduce the basic knowledge of WiFi signals regarding RSSI, CSI, and wireless hardware. Second, we explain the characteristics of WiAR dataset in terms of activities types, data format, data acquisition ways, and influence factors. Third, the proposed framework can estimate the quality of the shared signal data provided by other peers. Finally, we select and use five classification algorithms and two deep learning algorithms to evaluate the performance of WiAR dataset on human activity recognition. The results show that the accuracy of WiAR dataset is higher than 80% using machine learning algorithms and 90% using deep learning algorithms in different indoor environments.

INDEX TERMS Public dataset, human activity recognition, received signal strength indicator, channel state information, signal processing, machine learning, deep learning.

I. INTRODUCTION

Human Activity Recognition (HAR) is increasing popular in practical applications including smart homes [1]–[4], user authentication service [5]–[7], healthcare monitoring [8]–[10], and smart space management [11]–[13]. In the early stages of the research, sensor-based applications increase inconvenience for users in daily life due to that it requires users to wear smart devices on bodies. Vision-based applications are easy to leak personal privacy and are limited in Line-of-Sight (LoS) condition. However, the two problems cannot be avoided with the current technical level. With increasing coverage of the wireless signals both in public places and home (homestead, private residence), WiFi-based applications have attracted increasing attention from companies and scientific research institutions. The important point is that WiFi-based applications can make up for the above-mentioned two weaknesses by leveraging attributes of wireless signals such as propagation, penetrability and sensibility.

Researchers depend on different requirements of WiFi-based applications to collect activity data using wireless devices at the cost of enormous time and manpower resources. WiFi signals are highly sensitive to various experimental environments, locations, human behavior, and wireless devices. Therefore, the inconsistency of activity data hinders the comparison of related works and inspires our team to construct a public WiFi-based activity dataset. Furthermore, with the rapid development of deep learning in all aspects of life, researchers begin to use deep learning algorithms to explore WiFi-based human activity recognition. As is well known, the large amount of data required in deep learning is necessary but it cannot be achieved easily for researchers on the current technical level. Although several works [14], [15] attempt to leverage deep learning

The associate editor coordinating the review of this manuscript and approving it for publication was Syed Mohammad Zafaruddin.

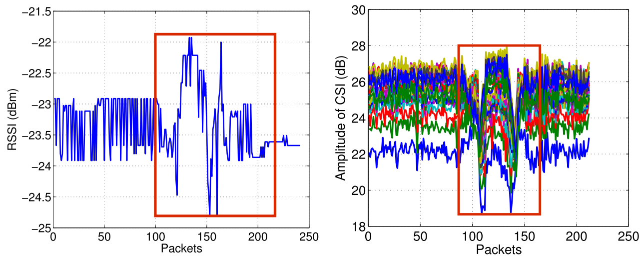
algorithms to recognize activities with satisfying accuracy, we believe that more samples can help researchers to achieve better performance for different activities in various indoor environments. There is no WiFi-based public dataset for human activity recognition as well as video-based public activity dataset [16] except the Widar dataset [17] concerning gestures recognition shared by Tsinghua university in 2019. Therefore, it is necessary and important to construct a public dataset for *Wi*Fi-based *A*ctivity *R*ecognition named *WiAR* and share it with other researchers. The advantages of constructing a WiFi-based public activity dataset contain three aspects: reducing the cost of time and labours, sharing large amounts of activity data and motivating the rapid development of wireless sensing in practical applications.

Constructing a public WiFi-based activity dataset needs to consider four impact factors including indoor environments, activity types, activity diversity, and the relative position between the transmitter and the receiver. First, the indoor environment is an essential factor for collected data since different indoor environments can produce various reflected signals caused by the multipath effect and the layout except for activity itself. Even the received signals in the indoor environment cover for the true signal data reflected off an activity. Therefore, selecting a suitable indoor environment can be helpful to improve the quality of the data. In the WiAR, the collected data derive from three indoor environments like an empty room, a meeting room and an office which are common places in daily life. To enrich the dataset, we also collect activity data in-home, corridor, and laboratory. Second, we collect sixteen activities which often occur in indoor environments. To better analyze the characteristics of each activity, we divide sixteen activities into upper activities, lower activities, and whole activities according to an activity of the key joints' position. Third, the diversity of human activity in this paper describes the differences between the same activity operated by different volunteers. We focus on the diversity caused by volunteers' habits. Finally, the position relationship between the transmitter and the receiver located in the indoor environment determines the quality of collected activity data and the accuracy of human activity recognition. In this paper, the position of the transmitter and receiver is located in the middle of the indoor environment. The mentioned factors help researchers to better analyze and verify the quality of the WiAR. The part of the WiAR dataset can be found in `https://github.com/linteresa/WiAR` and `https://download.csdn.net/download/guolinlin11/9895718`. Just to be clear, the paper mainly introduces the details of the WiAR, and the technical details regarding the mentioned methods in the paper are not our emphasis.

II. PRELIMINARY

A. RSSI AND CSI

In WiAR dataset, the collected WiFi signals consist of Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) to analyze human activity in three indoor environments. RSSI represents a sum of signal energy from multiple paths which include a direct path (LoS path) between the transmitter and the receiver, and multiple reflected paths caused by walls, furniture, and people in the macro-view as shown in Figure 1(a). RSSI is the received signal power in decibels (dBm) [18]:



(a) RSSI (b) CSI

FIGURE 1. RSSI and CSI.

$$RSSI = 10log_2\left(\|V\|^2\right) \tag{1}$$

where V denotes signal voltage. Due to the multipath effect, it's hard to distinguish signal components produced by different paths in an indoor environment. Therefore, we consider RSSI as coarse-grained information of WiFi signals to roughly sense dynamic change such as human movement.

CSI describes how signals propagate in the wireless channel combining the effect of time delay, energy attenuation and phase shift [8]. Compared to RSSI, CSI represents fine-grained information of WiFi signals with thirty subcarriers as well as rainbow reflected by sunlight. Leveraging the off-the-shelf Intel 5300 NIC with a modified driver, a group of sampled versions of channel frequency response (CFR) within the WiFi bandwidth is revealed to upper layers in the format of channel state information [19]. CSI of a single subcarrier is in the following mathematical formula:

$$H(k) = \|H(k)\| \, e^{j\angle H(k)} \tag{2}$$

where $H(k)$ is a CSI of the kth subcarrier. $\|H(k)\|$ and $\angle H\,(k)$ are CSI amplitude and CSI phase, respectively. CSI can capture more fine-grained changes like gestures, breath and heartbeat. Thirty subcarriers have various sensitivity to the same activity due to existing frequency selective fading. This character is utilized to explore the relationship between signal patterns and activities. As shown in Figure 1(b), we use different colours to represent 30 subcarriers and CSI has a unique signal pattern caused by an activity.

B. HARDWARE REQUIREMENTS

Commodity wireless devices can extract RSSI. However, CSI measurements need to use wireless devices with specifical wireless cards. Currently, Intel 5300, AR9590 and Intel 7265 wireless card can support the CSI measurement as shown in Figure 2. The widely used CSI tool is built on the Intel WiFi Wireless Link 5300 802.11n MIMO radios [19]

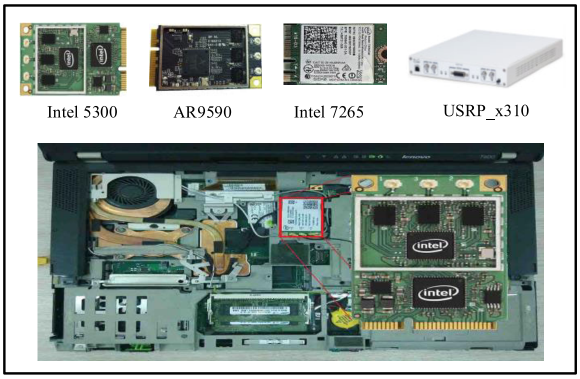


FIGURE 2. CSI extracted by different wireless cards.

TABLE 1. CSI tool.

Types	Subcarriers	Frequency	Modify-firmware	Year
IWL5300	30(2)*	20HMz	Y	2011
IWL5300	30(4)	40HMz	Y	2011
USRP	N/A	N/A	Y	2013
Atheros	56	20HMz	N	2015
Atheros	114	40HMz	N	2015
Intel 7265†	–	–	–	2019

and uses custom modified firmware. Atheros-based CSI Tool [20] is built on AR9590 wireless card and provides an open-source 802.11n measurement. It can extract PHY wireless communication information from the Atheros WiFi NICs, including RSSI, CSI, the received packet payload, and other additional information such as the timestamp, the data rate. Table 1 shows the differences in existing wireless devices regarding the extracted CSI in terms of subcarriers, frequency band, firmware. In China, Tsinghua University (THU), Peking University, Hong Kong University, Northwest University, and Xi'an Jiaotong University pay more attention to the field. Particularly, Liu's team [21] in Tsinghua University researches indoor localization, LoS detection and human activity recognition in wireless sensing domain. They design a visualization-based CSI tool named TNS-CSI [22] on the basis of Linux 802.11n CSI Tool, and the TNS-CSI Tool is easy to learn for new researchers, but it is expensive.

III. CHARACTERISTICS OF WIAR DATASET

A. WIAR DATASET

We construct a public WiFi-based Activity Recognition dataset named WiAR in three indoor environments. The details are described in terms of activity types, data format and data acquisition ways.

[1] The IWL5300 provides 802.11n channel state information in a format that reports the channel matrices for 30 subcarrier groups, which is about **one group for every two subcarriers at 20 MHz** or **one in 4 at 40 MHz**. Each channel matrix entry is a complex number, with signed 8-bit resolution each for the real and imaginary parts. It specifies the gain and phase of the signal path between a single transmit-receive antenna pair provided in the paper [23]

[2] The team's work [24] use Intel 7265 802.11n WiFi card provided by Intel Corporate Research Council/ University Research Office, which can also extract CSI for contactless WiFi sensing.

TABLE 2. WiAR dataset.

Types	Activities
Upper activities	Horizontal arm wave, Two hand wave, Toss paper, Draw tick, Phone, Draw x, Hand clap, High arm wave, Drink water, High throw.
Lower activities	Forward kick, Side kick.
Whole activities	Squat, Sit down, Bend, Walk.

1) ACTIVITY TYPES

The WiAR dataset contains sixteen activities operated by ten volunteers, and each activity collects 30 samples for each volunteer. To conveniently analyze the differences between activities, the sixteen activities provided in WiAR dataset are divided into three categories: upper body activities, lower body activities, and whole-body activities as shown in table 2. Upper body activities mean that volunteers finish the activity only using upper skeleton joints like gestures. Lower body activities only make lower skeleton joints of body movement. Whole-body activities denote the fusion of both upper body activities and lower body activities like walking. Note that we require volunteers to finish each activity with normal speed on the premise of keeping each volunteer's habit. Each activity corresponds to the unique WiFi RSSI and WiFi CSI in the ideal environment. As we all know, RSSI cannot capture the fine-grained details of human activity due to the multipath effect. CSI can capture the micro-dynamic change of human activity. Figure 3 shows the CSI changes and spectrograms caused by three similar activities using *pspectrum* function in Matlab. The *pspectrum* function sets four parameters like frequency resolution to extract more precise spectral range. The three similar activities' frequency is less than $5Hz$. According to the above analysis, we know that WiAR dataset can help researchers to explore new frameworks and methods for human activity recognition conveniently.

2) DATA FORMAT

Generally speaking, a volunteer spends $2-3s$ finishing an activity at normal speed. In WiAR dataset, we collect each activity sample with more than $7s$ data which contain $2-3s$ activity data (effective data) and $4-6s$ empty data (indoor environment data). Empty data can guarantee a stability signal pattern of the activity and decrease the influence of outliers and noises on the signal pattern of the true activity. The activity data denotes the start and the end of reflected signal data caused by the activity. How to determine the start and end of the activity from the signal sequence is an important issue which is the task of our other work.

WiAR dataset provides not only RSSI and CSI information but also raw WiFi signals reflected by human activity and several features extracted from raw data. The transmitter sends thirty packets per second and RSSI is a single numerical value for each packet. A RSSI sample with respect to an activity is one-dimensional data sequence $R = \{RSSI_1, RSSI_2, \cdots, RSSI_i, \cdots, RSSI_n\}$ where $RSSI_i$ denotes

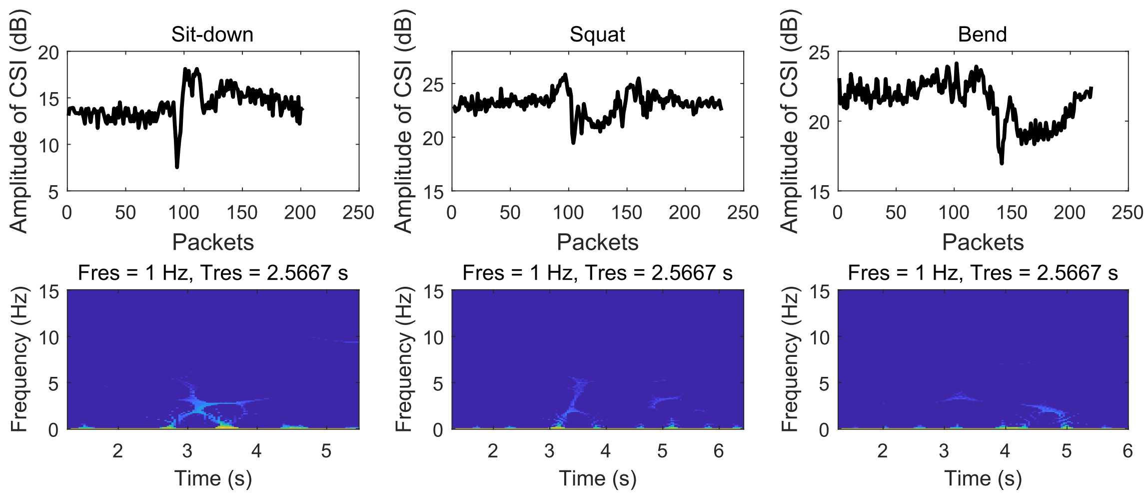


FIGURE 3. Time-frequency analysis of three similar activities. *Fres* denotes the frequency resolution and *Tres* represents time resolution for each activity.

the *ith* RSSI value in the sample and n is the length of the sample. CSI is a three-dimensional matrix $CSI_i = \{j * k * l\}$ where j is the number of transmitter's antennas, and k denotes the number of receiver's antennas, and l is thirty subcarriers. In this paper, j is 1 and k is 3. Therefore, a CSI value is $CSI_i = \{3 * 30\}$ and one CSI sample is $C = \{CSI_1, CSI_2, \cdots, CSI_i, \cdots, CSI_n\}$. Moreover, researchers could leverage raw activity data to obtain what they want according to their demands.

3) DATA ACQUISITION WAYS

The WiAR dataset is an open-source activity dataset and supports three data acquisition ways including manual-based, shared-based, and crowdsourcing-based. In this paper, we mainly introduce the details of manual-based way regarding constructing the WiAR dataset. Another two ways will be going to be explored in the following research work.

The manual-based way to collect activity data requires one operator and one volunteer in one room. The transmitter sends thirty packets per second that most of the WiFi-based sensing applications employ the parameter value. We first observe the real-time WiFi signal change to detect whether the collected device exists problems before collecting activity data. The volunteer locates in the middle of both the transmitter and receiver and the operator nears to the receiver to run the collected code. The volunteer toward the transmitter finishes each activity with thirty times. Each time collects one WiFi signal sequence with less than $10s$ as one sample of the activity. The volunteer begins to do the next activity after finishing the activity of thirty times. Once the volunteer feels tiredness, we pause and make him/her relax to ensure the quality of collecting activity data. The shared-based way is to receive other researchers' private data. Due to the limitation of a single research institute or a university on collecting activity data, we plan to receive activity data shared by other researchers to increase the size of activity dataset and the diversity of

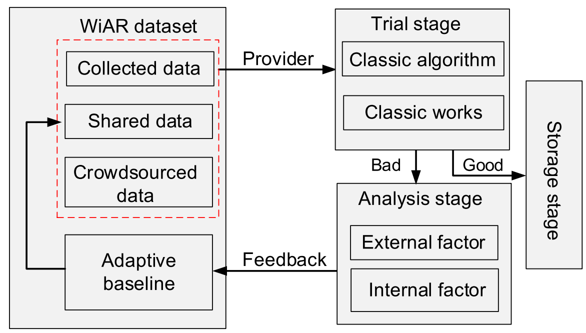


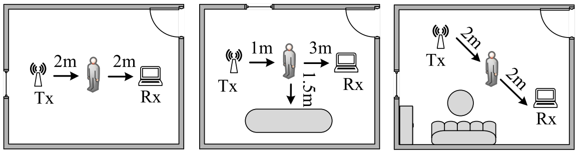
FIGURE 4. The analysis framework of the WiAR dataset.

activity types in different indoor environments. Before receiving the private activity data shared by researchers, we design a mechanism which uses classic classification algorithms to estimate the quality of the shared data in Figure 4. We also invite several research institutes to estimate the performance of the WiAR and select the optimal activity data according to the results of our and other institutes. The high-quality data is stored in WiAR dataset, and the low-quality data is treated as special data for researchers' analysis. With the development of wireless devices, we will explore the limitation of wireless devices on extracting CSI and the crowdsourcing-based way to collect activity data in daily living environments. Compared to the shared activity data, crowdsourcing-based way cannot require volunteers to do pre-established activities and can decrease the cost of labor and time. In summary, constructing the WiAR dataset is meaningful work for WiFi-based human activity recognition.

B. EXTERNAL FACTOR

1) ENVIRONMENTS

In this paper, we collect WiFi signals reflected by human activity in three indoor environments including one empty room, one meeting room, and one office as shown in Figure 5.



(a) Empty Room (b) Meeting Room (c) Office

FIGURE 5. The layout of indoor environments.

The details of three indoor environments are shown as follows.

- The empty room is a $6m * 8m$ room and only contains a pair of the transceiver, one volunteer who does an activity, and one operator who finishes a series of operations on the receiver. The distance between the receiver and the transmitter is $4m$ and the volunteer toward the transmitter locates in the centre of them.
- The meeting room is $6m * 10m$ and contains a small amount of office furniture such as tables and chairs. The distance between a receiver and a transmitter is $4m$. The volunteer is closer to the transmitter with $1m$ distance and the receiver with $3m$ distance. This configuration is to augment signal changes reflected off the activities. Furthermore, the distance between one volunteer and one desk is $1.5m$.
- The office is $6m * 8m$ with several commonly used furniture such as one sofa, one desk, and one book cabinet. The distance between a receiver and a transmitter is $4m$ and the volunteer toward the transmitter locates in the centre of them.

Collected WiFi signals in the empty room contain fewer noises than other indoor environments. We consider the activity data collected in the empty room as a baseline dataset to explore the characteristics of WiFi signals reflected by human activity. For the other two indoor environments, we leverage the collected activity data to analyze the effect of furniture on WiFi signals. In summary, we consider several factors like furniture, indoor space, and moving persons to analyze the impacts on collected signals and quantify the relationship between signal pattern and human activity.

Moreover, we also increase the number of moving people around a volunteer to explore the impact of multiple people on human activity recognition. To increasing diversity of indoor environments, we also consider two outdoor environments including the playground and the corridor. Compared to the empty room, playground environment has less reflected signals since there are no walls. The analysis results are that the playground and the empty room can show the precise signal pattern of each activity due to both environments with fewer noises. The corridor is a narrow environment which makes it difficult for us to distinguish the signals reflected by human activities from the signals reflected by the walls. We try to explore the distribution of reflected signals to analyze the differences between walls and activities in future work.

TABLE 3. Volunteers' attributes.

Label	Sex	Height(cm)	Weight(kg)	Experience
1	Male	173	85	Yes
2	Male	180	75	No
3	Male	165	65	No
4	Female	160	60	No
5	Female	162	53	No
6	Female	170	60	No
7	Female	165	50	Yes
8	Female	155	65	No
9	Male	180	85	Yes
10	Male	175	70	No

2) VOLUNTEERS

Recent advances [5], [6] leverage the unique character of activities to determine personal identity. Therefore, the differences among individuals on human activity recognition is not neglected. In WiAR dataset, we select five males and five females as volunteers to perform sixteen predetermined activities. The effect of volunteers on reflected signals are evaluated in terms of sex, height, weight, and the experience on exercise as shown in table 3. The receiver receives thirty packets per second and each activity corresponding to the number of packets is different since different volunteers performing the same activity take a different amount of time to finish it. Even the same volunteer performing the same activity many times complete it in a different amount of time. According to the brief analysis of experimental data, the impact of height and experience on activity recognition is more significant than the effect of sex and weight. The following work will explore the precise influence on human activity recognition.

C. INTERNAL FACTORS

1) ANTENNAS

We use a transmitter with one antenna and a receiver with three antennas to collect activity data. Although multiple antennas increase the diversity of activity data in the space dimension, it increases the difficulty of human activity recognition since WiFi signals received by different antennas for the same activity exist differences. For example, the signal pattern reflected by a bend has the difference between three antennas as shown in Figure 6. $Antenna_1$ shows the precise signal pattern compared to the other two antennas which make it easy for us to draw the wrong conclusion since the waveforms are challenging to be distinguished. In this paper, we use received signal data of each antenna to analyze activities and recognize them. The final result of each activity is the average of three antennas' accuracy. Moreover, we attempt to leverage deep learning algorithms to solve the problem and learn the diversity of signal pattern corresponding the same activity in space dimension.

TABLE 4. Number of matrices and carrier grouping.

BW	Grouping Ng	Ns	Carriers for which matrices are sent
20MHz	1	56	All data and pilot carriers: -28,-27,...,-2,-1,1,2,...,27,28
	2	30	-28,-26,-24,-22,-20,-18,-16,-14,-12,-10,-8,-6,-4,-2,-1,1,3,5,7,9,11,13,15,17,19,21,23,25,27,28
	4	16	-28,-24,-20,-16,-12,-8,-4,-1,1,5,9,13,17,21,25,28
40MHz	1	114	All data and pilot carriers: -58,-57,...,-3,-2,2,3,...,57,58
	2	58	-58,-56,-54,-52,-50,-48,-46,-44,-42,-40,-38,-36,-34,-32,-30,-28,-26,-24,-22,-20,-18,-16,-14,-12,-10,-8,-6,-4,-2,2,4,6,8,10,12,14,16,18,20,22,24,26,28,30,32,34,36,38,40,42,44,46,48,50,52,54,56,58
	4	30	-58,-54,-50,-46,-42,-38,-34,-30,-26,-22,-18,-14,-10,-6,-2,2,6,10,14,18,22,26,30,34,38,42,46,50,54,58

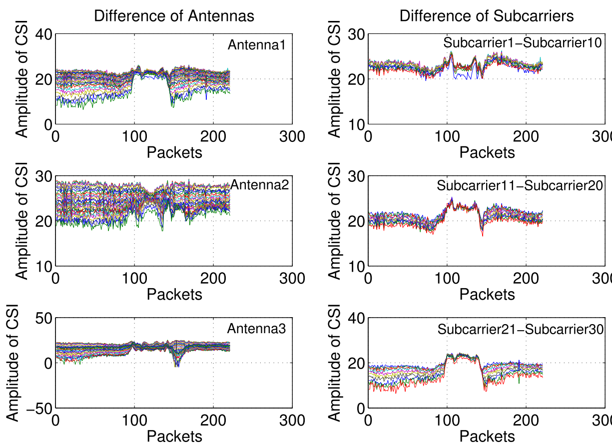


FIGURE 6. Difference of antennas and subcarriers.

2) SUBCARRIERS

CSI is represented at subcarrier level in Orthogonal Frequency Division Multiplexing (OFDM) system. WiFi frequency has 2.4GHz and 5GHz. The length of the waveform in 2.4GHz is longer than 5GHz and its signal is instability. Compared to the 2.4GHz, 5GHz has a robust through-wall ability. Table 4 lists the number of matrices and carrier grouping for different bandwidths. In WiAR dataset, we use 20MHz bandwidth with 30 subcarriers in 5GHz which can provide stable signals compared to 2.4GHz. Collected activity data for each sample contain many packets with three antennas corresponding to 90 subcarriers as shown in the following equation (3).

$$P = \begin{Bmatrix} H_1^1, H_1^2, H_1^3, H_1^4, \ldots, H_1^i, \ldots, H_1^{30} \\ H_2^1, H_2^2, H_2^3, H_2^4, \ldots, H_2^i, \ldots, H_2^{30} \\ H_3^1, H_3^2, H_3^3, H_3^4, \ldots, H_3^i, \ldots, H_3^{30} \end{Bmatrix} \tag{3}$$

where P is a CSI matrix, and H_1^i denotes the *ith* subcarrier of the first antenna. Different subcarriers reflected off human activity have various degrees of sensitivities due to the frequency selective fading. We select 10 subcarriers as a group, and each group of subcarriers has a slight difference between signal pattern reflected by the same activity. As shown in Figure 6, the high-frequency subcarriers keep a standard signal pattern of a bend. Moreover, the signal pattern corresponding to an activity holds a tight trend, and signals without an activity show a loose trend. Based on the above analysis, the high-frequency subcarriers are more sensitive to human activity.

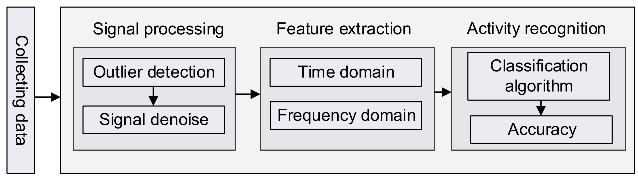


FIGURE 7. General framework of human activity recognition.

IV. PERFORMANCE ANALYSIS

In this section, we first explain the general framework of WiFi-based human activity recognition. Then we introduce several metrics used in related work to evaluate the performance of human activity recognition. Finally, we analyze the performance of WiAR dataset on human activity recognition using five classification algorithms and two deep learning algorithms.

A. GENERAL FRAMEWORK

Human activities interrupt the propagation of WiFi signals and lead to reproducing a unique signal pattern. Based on this view, we explore the relationship between signal pattern and an activity to recognize human activity in different indoor environments. Moreover, according to the survey on WiFi-based human activity recognition works in the past ten years, we summarize the general framework of WiFi-based human activity recognition. The general structure consists of four stages: collecting data, signal processing, features extraction, and human activity recognition as shown in Figure 7.

Collecting data need to design effective experiments which consider several factors including the distance between the pair of transmitter and receiver, the complexity of the indoor environment, and the standard of activities operated by volunteers. We cannot directly use the raw data received by a receiver since it contains noises and outliers. The following signal processing can weaken these noises by using denoising methods. In this paper, we only use the low-pass filter to remove noises and keep low-frequency signals data. Related work often uses several filters like low-pass filter, mean filter, and Kalman filter to implement denoising. Moreover, there

TABLE 5. Metrics used in related work.

Works	Activity	Evaluation Metrics
WiGest [1]	Right-left, Up-down, Infinity, Open-case	RSSI variance, Spectrograms of CWT
WiFall [8]	Sitting, Stand up, Walking, Falling	Normalized Standard Deviation (STD), Offset of Signal Strength, Median Absolute Deviation (MAD), Interquartile Range, Signal Entropy, Period of the motion, Velocity of Signal Change
E-eyes [25]	Cooking, Brushing, Bathing, Watching TV, Sleeping, Washing dishes, Walking	Moving variance, Earth mover's distance (EMD), Distribution of CSI, Dynamic Time Warping (DTW) distance
Wei et.al [26]	Laying, Sitting, Standing, Walking	SNR, CSI vectors
CARM [27]	Running, Walking, Sitting, Falling, Brushing teeth, Opening refrigerator, Pushing one hand, Boxing,	Frequency components§, Duration¶
WifiU [5]	Walking (Gait analysis)	CSI Spectrogram signatures, Gait cycle time, Torso and leg speeds, Walking speed, Footstep length
Smokey [28]	Sleeping, Breathing	Temporal correlation, Frequency correlation, Standard deviation of the periods
Shi et.al [6]	Walking activities (entrance-seat, seat-cabinet), Stationary activities (eating)	Amplitude of CSI, Relative phase of CSI
Guo et.al [11]	Participant number, Human density, Walking speed, Direction derivation	Amplitude of CSI, Variance of CSI, Amplitude distribution of CSI, Earth mover distance, Phase difference of CSI
ABLSTM [29]	Lie down, Fall, Walking, Running, Sit down, Stand up	BLSTM learns several features, and then using AM to select optimal features
EI [30]	Wiping the whiteboard, Rotating the chair, Walking, Sitting, Moving a suitcase, Standing up and sitting down.	Domain-specific features, Domain-independent features, Environment-independent features.
Zhang et.al [24]	Push-up, Sit-up, Walkout, Mountain climber, Plank hold, Lunge, Leg lift with hip raise, Walking, Sitting.	Classical methods: the mean and standard deviation of CSI, the maximum and minimum value, the skewness, the kurtosis, root sum square, the q-quantiles; Automatically extracting informative features using deep learning algorithms

are several works using PCA [27] and DWT [1] to remove noises. After obtaining clean reflected signals, we extract statistical features as the inputs of classification algorithms. Features widely used in WiFi-based human activity recognition applications are divided into three categories: statistic metrics, time-domain metrics, and frequency-domain metrics as shown in table 5. We recommend readers to read this survey [31] with respect to features extraction to obtain a broad understanding of the WiFi-based human activity recognition. At present, researchers often use classical classification algorithms like NB, RF, DT, KNN, and SVM to evaluate the performance of WiFi-based human activity recognition. With the rapid development of deep learning in wireless sensing domain, we attempt to leverage deep learning algorithms to analyze the dataset. CNN is a common neural network structure and LSTM is good at dealing with time-sequence signal data. Therefore, we select the two deep learning algorithms as a comparison object, and the innovation points on CNN and LSTM are not the emphasis in the paper. Based on the thought, we direct use CNN and LSTM to evaluate the performance of the dataset on human activity recognition.

B. EVALUATION METRICS

We introduce evaluation metrics of human activity recognition according to our survey on related work. Different activities form various signal patterns. Based on this point, we leverage the unique signal pattern to recognize the corresponding activity. Early works often use RSSI variance, the distribution of RSSI to sense coarse-grained human activities such as falling, walking. With the CSI-tool being proposed by Halperin *et al.* [19], researchers begin to use CSI to recognize human activities in terms of speed, direction, granularity. We know that CSI is fine-grained information and

[4] Frequency represents the change speed of multiple paths' length due to body movements during the activity.

[5] Duration represents the time volunteers take to perform an activity.

TABLE 6. Performance comparison by five classification algorithms and two deep learning algorithms.

Method	Volunteer 1			Volunteer 2			Volunteer 3		
	$Antenna_1$	$Antenna_2$	$Antenna_3$	$Antenna_1$	$Antenna_2$	$Antenna_3$	$Antenna_1$	$Antenna_2$	$Antenna_3$
KNN	0.91875	0.86875	0.91875	0.90625	0.9375	0.8750	0.89375	0.89375	0.9250
NB	0.83125	0.85625	0.8500	0.8500	0.9500	0.93125	0.81875	0.8250	0.89375
RF	0.8375	0.8750	0.89375	0.88125	0.8750	0.9625	0.85625	0.90625	0.89375
DT	0.7875	0.7875	0.84375	0.90625	0.8375	0.90625	0.8000	0.84375	0.83125
SVM	0.8875	0.90625	0.89875	0.86875	0.9000	0.95625	0.8825	0.8625	0.9250
CNN	0.9085	- -	- -	0.9250	- -	- -	0.9000	- -	- -
LSTM	0.9180	- -	- -	0.9350	- -	- -	0.9175	- -	- -

can capture fine-grained gestures or vital signs. Table 5 shows common metrics used in WiFi-based sensing applications. In time-domain, extracting statistic metrics can describe the trend of signal change, the intensity of signal change, and the abnormal signal sequence. The CSI variance can describe the degree of changing of the signal patterns reflected by an activity. Therefore, we can use variance to detect the occurrence of human activity or anomalous events like falling. We obtain fine-grained features which can uniquely describe each activity to determine which types the unknown human behavior belongs to. We use variances of seven subcarriers to recognize three activities each of which contains twenty samples as shown in Figure 8. The solid black line denotes the boundary of each class, and the two black dotted lines explain the high error of activity recognition rate due to the similar values of features. The second class keeps a stable change compared with the other two classes. However, the overlap between the second class and the third class leads to the high error on human activity recognition. Although the first class has a distinct difference compared with the other two classes, it on human activity recognition cannot obtain high stability with time due to the large fluctuation of features extracted by collected data.

Due to the impact of the dynamic indoor environment on WiFi signals, the statistic metrics cannot capture the true signal pattern caused by human activity. In frequency-domain, each activity has a unique frequency range which does not change in the dynamic indoor environment. Note that an activity with normal speed can keep a stability frequency range regarding reflected signals. Once improving the speed of the activity, the stability frequency will increase. Therefore, it is difficult to recognize multiple activities only using frequency-domain metrics. Furthermore, the CSI phase is utilized to analyze the displacement of the limbs and trunk for sensing human activity.

The CSI distribution can denote the disorder level of an activity regarding the amplitude change of signal pattern. The correlation coefficient between signal patterns can help us to select efficient subcarriers and roughly determine human activity. For the correlation coefficient, we can compute the correlation coefficient of subcarriers, antennas, and samples to improve the accuracy of human activity recognition. To recognize a specific activity, we construct a model to describe it in different indoor environments. Although different users

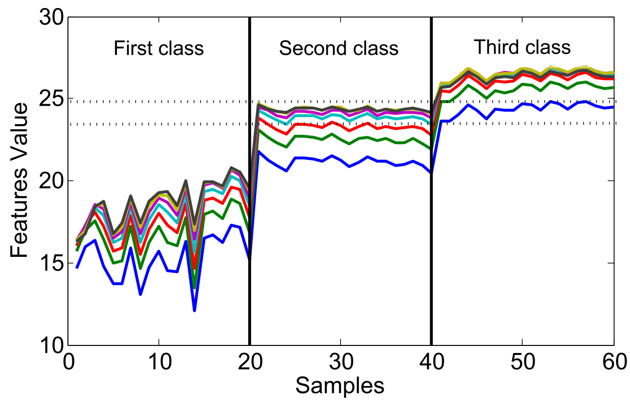


FIGURE 8. The impact of features selection on human activity recognition.

have differences in finishing the same activity, the model can adaptively learn new changes in signal patterns reflected by the same activity. In future work, it is necessary to construct a model between signal pattern and specific activity, which is an interesting topic in pervasive computing domain.

C. HUMAN ACTIVITY RECOGNITION

We use KNN, RF, DT, NB, SVM, CNN, and LSTM algorithms to evaluate the performance of the WiAR on human activity recognition. We choose these algorithms since they are widely used in various fields and obtain satisfactory results with less cost. In the study, we show the results of human activity recognition using the above-mentioned algorithms on the WiAR as shown in table 6. We randomly select three volunteers' activity data as test samples to analyze the differences among volunteers and the impact of antennas on the accuracy of human activity recognition. The results of three volunteers show a subtle difference because we require each volunteer's activity to obey the standard which is to guarantee the quality of collected activity data. In our study, we only list the accuracy of human activity recognition on simple features like the variance of activity data. KNN algorithm achieves average accuracy of 90.42%, 86.74% of NB, 88.86% of RF, 83.28% of DT, and 89.86% of SVM in three indoor environments. For a similar activity like drinking water, phone, the case causes a high error compared with normal activities. To increase the number of samples, we directly use three antennas' data as inputs of two deep learning algorithms not compute the accuracy of each antenna separately.

Antenna$_1$ corresponding to the accuracy represents the whole performance on sixteen activities for each volunteer. Compared to machine learning algorithms, the accuracy of activity recognition using deep learning algorithms is higher than 90% averagely.

V. RELATED WORK

The section introduces existing public video-based and sensor-based activity dataset to support the feasibility of the WiAR. Then, we list several WiFi-based human behavior recognition works in terms of coarse-grained activity, gestures, and vital signs. Finally, we analyze the advantage and disadvantage of our work on human activity recognition domain.

A. VIDEO-BASED AND SENSOR-BASED ACTIVITY DATASET

Human activity recognition is widely applied in Human-Computer Interaction (HCI), smart home, security monitoring, and disaster rescue domains. Video-based human activity recognition applications have a great deal of theory and mature technologies. Video-based human activity recognition applications have been applied in our daily life like crime detection application. According to our survey, we know that several public datasets provide researchers with large activity samples to explore and verify their methods. Video-based public datasets like USC [32], UCI dataset [33] contribute to the rapid development of video-based human activity recognition. Sensor-based activity dataset KARD [34] provides video, skeleton joints, and depth information. Our early work [35] leverages the fusion information of skeleton joints and WiFi signals to explore characteristics of human activity. Based on this thought, we always attempt to construct the WiFi-based activity dataset which consists of WiFi signals reflected by human activities. Moreover, the latest activity data AVA [16] proposed by the Google company, provides innovative thoughts to analyze human behavior or multiple people in classic movies like ''The Matrix''. We often find some questions about WiFi-based public activity dataset from some researchers in ''baidu.com''. Both works motivate us to construct the public WiAR dataset, and we believe that the work is worth doing.

B. WIFI-BASED ACTIVITY RECOGNITION

WiFi-based applications are widely proposed like indoor localization and tracking, smart home, security monitoring, and health monitor in recent years. We introduce the development of WiFi-based activity recognition and related technology. With the wide coverage of WiFi signals, WiFi-based indoor localization works [36]–[38] leverage CSI amplitude and CSI phase, AOA to locate people or wireless devices. In the following, the localization of multiple objects [39], [40] is established by these works by using multiple APs. Mobility factor is an essential influence on the indoor environment. Therefore, researchers explore the impact of moving people in the indoor environment and propose several interesting technologies to detect people mobility and analyze the influence of mobility on WiFi signals [41]–[46]. It helps us learn the impact of the dynamic indoor environment on WiFi signals. The following problem is to distinguish the impact of mobility factor on WiFi signals from the impact of human activity on WiFi signals and then explore WiFi-based human behavior recognition [47] in different indoor environments.

WiFi-based human activity recognition explores a specific activity like the solitary elder's falling [8] to monitor the elder's safety, smoking behavior [28] in public places with non-smoking, sleeping behavior [48] to monitor health conditions. To expand the range of WiFi-based human activity recognition, researchers explore daily activity recognition in different indoor environments. For example, E-eye [25] explores walking and location-activity using fingerprint technology, and CARM [27] constructs a model between signal patterns and activities to represent activities without less training cost. Researchers also explore fine-grained human behavior like gait analysis [5], gestures recognition [1], [2], [49], breathing and heart-rate detection [9], [10], and emotion sensing [50] using CSI and signals processing technologies in fixed location of indoor environment. Several researchers pay more attention to locate the track of human movement [51], hand-free drawing [52]–[55], human figure [56] in more complex way.

Although the works as mentioned above achieve perfect performance in experiment environment, it's hard to apply these ideas in our daily life due to the complexity of the actual indoor situation, the limit of signal process technology, and the privacy of the indoor environment. Now, we only consider the first two limitations to explore, and the privacy of the indoor environment is neglected. We construct a public WiFi-based activity recognition dataset named WiAR which provides activity data for researchers to explore and solve the above-mentioned problems.

VI. CONCLUSION

We construct a WiFi-based Activity Recognition dataset named WiAR with sixteen activities operated by ten volunteers in three indoor environments. We aim to provide a public platform to compare the performance between different WiFi-based systems and promote the rapid development of human activity recognition in the practical application domain. The following work, we will be increasing the number of activity types which cover in whole daily life, enriching the diversity of indoor environments, and considering the human behavior of different ages.

REFERENCES

[1] H. Abdelnasser, M. Youssef, and K. A. Harras, ''WiGest: A ubiquitous WiFi-based gesture recognition system,'' in *Proc. IEEE INFOCOM*, Apr./May 2015, pp. 1472–1480.

[2] Q. Pu, S. Gupta, S. Gollakota, and S. Patel, ''Whole-home gesture recognition using wireless signals,'' in *Proc. ACM MobiCom*, 2013, pp. 27–38.

[3] Z. Yang, C. Wu, Z. Zhou, X. Zhang, X. Wang, and Y. Liu, ''Mobility increases localizability: A survey on wireless indoor localization using inertial sensors,'' *ACM Comput. Surv.*, vol. 47, no. 3, 2015, Art. no. 54.

[4] C. Duan, X. Rao, L. Yang, and Y. Liu, ''Fusing RFID and computer vision for fine-grained object tracking,'' in *Proc. IEEE INFOCOM*, May 2017, pp. 1–9.

[5] W. Wang, A. X. Liu, and M. Shahzad, "Gait recognition using WiFi signals," in *Proc. ACM UbiComp*, 2016, pp. 363–373.
[6] C. Shi, J. Liu, H. Liu, and Y. Chen, "Smart user authentication through actuation of daily activities leveraging WiFi-enabled IoT," in *Proc. ACM MobiHoc*, 2017, Art. no. 5.
[7] C. Wang, X. Guo, Y. Wang, Y. Chen, and B. Liu, "Friend or foe?: Your wearable devices reveal your personal PIN," in *Proc. ACM ASIA CCS*, 2016, pp. 189–200.
[8] C. Han, K. Wu, Y. Wang, and L. M. Ni, "WiFall: Device-free fall detection by wireless networks," in *Proc. IEEE INFOCOM*, Apr./May 2014, pp. 271–279.
[9] Y. Ren, C. Wang, J. Yang, and Y. Chen, "Fine-grained sleep monitoring: Hearing your breathing with smartphones," in *Proc. IEEE INFOCOM*, Apr./May 2015, pp. 1194–1202.
[10] F. Adib, H. Mao, Z. Kabelac, D. Katabi, and R. C. Miller, "Smart homes that monitor breathing and heart rate," in *Proc. ACM CHI*, 2015, pp. 837–846.
[11] X. Guo, B. Liu, C. Shi, H. Liu, Y. Chen, and M. C. Chuah, "WiFi-enabled smart human dynamic monitoring," in *Proc. ACM SenSys*, 2017, Art. no. 16.
[12] Z. Yin, C. Wu, Z. Yang, and Y. Liu, "Peer-to-peer indoor navigation using smartphones," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 5, pp. 1141–1153, May 2017.
[13] Y. Wang, J. Yang, H. Liu, Y. Chen, M. Gruteser, and R. P. Martin, "Measuring human queues using WiFi signals," in *Proc. MobiCom*, 2013, pp. 235–238.
[14] Q. Gao, J. Wang, X. Ma, X. Feng, and H. Wang, "CSI-based device-free wireless localization and activity recognition using radio image features," *IEEE Trans. Veh. Technol.*, vol. 66, no. 11, pp. 10346–10356, Nov. 2017.
[15] J. Wang, X. Zhang, Q. Gao, H. Yue, and H. Wang, "Device-free wireless localization and activity recognition: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 6258–6267, Jul. 2017.
[16] C. Gu, C. Sun, D. A. Ross, C. Vondrick, C. Pantofaru, Y. Li, S. Vijayanarasimhan, G. Toderici, S. Ricco, R. Sukthankar, C. Schmid, and J. Malik, "AVA: A video dataset of spatio-temporally localized atomic visual actions," 2017, *arXiv:1705.08421*. [Online]. Available: https://arxiv.org/abs/1705.08421
[17] Z. Yang. *Widar Dataset*. Accessed: 2019. [Online]. Available: http://tns.thss.tsinghua.edu.cn/widar3.0/
[18] Z. Yang, Z. Zhou, and Y. Liu, "From RSSI to CSI: Indoor localization via channel response," *ACM Comput. Surv.*, vol. 46, no. 2, pp. 25:1–25:32, Dec. 2013.
[19] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: Gathering 802.11n traces with channel state information," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 41, no. 1, p. 53, 2011.
[20] Y. Xie and M. Li. (2015). *Atheros CSI Tool*. [Online]. Available: http://pdcc.ntu.edu.sg/wands/Atheros/#UAV
[21] Y. Zheng, W. Chenshu, Z. Zimou, and L. Yunhao. (2010). *WiFi RADAR*. [Online]. Available: http://tns.thss.tsinghua.edu.cn/wifiradar/index.html#page-title-exp
[22] Y. Liu. *TNS-CSI Tool*. Accessed: 2014. [Online]. Available: http://tns.thss.tsinghua.edu.cn/wifiradar/wifiradar.html
[23] D. Halperin, W. Hu, A. Sheth, and D. Wetherall. (2010). *Linux 802.11n CSI Tool*. [Online]. Available: http://dhalperi.github.io/linux-80211n-csitool/
[24] F. Zhang, K. Niu, J. Xiong, B. Jin, T. Gu, Y. Jiang, and D. Zhang, "Towards a diffraction-based sensing approach on human activity recognition," *ACM Interact., Mobile, Wearable Ubiquitous Technol.*, vol. 3, no. 1, 2019, Art. no. 33.
[25] Y. Wang, J. Liu, Y. Chen, M. Gruteser, J. Yang, and H. Liu, "E-eyes: Device-free location-oriented activity identification using fine-grained WiFi signatures," in *Proc. ACM MobiCom*, 2014, pp. 617–628.
[26] B. Wei, W. Hu, M. Yang, and C. T. Chou, "Radio-based device-free activity recognition with radio frequency interference," in *Proc. ACM IPSN*, 2015, pp. 154–165.
[27] W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and modeling of WiFi signal based human activity recognition," in *Proc. ACM MobiCom*, 2015, pp. 65–76.
[28] X. Zheng, J. Wang, L. Shangguan, Z. Zhou, and Y. Liu, "Smokey: Ubiquitous smoking detection with commercial WiFi infrastructures," in *Proc. IEEE INFOCOM*, Apr. 2016, pp. 1–9.
[29] Z. Chen, L. Zhang, C. Jiang, Z. Cao, and W. Cui, "WiFi CSI based passive human activity recognition using attention based BLSTM," *IEEE Trans. Mobile Comput.*, vol. 18, no. 11, pp. 2714–2724, Nov. 2018.
[30] W. Jiang, C. Miao, F. Ma, S. Yao, Y. Wang, Y. Yuan, H. Xue, C. Song, X. Ma, D. Koutsonikolas, W. Xu, and L. Su, "Towards environment independent device free human activity recognition," in *Proc. ACM MobiCom*, 2018, pp. 289–304.
[31] Y. Ma, G. Zhou, and S. Wang, "WiFi sensing with channel state information: A survey," *ACM Comput. Surv.*, vol. 3, no. 46, pp. 46:1–46:36, 2019.
[32] M. Zhang and A. A. Sawchuk. *USC-SIPI Dataset*. Accessed: 2012. [Online]. Available: http://sipi.usc.edu/HAD/://archive.ics.uci.edu/ml/machine-learning-databases/00240/
[33] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. Reyes-Ortize. *UCI Dataset*. Accessed: 2015. [Online]. Available: http://archive.ics.uci.edu/ml/machine-learning-databases/00240/
[34] S. Gaglio, G. Lo Re, and M. Morana, "Human activity recognition process using 3-D posture data," *IEEE Trans. Human-Mach. Syst.*, vol. 45, no. 5, pp. 586–597, Oct. 2014.
[35] L. Guo, L. Wang, J. Liu, W. Zhou, and B. Lu, "HuAc: Human activity recognition using crowdsourced WiFi signals and skeleton data," *Wireless Commun. Mobile Comput.*, vol. 2018, Jan. 2018, Art. no. 6163475.
[36] S. Sen, J. Lee, K.-H. Kim, and P. Congdon, "Avoiding multipath to revive inbuilding WiFi localization," in *Proc. ACM MobiSys*, 2013, pp. 249–262.
[37] A. T. Mariakakis, S. Sen, J. Lee, and K.-H. Kim, "SAIL: Single access point-based indoor localization," in *Proc. ACM MobiSys*, 2014, pp. 315–328.
[38] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, "SpotFi: Decimeter level localization using WiFi," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 45, no. 4, pp. 269–282, 2015.
[39] X. Guo, D. Zhang, K. Wu, and L. M. Ni, "MODLoc: Localizing multiple objects in dynamic indoor environment," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 11, pp. 2969–2980, Nov. 2014.
[40] C. Xu, B. Firner, R. S. Moore, Y. Zhang, W. Trappe, R. Howard, F. Zhang, and N. An, "SCPL: Indoor device-free multi-subject counting and localization using radio signal strength," in *Proc. IEEE IPSN*, 2013, pp. 79–90.
[41] K. Kleisouris, B. Firner, R. Howard, Y. Zhang, and R. P. Martin, "Detecting intra-room mobility with signal strength descriptors," in *Proc. MobiHoc*, 2010, pp. 71–80.
[42] J. Xiao, K. Wu, Y. Yi, L. Wang, and L. M. Ni, "FIMD: Fine-grained device-free motion detection," in *Proc. IEEE ICPADS*, Dec. 2012, pp. 229–235.
[43] C. Wu, Z. Yang, Z. Zhou, X. Liu, Y. Liu, and J. Cao, "Non-invasive detection of moving and stationary human with WiFi," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2329–2342, Nov. 2015.
[44] K. Qian, C. Wu, Z. Yang, Y. Liu, and Z. Zhou, "PADS: Passive detection of moving targets with dynamic speed using PHY layer information," in *Proc. IEEE ICPADS*, Dec. 2014, pp. 1–8.
[45] Z. Zhou, Z. Yang, C. Wu, Y. Liu, and L. M. Ni, "On multipath link characterization and adaptation for device-free human detection," in *Proc. ACM ICDCS*, 2015, pp. 389–398.
[46] Z. Zhou, Z. Yang, C. Wu, L. Shangguan, and Y. Liu, "Towards omnidirectional passive human detection," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 3057–3065.
[47] S. Wang and G. Zhou, "A review on radio based activity recognition," *Digit. Commun. Netw.*, vol. 1, no. 1, pp. 20–29, 2015.
[48] X. Liu, J. Cao, S. Tang, and J. Wen, "Wi-sleep: Contactless sleep monitoring via WiFi signals," in *Proc. IEEE RTSS*, Dec. 2014, pp. 346–355.
[49] P. Melgarejo, X. Zhang, P. Ramanathan, and D. Chu, "Leveraging directional antenna capabilities for fine-grained gesture recognition," in *Proc. ACM UbiComp*, 2014, pp. 541–551.
[50] M. Zhao, F. Adib, and D. Katabi, "Emotion recognition using wireless signals," in *Proc. ACM MobiCom*, 2016, pp. 95–108.
[51] J. Wilson and N. Patwari, "See-through walls: Motion tracking using variance-based radio tomography networks," *IEEE Trans. Mobile Comput.*, vol. 10, no. 5, pp. 612–621, May 2011.
[52] D. Vasisht, J. Wang, and D. Katabi, "RF-IDraw: Virtual touch screen in the air using RF signals," in *Proc. ACM S3*, 2014, pp. 1–4.
[53] L. Sun, S. Sen, D. Koutsonikolas, and K.-H. Kim, "WiDraw: Enabling hands-free drawing in the air on commodity WiFi devices," in *Proc. ACM MobiCom*, 2015, pp. 77–89.
[54] S. Agrawal, I. Constandache, S. Gaonkar, R. R. Choudhury, K. Caves, and F. DeRuyter, "Using mobile phones to write in air," in *Proc. ACM MobiSys*, 2011, pp. 15–28.
[55] M. Kotaru and S. Katti, "Position tracking for virtual reality using commodity WiFi," in *Proc. ACM CVPR*, Jul. 2017, pp. 68–78.

[56] F. Adib, C.-Y. Hsu, H. Mao, D. Katabi, and F. Durand, "Capturing the human figure through a wall," *ACM Trans. Graph.*, vol. 34, no. 6, 2015, Art. no. 219.

LINLIN GUO received the B.S. degree from the Computer and Technology Department, Taishan University, in 2011, and the M.S. degree from Qufu Normal University, in 2014. She is currently pursuing the Ph.D. degree with the School of Software Technology, Dalian University of Technology. Her research interests include device-free wireless localization and human activity recognition, wireless networks, and machine learning.

LEI WANG received the B.S., M.S., and Ph.D. degrees from Tianjin University, China, in 1995, 1998, and 2001, respectively. He was a member of Technical Staff with Bell Labs Research, China, a Senior Researcher with Samsung, South Korea, a Research Scientist with Seoul National University, and a Research Associate with Washington State University, Vancouver, WA, USA. He is currently a Full Professor with the School of Software, Dalian University of Technology, China. He has published more than 130 articles and the articles have more than 600 citations. His research interests include wireless ad hoc networks, sensor networks, social networks, and network security.

CHUANG LIN (M'14) received the Ph.D. degree in signal processing from the Harbin Institute of Technology, Harbin, China, in 2008. He is currently an Associate Professor with the CAS Key Laboratory of Human-Machine Intelligence-Synergy Systems, Research Center for Neural Engineering, Institute of Biomedical and Health Engineering, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. His research interests include biomedical signal processing, pattern recognition, and machine learning.

JIALIN LIU received the B.S. and M.S. degrees from the School of Software, Dalian University of Technology, Dalian, China, in 2015 and 2017, respectively, where she is currently pursuing the Ph.D. degree. Her research interests include wireless sensor networks and wireless network communications.

BINGXIAN LU received the B.S., M.E., and Ph.D. degrees from the Dalian University of Technology, China, in 2012, 2014, and 2019, respectively, where he is currently an Assistant Professor with the School of Software. His research interests include wireless networks, mobile computing, and pervasive computing applications. He is a member of the ACM.

JIAN FANG received the B.S. and M.S. degrees from the School of Software, Dalian University of Technology, Dalian, China, in 2015, where he is currently pursuing the Ph.D. degree. His research interests include wireless sensor networks and wireless network communications.

ZHONGHAO LIU is currently pursuing the B.S. degree with the School of Software, Dalian University of Technology. His research interests include deep learning and wireless sensing.

ZEYANG SHAN is currently a Senior Student with the School of Software, Dalian University of Technology. His research interests include wireless networks, computer vision, and machine learning.

JINGWEN YANG is currently a Senior Student with the School of Software, Dalian University of Technology. Her research interests include wireless networks and machine learning.

SILU GUO is currently a Senior Student with the School of Computer Science and Data, Sun Yat-sen University. Her research interests include computer vision and machine learning, particularly in the automotive domain.