A WiFi-Based Smart Home Fall Detection System Using Recurrent Neural Network

Jianyang Ding, *Graduate Student Member, IEEE*, and Yong Wang, *Member, IEEE*

***Abstract*—Falls among the elderly living on their own have been regarded as a major public health worry that can even lead to death. Fall detection system (FDS) that alerts caregivers or family members can potentially save lives of the elderly. However, conventional FDS involves wearable sensors and specialized hardware installations. This article presents a passive device-free FDS based on commodity WiFi framework for smart home, which is mainly composed of two modules in terms of hardware platform and client application. Concretely, commercial WiFi devices collect disturbance signal induced by human motions from smart home and transmit the data to a data analysis platform for further processing. Based on this basis, a discrete wavelet transform (DWT) method is used to eliminate the influence of random noise presented in the collected data. Next, a recurrent neural network (RNN) model is utilized to classify human motions and identify the fall status automatically. By leveraging Web Application Programming Interface (API), the analyzed data is able to be uploaded to the proxy server from which the client application then obtains the corresponding fall information. Moreover, the system has been implemented as a consumer mobile App that can help the elderly saving their lives in smart home, and detection performance of the proposed FDS has been evaluated by conducting comprehensive experiments on real-world dataset. The results confirm that the proposed FDS is able to achieve a satisfactory performance compared with some state-of-the-art algorithms.**

***Index Terms*—Artificial intelligence, channel state information, data processing, mobile applications, smart homes, wireless communication, Web services.**

I. INTRODUCTION

FALLS are the leading cause of fatal and nonfatal injuries to the elderly in the modern society. According to the center for Disease Control and Prevention, one out of three adults aged 65 and over fall each year at home [1], [2]. Falls not only bring a main threat to the elderly's health, but also account for a large part of medical cost. Most of the elderly are unable to get up by themselves after a fall, and studies have shown that the medical outcome of a fall is largely dependent on the response and rescue time [2]. The delay of medical treatment after a fall can increase the mortality risk in clinical conditions, half of those who experienced an extended period of lying on the floor died within six months after an incident [3]. In addition to physical injuries and high medical cost, falls can cause psychological damage to the elderly as well, which is termed as the fear of falling cycle by the fall researchers [3]. The fear cycle refers to the fact that after a fall, even without injury, the elderly become so afraid of falling again that they would reduce physical activities [3]. This in turn decreases their fitness, mobility and balance, and leads to decreased social interactions, reduced life satisfaction, and increased depression. This fear cycle further increases the risk of another fall. Especially for the elderly who live alone and independently, about 50% of the falls occur within their own home, so timely and automatic detection of falls has the potential to save the lives of the elderly [4].

Up to now, many health-monitoring approaches are already common in people's daily life, and also various applications are widely developed [5]–[10]. These approaches utilizing wearable sensors can efficiently monitor the elderly's physical conditions at home, and their performance is satisfactory. However, all of these approaches require users to wear dedicated devices or sensors on their bodies all the time, which has somewhat limited a large-scale deployment of such systems. Recently, with the rapid development and ubiquity of commercial WiFi devices, there are increasingly applications using WiFi signal [11]–[13]. Specifically, most of the modern off-the-shelf WiFi devices operate on both the 2.4 GHz and 5 GHz frequency bands [14]. Owing to the advantages of wide bandwidth and supporting multiple input multiple output (MIMO) techniques, current commercial WiFi devices start to track fine-grained channel measurements using orthogonal frequency division modulation (OFDM) technology at the physical layer [14]. In particular, the OFDM channel is a relatively wide channel divided into multiple subcarriers where each subcarrier has a different signal amplitude and phase in terms of each transmitted signal [15]. For instance, the mainstream WiFi systems, such as 802.11 a/g/n, are based on OFDM where a wideband 20 MHz channel is partitioned into 52 subcarriers [15]. Owing to the frequency diversity of these subcarriers, both the shadow fading and multipath effect at different subcarriers can lead to different amplitude and phase. This means that a small body movement in indoor environments would result in the change of channel state information (CSI) at all the subcarriers [16]. Based on this view, various human motions occurring between a pair of WiFi

Manuscript received November 29, 2019; revised March 13, 2020, June 12, 2020, and August 19, 2020; accepted August 31, 2020. Date of publication September 3, 2020; date of current version November 25, 2020. This work was supported in part by the Natural Science Foundation of China under Grant 61671346, and in part by the Natural Science Basic Research Plan in Shaanxi Province of China under Grant 2020JM-180. *(Corresponding author: Jianyang Ding.)*

Jianyang Ding is with the School of Telecommunications Engineering, Xidian University, Xi'an 710071, China (e-mail: jyding@stu.xidian.edu.cn).

Yong Wang is with the State Key Laboratory of Integrated Services Networks, Xidian University, Xi'an 710071, China (e-mail: johnnyly@xidian.edu.cn).

Digital Object Identifier 10.1109/TCE.2020.3021398

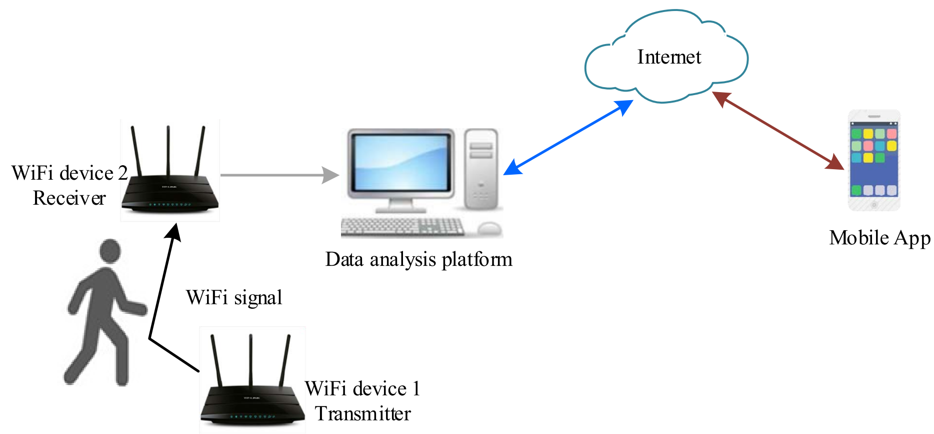


Fig. 1. Fall detection system.

transmitter and receiver influence the indoor electromagnetic environments in a unique manner which would be changed into the impact on the characteristics of WiFi signal. Then, the significant impact is in turn manifested as distinct perturbation in WiFi CSI [17]. Besides, different motions yield different impacts on the characteristics of WiFi signal, and thus fall detection is able to be feasible by examining the representative patterns of the amplitude information of WiFi CSI. In addition, due to these advantages of low cost, no invasion, and wide deployment of WiFi devices in indoor environments (e.g., home and office), fall detection can become reality. Previous studies [18]–[24] have confirmed that WiFi infrastructures can support a high-accuracy-low-cost fall detection for the elderly with simple deployment, engaging user experience, and limited personal privacy. More importantly, the passive device-free fall detection using WiFi CSI does not require the users to take any dedicated device or sensor, which means that the nature of this approach is "set it and forget it" requiring no interaction on the elderly's part after initial set up. As a result, this detection approach could help to reveal a wealth of important health information, particularly for the elderly. A change in the CSI amplitude, for example, could mean that the person has suffered an injury or is at an increased risk of falling. By doing this, it can be applied to some specific scenarios on remote heath monitoring, such as hospitals, nursing homes, and the elderly living on their own. Due to the advantage of passive device-free detection, the elderly may feel that they are not offended. In the present study, our proposed fall detection system (FDS) thus takes advantage of the amplitude information of fine-grained WiFi CSI to capture the minute movement for fall detection in smart home.

In order to achieve automatic passive fall detection in smart home, an effective system using commercial WiFi devices and the emerging technologies is presented in this article. At first, we build an environment change indicator exploiting motion-induced signal fluctuation to infer potential motion interference with a pair of commercial WiFi devices installed in residential units. In the case of a human motion occurring in the target area, the detection data is collected and it is constantly transmitted to the data analysis platform for further processing. Data analysis on the collected data using discrete wavelet transform (DWT) [24], [25] and recurrent neural network (RNN) [26]–[28] model plays an important role in fall status decisions for the elderly. Concretely, in order to preserve data details while filtering out the noise presented in the collected data, the DWT method is leveraged to eliminate the influence of the random noise by signal decomposition. Next, the RNN model is used to classify various human motions by utilizing the denoised data above, and then identify fall status automatically. As the term recurrent implies, the RNN model takes not only the current input data but also several previous input data. That is to say, it has a memory that can obtain the variation in input data. Thus, the selected strategy has the capacity for capturing the complicated non-linear relationship between input and output data during training efficiently. To conduct remote monitoring better, the real-time data analyzed is uploaded to a configured proxy server. In addition, the client application interacts with the server and obtains the motion information in the form of texts and graphs from the server in real time. Specially, both of them take use of a lightweight architectural style Web Application Programming Interface (API) [9] to facilitate communication utilizing Web services. Then, the consumer or the community owner can be aware of the fall behavior via a mobile phone or a management platform, and takes emergency measures to save the lives of the elderly in time in smart home. Fig. 1 displays the concrete process of fall detection showing the data flow from home WiFi devices to end consumer application.

The rest of this article is organized as follows. We first review the related work in Section II. Then we present the detailed system design in Section III. Followed by the motions dataset collection, evaluation, and comparison results in Section IV. In Section V, we present the mobile App and its analysis. Finally, we conclude the work in Section VI.

II. Related Work

This section reviews related work of fall detection in indoor environments. Moreover, existing systems can be classified into two categories: Sensors-based fall detection and WiFi CSI-based fall detection.

A. Sensors-Based Fall Detection

Due to the importance of fall detection, several fall detection approaches based on sensors have been proposed, which can be broadly classified as videos, wearable sensors, and ambient sensors. Khan and Sohn [5] proposed a video sensor-based human activity recognition system for the elderly care by recognizing six abnormal activities, including forward fall, backward fall, chest pain, faint, vomit, and headache, selected from the daily life activities. Besides, the proposed system took use of the kernel discriminant analysis (KDA) to increase discrimination among different classes of activities by utilizing non-linear technique. Then, Hidden Markov Model (HMM) was employed for training and recognition of human activities. Yang and Tian [29] presented a novel framework for recognizing various human activities from video sequences captured by depth cameras, and extended the surface normal to polynormal by assembling local neighboring hypersurface normals from a depth sequence to jointly characterize local motion and shape information. Usually, these video-based approaches are highly accurate. However, these approaches are affected heavily by some issues, such as high installation overhead, needing light, out of sight range, personal privacy problem, etc.

Wang *et al.* [6] proposed an enhanced fall FDS for the elderly monitoring which was based on smart sensors worn on the body and operating through consumer home networks. With treble thresholds, accidental fallings can be detected in the home healthcare environment. By leveraging information gathered from an accelerometer, a cardiotachometer, and smart sensors, the impacts of falls can be logged and distinguished from normal daily activities. Yang *et al.* [10] presented a wavelet-neural network recognition system for personal fitness assistance and the elderly daily activity monitoring applications by utilizing Internet of Thing (IoT) technology. This discrete wavelet transform radial basis neural network analyzed vibration induced by human motions, and identified motion status automatically. Lara and Labrador [30] surveyed the state of the art in human activity recognition based on wearable sensors, and proposed a two-level taxonomy in accordance to the learning approach and the response time. Gunadi *et al.* [31] used Kinect device that can be utilized to detect the elderly. Kinect can detect a person in front of it and process it to create a skeleton of the person. Although these wearable sensors-based detection approaches are very effective, especially in indoor environments, they may not always be accepted by the elderly. In addition, some people are unwilling to wear the dedicated sensors on their bodies all the time. As a result, this disadvantage somehow restricts large-scale deployment of such systems in typical indoor environments.

Additionally, Nadee and Chamnongthai [32] presented an elderly-falling detection system leveraging ultrasonic sensors. The ultrasonic technology-based multi sensors were couple of receiver and transmitter together, which could be connected to Arduino microcontroller in order to send the elderly person's fall related signal using WiFi to the processing unit. Li *et al.* [33] developed an acoustic FDS (acoustic-FADE) that automatically detected a fall and reported it promptly to the caregiver. Acoustic-FADE consisted of a circular microphone array that captured the sounds in a room. Concretely, when a sound was detected, acoustic-FADE located the source, enhanced the signal, and classified it as "fall" or "non-fall". Rimminen *et al.* [34] used a near-field imaging (NFT) to conduct detection utilizing floor sensor and pattern recognition. The floor sensor detected the locations and patterns of the elderly by measuring impedances with a matrix of thin electrodes under the floor. These fall detection approaches based on ambient sensors can guarantee certain accuracy as presented, but other sources of pressure, vibration, or sound in a room could cause false alarms. Besides, in order to ensure high detection performance, a high-density deployment in indoor environments is required.

B. WiFi CSI-Based Fall Detection

Since WiFi signal has been verified to be reliable indicator for device-free passive fall detection, more researchers seek for the opportunity to identify fall motion in indoor environments. Wang *et al.* [3] presented the design and implementation of RT-Fall, a real-time, contactless, and low-cost accurate indoor fall detection system using the commodity WiFi devices. Wang *et al.* [18] proposed a monitoring framework that can run on a single WiFi AP with its connected devices and used the associated profile matching algorithms to compare amplitude profiles against those from known activities. Wang *et al.* [19] presented a human activity recognition and monitoring system based on CSI. Besides, the system considered two theoretical underpinnings: a CSI-speed model and a CSI-activity model. By using these two models, the correlation between CSI value dynamics and a specific activity could be built quantitatively. Abdelnasser *et al.* [20] proposed a novel system that leveraged changes in WiFi signal strength to sense in-air hand gestures around the user's mobile device. Besides, the system utilized standard WiFi equipment, with no modifications, and required no training for gesture recognition. Chen *et al.* [21] presented a new deep learning-based approach, i.e., attention based bi-directional long short-term memory, for passive human activity recognition using WiFi signal. Additionally, the BLSTM was employed to learn representative features in two directions from raw WiFi CSI measurements. Zhang *et al.* [22] designed and implemented a real-time, non-intrusive, and low-cost indoor fall detector by leveraging the fine-grained CSI and multi-antenna setting in commercial WiFi devices. Wang *et al.* [23] firstly looked for the correlations between different radio signal variations and activities by analyzing radio propagation model. Based on this observation, they proposed a truly unobtrusive FDS that can detect the fall of the human without hardware modification, extra environmental setup, or any wearable device. Palipana *et al.* [24] considered an emerging non-wearable fall detection approach based on WiFi CSI, and took an altogether different direction, time-frequency analysis as used in radar fall detection. Although these approaches have these advantages of low cost, easy deployment, and passive device-free detection, the abilities of motions monitoring and remote health monitoring are limited.

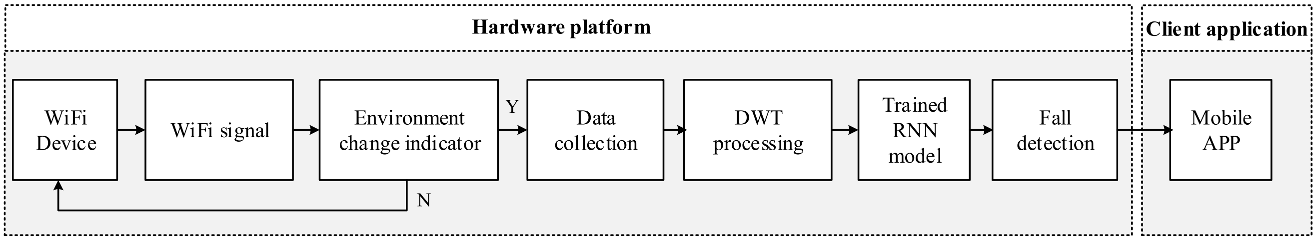


Fig. 2. Technical diagram of fall detection.

III. System Design

The basic idea of our system is to extract the detection data from the receiver in smart home and conduct fall recognition on the data analysis platform. Meanwhile, the detection result is sent to the client application. Fig. 2 shows the technical diagram of fall detection. Note that, one important question for the correct operation of the proposed FDS is how to know that one person is performing a motion in smart home or when the data is collected. This can help avoiding false motion generated by other noise in indoor environments from nearby users and also leads to energy-efficiency. Our solution to that is to build the environment change indicator inferring potential motion interference. Based on its decision, if there is a response "yes", the proposed FDS would start performing data collection and subsequent processes, otherwise continue conducting motions monitoring. In view of this, the proposed system can be divided into two main modules, including hardware platform and client application.

A. Hardware Platform Module

As shown in Fig. 2, the hardware platform module of the system is comprised of the following building blocks.

1) Environment Change Indicator: It is widely recognized that the amplitude of WiFi signal would fluctuate remarkably when an entity moves within the area of interests, and remain relatively stable in the case of no motion interfering. Based on this basis, the environment change indicator is introduced to exploit such motion-induced signal fluctuation for inferring potential motion interference. It can help determining if the proposed FDS starts the data collection in the next step by the system's feedback.

Concretely, the transmitter is set to transmit continuously WiFi signal to the receiver through multiple paths. At the same time, the WiFi CSI accessed from the receiver is timely transmitted to the data analysis platform, and then it is analyzed if there is an environment change caused by human motions. Based on this view above, the environment change indicator is built using the amplitude variation of CSI, it is given by

$$|f(t_x) - \mu| \geq \alpha,$$
$$\mu = m^{-1} \cdot \big(f_p(t_1) + f_p(t_2) + \cdots + f_p(t_m)\big), \quad (1)$$

where $f(t_x)$ represents the amplitude value of WiFi CSI at a certain time and $f_p(t_1), f_p(t_2), \ldots f_p(t_m)$ is the pre-collected data in indoor environments, and α represents the corresponding threshold to trigger the data collection for various motions, respectively. Specifically, the threshold is able to be determined by some preliminary measurements. Different from relying on scenario-tailored calibration, we do not need to calibrate for each different case because the threshold can apply to various indoor environments gracefully. More importantly, the design of the environment change indicator is lightweight since the calculation of mean value is effective and fast.

2) Data Collection: As discussed above, when receiving a positive response "yes" from the designed environment change indicator, the system starts collecting the detection data. Concretely, when the WiFi signal $f(t_x)$ satisfies (1), it can be thought that there is a motion occurring in the area of interests. At the same time, the detection data will also be collected from this moment. Moreover, we can assume that an entity performs a motion indoors at time t_1. In view of this, with commercial WiFi Network Interface Cards (NICs) and slight firmware modification, the detection data containing human motion information is collected with a predefined time window where the window size is set as n, and we have

$$f(t) = \big[f(t_1), f(t_2), \ldots f(t_n)\big], \quad (2)$$

where $f(t)$ has a dimension of $1 \times n$. Then, the collected data will be used for next data processing.

3) Data Processing: Since the collected data $f(t)$ is obtained from smart home, it inevitably contains the random noise from various sources, such as nearby electronic devices interfering. This random noise is able to add false edges, and then influence the accuracy of fall detection and the robustness in smart home. In order to improve system quality, we need to remove the influence of the random noise presented in the raw data first.

Owing to the advantages of being computationally efficient (linear time complexity) to fit on mobile devices and making no particular consumptions with respect to the nature of data, a wavelet based denoising strategy is introduced to eliminate the random noise presented in the collected data. We divide the denoising into three parts, including signal decomposition, detail coefficients processing, and signal reconstruction. DWT can decompose the data into two terms: the approximation coefficients and detail coefficients. Of the two coefficients, the former can describe the data shape and the latter can capture both the random noise and fine data details. In addition, this splitting is applied recursively a number of steps (i.e., levels), J, to the approximation coefficients only to obtain finer details from the data. Finally, DWT produces a coarse approximation projection (scaling) coefficients $\alpha^{(J)}$, together with a sequence of finer detail projection (wavelet) coefficients

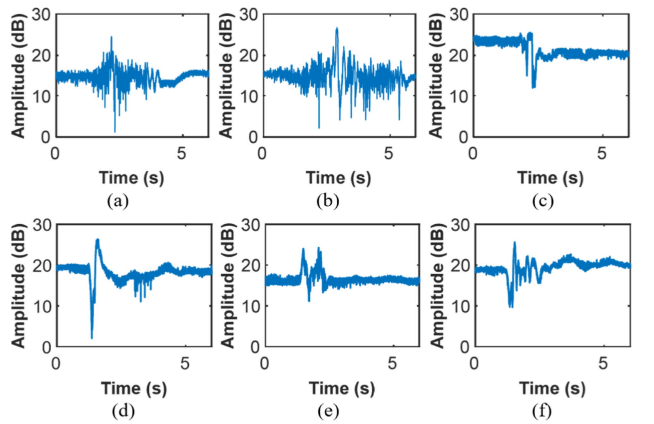


Fig. 3. The raw data amplitude of six motions. (a) Jumping. (b) Walking. (c) Bending. (d) Falling. (e) Standing up. (f) Lying.

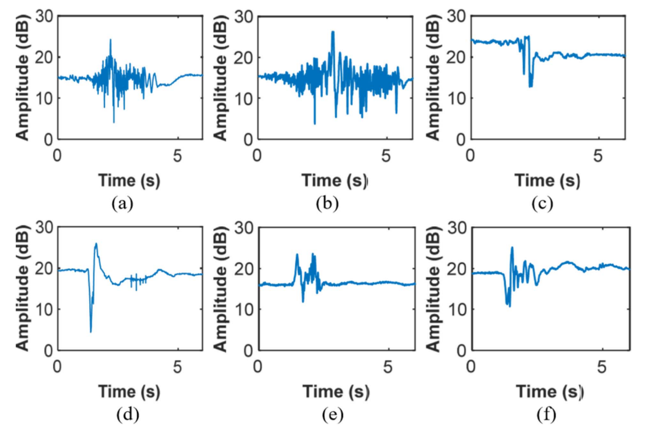


Fig. 4. The data amplitude of six motion after denoising. (a) Jumping. (b) Walking. (c) Bending. (d) Falling. (e) Standing up. (f) Lying.

$\beta^{(1)}, \beta^{(2)}, \ldots \beta^{(J)}$. The DWT coefficients in each level can be calculated as

$$\alpha_k^{(J)} = \left\langle f(t_n), g_{n-2^J k}^{(J)} \right\rangle_n = \sum_{n \in Z} f(t_n) g_{n-2^J k}^{(J)}, \; J \in Z,$$
$$\beta_k^{(j)} = \left\langle f(t_n), h_{n-2^j k}^{(j)} \right\rangle_n = \sum_{n \in Z} f(t_n) h_{n-2^j k}^{(j)}, \; j \in \{1, 2, \ldots J\}, \tag{3}$$

where $f(t_n)$ is the n-th data of $f(t)$, $\langle \cdot \rangle$ represents the dot product operation, g's and h's, also known as the wavelet basis, are two sets of discrete orthogonal functions. The inverse DWT is given by

$$f(t_n) = \sum_{k \in Z} \alpha_k^{(J)} g_{n-2^J k}^{(J)} + \sum_{j=1}^{J} \sum_{k \in Z} \beta_k^{(j)} h_{n-2^j k}^{(j)}. \tag{4}$$

To remove the random noise component while retaining sufficient details for FDS, a soft threshold method is applied to the detail coefficients. Concretely, we set the coefficients with very small absolute value to zero, and the coefficients with large absolute value are decreased. Then, the detail coefficients after estimation are utilized to reconstruct the detection data directly as follows:

$$\hat{f}(t_n) = \sum_{k \in Z} \alpha_k^{(J)} g_{n-2^J k}^{(J)} + \sum_{l=1}^{J} \sum_{k \in Z} \hat{\beta}_k^{(l)} h_{n-2^l k}^{(l)}, \tag{5}$$

where $\hat{\beta}_k^{(l)}$ denotes estimated detail coefficients. Then, we can obtain the denoised data $\hat{f}(t)$. Besides, the raw data amplitude of six human motions in daily life is shown in Fig. 3 and Fig. 4 shows the results after denoising.

4) Motions Classification Based on RNN: In the present study, the RNN model is introduced to classify human motions and then identify the fall status. The first step is to create an appropriate input vector from the denoised data. Thus, the input vector can be expressed by

$$\mathbf{x} = \left[\hat{f}(t_1), \hat{f}(t_2), \ldots \hat{f}(t_n)\right]^T = \left[\hat{f}(t)\right]^T, \tag{6}$$

where the input vector has a dimension of D_x.

Then, we consider an RNN model taking P sets of the collected data to make a decision. Fig. 5 illustrates the RNN model with the long short-term memory (LSTM) blocks where $\mathbf{x}^{(p)}$ and $\mathbf{h}^{(p)}$ represent input vector and hidden layer at the p-th time step, respectively. Besides, the dimension of the hidden layer is assumed to be D_h. In addition to the hidden layer, the LSTM blocks also have a unit, called cell state $\mathbf{c}^{(p)}$, which can control the information flow through using three gates, including forget, input, and output gates.

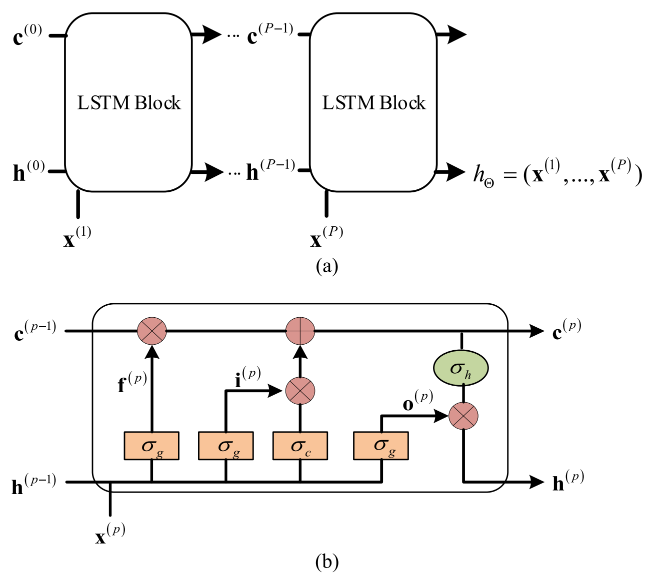


Fig. 5. The RNN model with the LSTM blocks. (a) Overall structure. (b) Detailed structure of the LSTM blocks at the p-th time step.

With regard to the input vector, each gate vector can be calculated as follows:

$$\mathbf{f}^{(p)} = \sigma_g\left(\mathbf{W}_f \mathbf{x}^{(p)} + \mathbf{U}_f \mathbf{h}^{(p-1)} + \mathbf{b}_f\right),$$
$$\mathbf{i}^{(p)} = \sigma_g\left(\mathbf{W}_i \mathbf{x}^{(p)} + \mathbf{U}_i \mathbf{h}^{(p-1)} + \mathbf{b}_i\right),$$
$$\mathbf{o}^{(p)} = \sigma_g\left(\mathbf{W}_o \mathbf{x}^{(p)} + \mathbf{U}_o \mathbf{h}^{(p-1)} + \mathbf{b}_o\right), \tag{7}$$

where $\mathbf{W}_f$, $\mathbf{W}_i$, and $\mathbf{W}_o$ are the input weights and have a dimension of $D_h \times D_x$, $\mathbf{U}_f$, $\mathbf{U}_i$, and $\mathbf{U}_o$ are the cyclic weights and have a dimension of $D_h \times D_h$. $\mathbf{b}_f$, $\mathbf{b}_i$, and $\mathbf{b}_o$ are the bias and have a dimension of $D_h \times 1$. In addition, $\sigma_g(\cdot)$ denotes an element-wise activation function for all gates, which is given by using a sigmoid function, i.e., $\sigma_g(z) = 1/(1+e^{-z})$. Both the previous cell state and hidden layer of the LSTM blocks at the first time step are initialized as zero vectors. Owing to these vectors, the cell state and hidden layer in LSTM can be updated in real time as follows:

$$\mathbf{c}^{(p)} = \mathbf{f}^{(p)} \circ \mathbf{c}^{(p-1)} + \mathbf{i}^{(p)} \circ \sigma_c\Big(\mathbf{W}_c\mathbf{x}^{(p)} + \mathbf{U}_c\mathbf{h}^{(p-1)} + \mathbf{b}_c\Big), \tag{8}$$

and we can have

$$\mathbf{h}^{(p)} = \mathbf{o}^{(p)} \circ \sigma_h\Big(\mathbf{c}^{(p)}\Big), \tag{9}$$

where $\circ$ represents the Hadamard product operator, $\sigma_c(\cdot)$ and $\sigma_h(\cdot)$ represent the element-wise activation functions for the cell state and hidden layer, respectively. In our study, the hyperbolic tangent is leveraged for these activation functions. Finally, the RNN model output can be obtained directly from the hidden layer at the last time step, and it is given by

$$h_\Theta\Big(\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(P)}\Big) = \sigma\Big(\mathbf{V}\mathbf{h}^{(P)} + b\Big), \tag{10}$$

where $\mathbf{V}$ is the D_h dimension row vector, and b denotes a bias constant, and the set Θ contains every parameter of the proposed RNN model, for instance, elements in the matrices $\mathbf{U}$ and $\mathbf{W}$, vectors $\mathbf{b}$ and $\mathbf{V}$, and the constant b.

Every parameter in the RNN model is able to be adjusted appropriately by training motions dataset. The sequence of P input data vectors is denoted as $\mathbf{X} = (\mathbf{x}^{(1)}, \ldots \mathbf{x}^{(P)})$ and the corresponding labels are denoted as y, where y can be viewed as walking, falling, etc. From the denoised data and corresponding motion labels, a set of input and output pairs ($\mathbf{X}$, y) are produced to train and verify the proposed RNN model. Besides, ς is introduced as such a dataset, and every parameter in the model can be adjusted in the direction of minimizing the cost function, which is expressed by

$$J(\Theta) = -\frac{1}{|\varsigma|}\sum_{g\in\varsigma} C(g), \tag{11}$$

where $|\cdot|$ denotes the number of elements in a set, $C(g)$ is the cost of the g-th input and output pair and it measures how accuracy the proposed model generates the output compared to the ground truth data.

In order to evaluate the cost performance, cross-entropy is introduced as

$$C(g) = y^{(g)}\log h_\Theta\Big(\mathbf{X}^{(g)}\Big) + \Big(1 - y^{(g)}\Big)\log\Big(1 - h_\Theta\Big(\mathbf{X}^{(g)}\Big)\Big), \tag{12}$$

where the superscript indicates the index of the input and output pairs. Then, every parameter in the RNN model can be updated in an iterative manner by taking use of the gradient descent method, which is given by

$$\Theta_{n+1} = \Theta_n - \eta\nabla_\Theta J(\Theta), \tag{13}$$

where ∇_Θ represents the gradient operation with regard to Θ, and η is the learning rate which is set to be 5×10^{-4}. Many variations of the gradient descent methods have been studied widely in the previous works like Adam optimizer. It is well known that these optimizers can change adaptively the learning rate to achieve the minimum cost precisely.

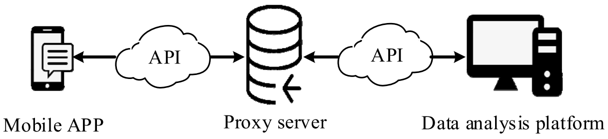


Fig. 6. Mobile App architecture.

Owing to containing many significant parameters, the proposed RNN model can capture non-linearity relationship between the input and output layers efficiently, but it has a high risk of over-fitting. As a result, an early stopping is employed in this study to avoid this key issue, and here we adopt Adam optimizer. In addition, the dataset of input and output pairs, ς, are separated into three non-overlapping datasets, including training dataset ς_{tr}, validation dataset ς_v, and testing dataset ς_{te}. Then, we train the proposed RNN model to determine all the model parameters based on the training dataset with true labels. At each iteration, these values of the cost function (11) with regard to the validation dataset are evaluated and tracked, and we can select optimal parameters when the cost function is minimized.

B. Client Application Module

A cross-platform Integrated Development Environment (IDE) [35] is utilized to develop the front-end mobile user interface. The advantage of using such an environment is that it can leverage standard Web development languages. Besides, it also ensures the cross-platform feature for application which means that only one application is developed for different mobile phone platforms without the need for reimplementation. In addition, the application takes use of two types of identity authentication. Specifically, the first one is that the regular username-password combination is used to initiate connection. Once the user is authenticated, a random generated string called API key is utilized to authenticate operations. This key is able to be changed anytime, and API key changes per session. For example, when the user logs out, the API key is changed. The second one is that an additional parameter called secret key is leveraged to make granting privilege, such as making a user a community owner. This key changes daily, weekly or monthly and is only to be known by the top-level users. Fig. 6 displays the mobile App architecture showing the information flow from data analysis platform to end user application.

IV. Evaluation

The proposed FDS has the capacity for making the fall distinguishable from the other motions, and telling whether the elderly are having a fall or not in smart home efficiently. To validate the architecture of the proposed FDS, a prototype is designed, built, and tested. Then, we conduct some real-world experiments to evaluate the performance of the proposed FDS in three typical indoor environments, including laboratory, office room, and dormitory, and further show the generality of our system. Moreover, in order to verify the high performance, the four state-of-the-art algorithms are evaluated and compared, i.e., Hidden Markov Model (HMM) [19], Long Short-Term Memory (LSTM) [21], Random Forest (RF) [36], [37], and Support Vector Machine (SVM) [36], [38]. Besides, we extend performance comparison with the results of former research, including E-eyes [18], CARM [19], and ABLSTM [21].

A. Dataset Collection

In order to collect motions dataset, a pair of commercial WiFi devices running on 5 GHz with bandwidth channel of 20 MHz are utilized, and the WiFi devices equipped with three antennas act as a transmitter and a receiver, respectively. The antennas in the WiFi devices are Omni-directional and run on 2.4 GHz and 5 GHz frequency bands, and the gain is 8 dBi. During the whole testing, the shape of the antennas remains unchanged. Besides, in order to collect raw CSI data to obtain precise information of human motions, the data sample rate is set as 1 KHz. Based on this, we can access up to nine transmission links where each of them has 30 subcarriers. With WiFi NICs and slight firmware modification, the detection data containing human motions information is able to be accessed at the receiver by leveraging CSI tool [39] installed in the data analysis platform. In the present study, to make the dataset diverse, we collect human's motions dataset in three different indoor environments with regard to laboratory, office room, and dormitory. Specifically, these testing scenarios contain various furniture and electronic devices, which are no different from real residential units. During dataset collection, the WiFi devices are installed on the metallic support in indoor environments, and the height of the support as well as the distance between the supports can be adjusted appropriately according to the needs of these experiments.

Totally, ten people are involved for dataset collection with six common daily motions with regard to "jumping", "walking", "bending", "falling", "standing up", and "lying". Specially, each of all the testing objects is asked to perform each motion for a period of 6 seconds. Besides, each of them is also asked to perform each motion 30 times in the same testing area. In particular, all the testing objects need to remain stationary at the beginning and the end of all the motions for reducing the random noise.

B. Fall Detection

The recognition accuracies for all the six motions in three different indoor environments are shown in Fig. 7. It can be found that the proposed FDS can achieve average accuracies of 82%, 85%, and 90% for all the motions, respectively. The recognition accuracies in the laboratory perform the worst. In contrast, the recognition accuracies in the dormitory have the best performance. The possible reason is that the laboratory area is much larger than that of the office room and dormitory, which means that the laboratory can yield a more complicated multiple environment.

The recognition accuracies for different motions have large difference. Especially, the human motions with large body movement speed, i.e., "walking", "falling", and "lying", have better recognition performance. Among them, the motion of "falling" yields the highest recognition accuracy. The reason is that this motion would generate a significant influence on the characteristics of WiFi signal with distinct patterns compared with the others. Another observation is that the motion of "standing" has the lowest recognition accuracy. The possible reason is that this motion shares similar impact on WiFi signal with the motion of "bending". Among the six motions, the motion of "falling" is of great importance, especially for the elderly living on their own. The proposed FDS is able to achieve recognition accuracies of 90%, 91%, and 93% for the motion of "falling" in three typical indoor environments, respectively.

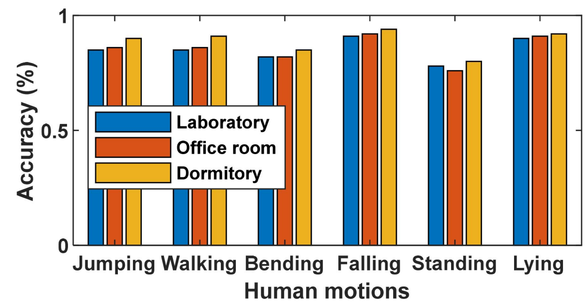


Fig. 7. The recognition accuracies for different human motions in three different indoor environments.

C. Comparative Evaluation

The recognition accuracies for the existing state-of-the-art algorithms and the proposed FDS are shown in Fig. 8. As it is indicated, the RF performs the worst and the SVM slightly outperforms the RF. In addition, the HMM has a superior performance compared with the RF and SVM. Since the LSTM network also considers the temporal dependencies in sequential data for feature learning, it achieves a better performance than the HMM. Owing to the proposed effective system architecture, the proposed FDS can achieve the best performance for the recognition of all the six motions. Similarly, the recognition accuracies for different motions differ from each other. Among all the motions, the motion of "falling" can yield the highest recognition accuracy for all the algorithms, which will benefit many fall detection applications.

D. Results With Different Approaches

To validate its high effectiveness, we compare the proposed FDS with E-eyes, CARM, and ABLSTM fairly leveraging the data collected from the laboratory. Specially, our proposed FDS takes use of the denoised data after DWT processing, E-eyes uses the data after low-pass filtering, CARM utilizes the speeds and spectrograms of different motions extracted from raw CSI data, and ABLSTM directly uses the raw CSI data as input. The recognition accuracies for different approaches are shown in Fig. 9. It can be observed that E-eyes performs the worst and CARM slightly outperforms the E-eyes approach. In addition, the deep learning based approach of ABLSTM considers the temporal dependencies in sequential data for feature

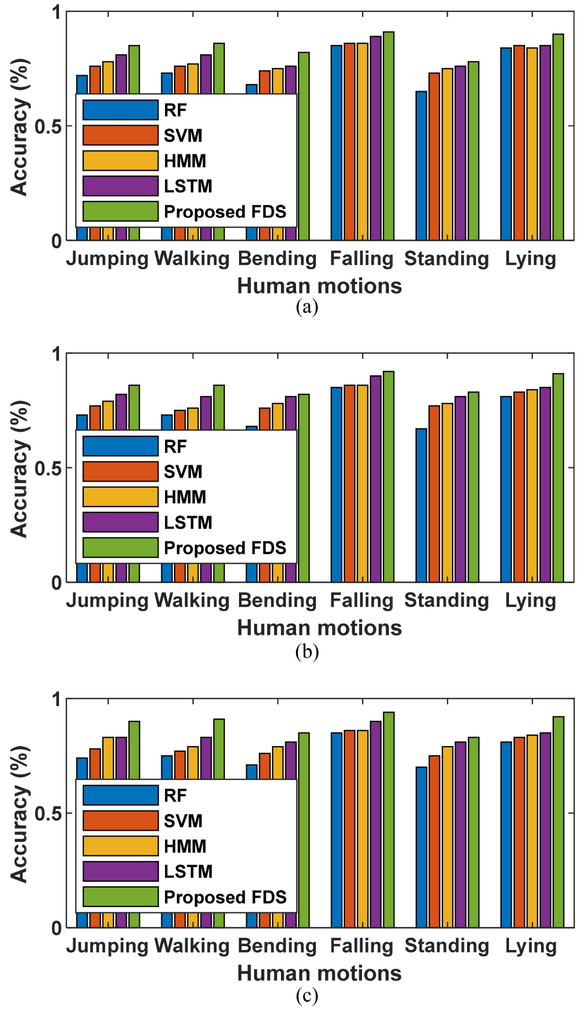


Fig. 8. The recognition accuracies for different human motions with different algorithms. (a) In the laboratory. (b) In the office room. (c) In the dormitory.

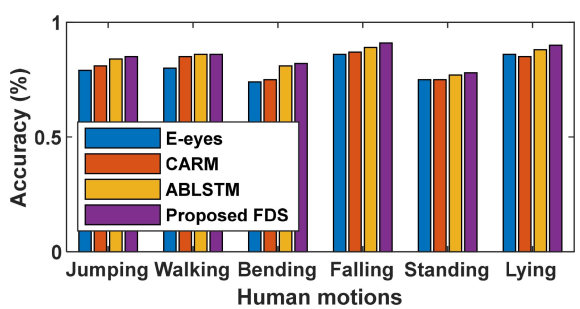


Fig. 9. The recognition accuracies for different human motions with different approaches in the laboratory.

learning and assigns different weights for all the learned features, so it can achieve a better performance compared with E-eyes and CARM. The proposed FDS approach is able to achieve the best performance for all the motions. The reason is that the proposed FDS uses the deep learning to learn the denoised data, instead of the raw CSI data. As a result, it has strong robustness to the random noise derived from indoor environments. Similarly, the motion of "falling" yields the highest recognition accuracy. In contrast, the recognition accuracies of "bending" and "standing" are still unsatisfied.

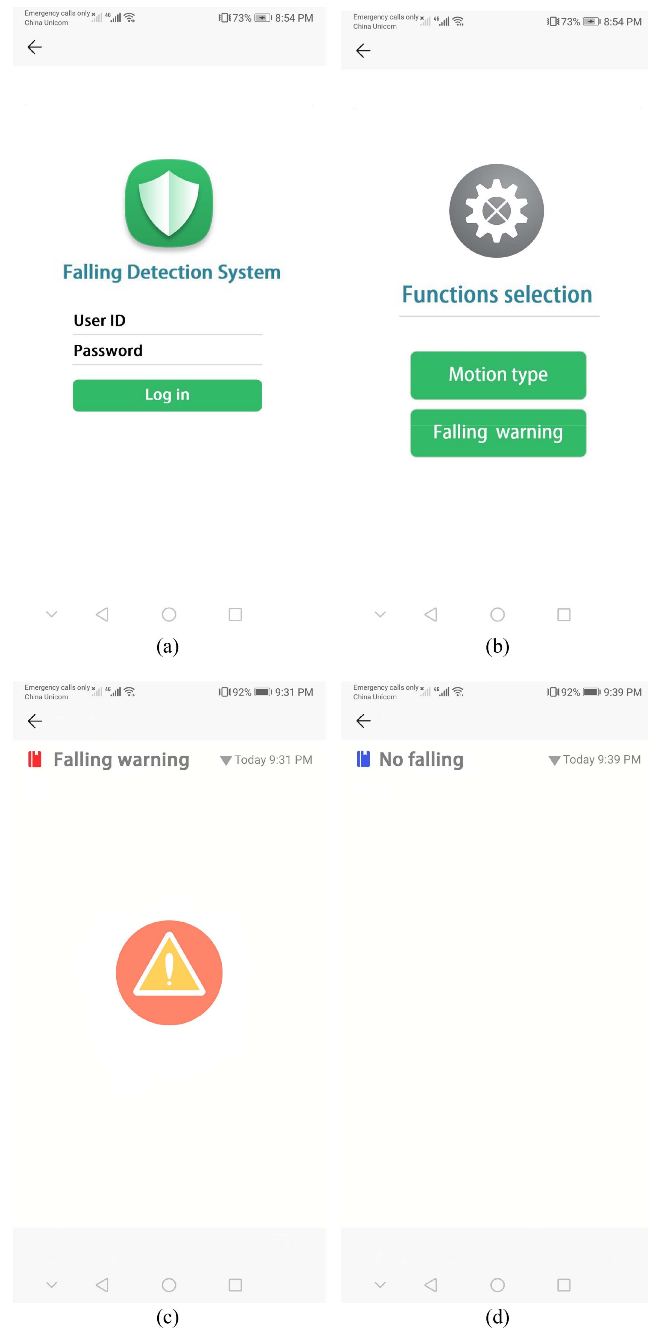


Fig. 10. Mobile App user interfaces. (a) Identity authentication. (b) Selected functions. (c) Falling warning page. (d) No falling page.

V. Mobile App Implementation

The proposed FDS has been implemented as a mobile App using open source technologies. Besides, the architecture of the mobile App is presented in Fig. 6. Specially, it is divided into three parts, namely mobile App, proxy server, and data analysis platform. The API is leveraged as a communication link to synchronize data among three parts. The data analysis platform is the main processing unit where algorithms are implemented. It is also responsible for synchronization of the detection data between local and proxy server. In addition, the basic function of the proxy server is connection and data storage, which is the data transit station and responsible for forwarding legal network information. Finally, by using the mobile App, the consumer can get important information from the proxy server in a timely manner. The working of the mobile application is presented in Fig. 10. Fig. 10(a) shows the identity authentication details page. After entering ID and password, the consumer can enter the mobile application by clicking the button "Log in". Once the consumer logs in, a service will run to get the consumer privileges and the user interface components that he/she will be able to see consequently.

Fig. 10(b) shows the corresponding functions list. For the consumer, there are two services available where the first one is the motion type and the second one is the falling warning. By clicking on the first button, the motion type in terms of six daily motions can be determined in smart home. Additionally, by clicking on the second button, the application is redirected to detection decision pages as shown in Fig. 10(c) and Fig. 10(d). Concretely, after completing the data analysis, the mobile App obtains the fall information and quickly displays the results. Fig. 10(c) shows the warning prompt when a fall occurs in smart home. At the middle of this page, there will be a round graph of warning sign, which means that a fall is occurring. Besides, there is a text prompt at the top left of this page as well. As a result, the consumer needs to take emergency measures to save the lives of the elderly. In contrast, when no fall occurs, there is a text prompt in terms of no falling at the top left of this page as shown in Fig. 10(d).

VI. Conclusion

This article presents a smart home FDS based on WiFi CSI framework using RNN, and the system mainly consists of two modules in terms of hardware platform and client application. And these technologies, including commercial WiFi devices, data analysis platform, API, and consumer mobile App, are combined together to implement the proposed FDS.

Comprehensive experiments have been conducted on real-world dataset taken from multiple typical indoor environments to evaluate the proposed FDS. Specially, the proposed FDS is able to achieve recognition accuracies of 90%, 91%, and 93% for the human motion of "falling", respectively. Furthermore, comparative evaluations we conduct show that the proposed FDS outperforms the existing detection algorithms.

Finally, the proposed FDS has been implemented as a mobile App for the consumers. The mobile App is able to provide a user-friendly way to monitor the fall status of the elderly from a distance. Using their smartphones, they are aware of the fall behavior and take emergency measures to save the lives of the elderly in smart home. Future research will focus on multiple people, more motions, recognition accuracies, and speeding up the total response time to further improve the user's experience.

References

[1] *Falls Among Older Adults: An Overview*, Older Adult Falls, Atlanta, GA, USA, 2013. [Online]. Available: http://www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html/

[2] E. Burns and R. Kakara, "Deaths from falls among persons aged ≥65 years—United States, 2007-2016," *Morbidity Mortality Weekly Rep.*, vol. 67, no. 18, pp. 509–514, May 2018.

[3] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, "RT-Fall: A real-time and contactless fall detection system with commodity WiFi devices," *IEEE Trans. Mobile Comput.*, vol. 16, no. 2, pp. 511–526, Feb. 2017.

[4] C. Han, K. Wu, Y. Wang, and L. M. Ni, "WiFall: Device-free fall detection by wireless networks," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, Toronto, ON, Canada, 2014, pp. 271–279.

[5] Z. A. Khan and W. Sohn, "Abnormal human activity recognition system based on R-transform and kernel discriminant technique for elderly home care," *IEEE Trans. Consum. Electron.*, vol. 57, no. 4, pp. 1843–1850, Nov. 2011.

[6] J. Wang, Z. Zhang, B. Li, S. Lee, and R. S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, Feb. 2014.

[7] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and R. S. Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 442–449, Nov. 2017.

[8] H.-T. Wu and C.-W. Tsai, "Toward blockchains for health-care systems: Applying the bilinear pairing technology to ensure privacy protection and accuracy in data sharing," *IEEE Consum. Electron. Mag.*, vol. 7, no. 4, pp. 65–71, Jul. 2018.

[9] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. K. Ganapathiraju, "Everything you wanted to know about smart health care: Evaluating the different technologies and components of the Internet of Things for better health," *IEEE Consum. Electron. Mag.*, vol. 7, no. 1, pp. 18–28, Jan. 2018.

[10] W.-R. Yang, C.-S. Wang, and C.-P. Chen, "Motion-pattern recognition system using a wavelet-neural network," *IEEE Trans. Consum. Electron.*, vol. 65, no. 2, pp. 170–178, May 2019.

[11] 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.

[12] T. Xin, B. Guo, Z. Wang, M. Li, Z. Yu, and X. Zhou, "FreeSense: Indoor human identification with Wi-Fi signals," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Washington, DC, USA, 2016, pp. 1–7.

[13] X. Li, S. Li, D. Zhang, J. Xiong, Y. Wang, and H. Mei, "Dynamic-MUSIC: Accurate device-free indoor localization," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput. (UbiComp)*, NewYork, NY, USA, 2016, pp. 196–207.

[14] *Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, IEEE Standard 802.11, Mar. 2012.

[15] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Predictable 802.11 packet delivery from wireless channel measurements," in *Proc. ACM SIGCOMM Conf.*, 2010, pp. 159–170.

[16] J. Zhang, B. Wei, W. Hu, and S. S. Kanhere, "WiFi-ID: Human identification using WiFi signal," in *Proc. IEEE Int. Conf. Distrib. Comput. Sens. Syst. (DCOSS)*, Washington, DC, USA, 2016, pp. 75–82.

[17] Y. Zeng, P. H. Pathak, and P. Mohapatra, "WiWho: WiFi-based person identification in smart spaces," in *Proc. 15th Int. Conf. Inf. Process. Sens. Netw.*, Vienna, Austria, 2016, pp. 1–12.

[18] 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 20th Annu. Int. Conf. Mobile Comput. Netw. (Mobicom)*, Maui, Hawaii, USA, 2014, pp. 617–628.

[19] 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 21st Annu. Int. Conf. Mobile Comput. Netw. (Mobicom)*, Pairs, France, 2015, pp. 65–76.

[20] H. Abdelnasser, M. Youssef, and K. A. Harras, "WiGest: A ubiquitous WiFi-based gesture recognition system," in *Proc. IEEE Conf. Comput. Commun.*, Kowloon, Hong Kong, 2015, pp. 1472–1480.

[21] 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. 2019.

[22] D. Zhang, H. Wang, Y. Wang, and J. Ma, "Anti-fall: A non-intrusive and real-time fall detector leveraging CSI from commodity WiFi devices," in *Proc. Int. Conf. Smart Homes Health Telematics*, Geneva, Switzerland, 2015, pp. 181–193.

[23] Y. Wang, K. Wu, and L. M. Ni, "WiFall: Device-free fall detection by wireless networks," *IEEE Trans. Mobile Comput.*, vol. 16, no. 2, pp. 581–594, Feb. 2017.

[24] S. Palipana, D. Rojas, P. Agrawal, and D. Pesch, "FallDeFi: Ubiquitous fall detection using commodity Wi-Fi devices," *Proc. ACM Interact. Mobile Wearable Ubiquitous Technol.*, vol. 1, no. 4, pp. 155–280, Dec. 2017.

[25] S. Sardy, P. Tseng, and A. Bruce, "Robust wavelet denoising," *IEEE Trans. Signal Process.*, vol. 49, no. 6, pp. 1146–1152, Jul. 2001.

[26] A. Murad and J.-Y. Pyun, "Deep recurrent neural networks for human activity recognition," *Sensors*, vol. 17, no. 11, p. 2556, Nov. 2017.

[27] M. Inoue, S. Inoue, and T. Nishida, "Deep recurrent neural network for mobile human activity recognition with high throughput," *Artif. Life Robot.*, vol. 23, no. 2, pp. 173–185, Jun. 2018.

[28] U. Md Zia, W. Khaksar, and J. Torresen, "Activity recognition using deep recurrent neural network on translation and scale-invariant features," in *Proc. IEEE Int. Conf. Image Process.*, Athens, Greece, 2018, pp. 475–479.

[29] X. Yang and Y. Tian, "Super normal vector for human activity recognition with depth cameras," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 5, pp. 1028–1039, May 2017.

[30] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1192–1209, 3rd Quart., 2013.

[31] K. Gunadi, L. Liliana, and J. Tjitrokusmo, "Fall detection application using Kinect," in *Proc. Int. Conf. Soft Comput. Intell. Syst. Inform. Technol.*, Kuta, Indonesia, 2017, pp. 279–282.

[32] C. Nadee and K. Chamnongthai, "Multi sensor system for automatic fall detection," in *Proc. Asia–Pac. Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA)*, Hong Kong, China, 2015, pp. 930–933.

[33] Y. Li, K. C. Ho, and M. Popescu, "A microphone array system for automatic fall detection," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 5, pp. 1291–1301, May 2012.

[34] H. Rimminen, J. Lindstrom, M. Linnavuo, and R. Sepponen, "Detection of falls among the elderly by a floor sensor using the electric near field," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 6, pp. 1475–1476, Nov. 2010.

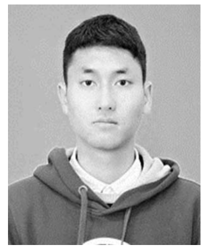
[35] A. R. Al-Ali, I. A. Zualkernan, M. Rashid, R. Gupta, and M. Alikarar, "A smart home energy management system using IoT and big data analytics approach," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 426–434, Nov. 2017.

[36] M. Afzaal, M. Usman, and A. Fong, "Tourism mobile app with aspect-based sentiment classification framework for tourist reviews," *IEEE Trans. Consum. Electron.*, vol. 65, no. 2, pp. 233–242, May 2019.

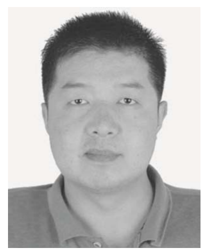
[37] S. Yousefi, H. Narui, S. Dayal, S. Ermon, and S. Valaee, "A survey on behavior recognition using WiFi channel state information," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 98–104, Oct. 2017.

[38] Y. Kim and H. Ling, "Human activity classification based on micro-doppler signatures using a support vector machine," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 5, pp. 1328–1337, May 2009.

[39] 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, Jan. 2011.



Jianyang Ding (Graduate Student Member, IEEE) was born in Henan, China. He received the B.E. degree from Xidian University, Xi'an, China, in 2018, where he is currently pursuing the Ph.D. degree in indoor positioning with the School of Telecommunications Engineering. His current research interests include wireless communication and signal processing.



Yong Wang (Member, IEEE) was born in Shaanxi, China. He received the B.S., M.E., and Ph.D. degrees from Xidian University, Xi'an, China, in 1997, 2002, and 2005, respectively, where he is currently a Professor with the State Key Laboratory of Integrated Services Networks. His research interests include full-duplex wireless communications and nonlinear predistorter technique.