WiBFall: A Device-Free Fall Detection Model for Bathroom

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Abstract. Falling detection, especially for elderly people in confined areas such as bathrooms is vital for timely rescue. The mainstream vision-based fall detection approaches however are not applicable here for strong privacy concerns. It is therefore necessary to design a privacy-preserving fall detection model that utilizes other signals such as widely existed Wi-Fi for this scenario. Existing Wi-Fi based fall detection approaches often suffer from environment noise removal, resulting in moderate accuracy. In this paper, a Wi-Fi based fall detection model for bathroom environment, termed WiBFall, is proposed. Firstly, time series CSI data is reconstructed into a two-dimensional frequency energy map structure to obtain more feature capacity. Secondly, the reconstructed CSI data stream is filtered by Butterworth filter for noise elimination. Finally, the filtered data is used to train the established deep learning network to get a high accuracy fall detection model for bathroom. The experimental results show that the WiBFall not only reaches a fall detection accuracy of up to 99.63% in home bathroom environment, but also enjoys high robustness comparing to other schemes in different bathroom settings.

Keywords: Fall detection · Channel state information · Deep neural network

1 Introduction

At present, falling has become the leading cause of death due to injury for people over 65 years old in China [1]. Among many falling scenes, bathroom poses a serious threat to the life and health of the elderly due to the high privacy and strong closure, resulting in poor timely assistance after a fall. Therefore, how to achieve efficient and convenient fall detection in such scenarios has attracted widespread attention from academia and industry.

Generally speaking, fall detection methods mainly include computer vision, wearable devices and so on, but these methods have some limitations in practical use. Computer vision is susceptible to illumination and obstruction and has poor privacy, while wearable devices are expensive and inconvenient to install and carry, so neither of which is suitable

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for fall detecting in the bathroom scene. In contrast, Wi-Fi perception technology has become an emerging direction of perception research with its advantages of low cost, contactless, non-light influence, and good privacy. Wi-Fi sensing technology works by sensing the disturbance of the signal caused by human movements. In 2000, Bahl et al. [2] first proposed Radar, a system which uses Wi-Fi signals for sensing, and realized the use of Wi-Fi signal strength information (Received Signal Strength, RSS) for indoor positioning. Subsequently, RSS gradually became the signal carrier in the Wi-Fi perception field for perception recognition. Since RSS can only realize coarse-grained perception, people had been looking for signal carriers that can realize fine-grained perception. In 2011, Halperin et al. [3] released the CSI tool to extract Channel State Information (CSI) from commercial network cards, which greatly facilitates the process of obtaining CSI information from commercial Wi-Fi devices, and also makes using more to perceive has become a new research hotspot. Nowadays, fine-grained CSI has become the mainstream carrier in the Wi-Fi perception field, and CSI-based gait recognition [3–5], sleep monitoring [6–8], fall detection [9–13], etc. have appeared.

In the existing fall detection research based on Wi-Fi perception, traditional machine learning algorithms are mostly used. They have problems such as insufficient feature extraction and complex extraction process, which affect the accuracy of model recognition. In addition, the existence of multipath effects makes the recognition model less robust. Existing researches on fall detection mainly focus on indoor scenes such as meeting rooms and bedrooms, while there are few studies on fall detection in bathroom environment. To this end, this article proposes a fall detection model suitable for bathroom environments using Wi-Fi perception technology and deep learning method, hoping to contribute to the bathing safety of people, especially for the elderly. The main contributions of this paper are summarized as follows.

(1) The one-dimensional time series data is reconstructed into a two-dimensional multi-carrier data stream, which is filtered by Butterworth filter. In this way, the method enhances the data feature capacity while remove environmental noise effectively.
(2) A lightweight fall detection model, WiBFall, based on deep learning, was proposed for bathroom scenes with an accuracy of 99.63%. The experimental results show that, compared with the existing similar algorithms, WiBFall has higher accuracy.

2 Related Work

According to the types of wireless signals, the existing fall detection work can be divided into three categories: radar-based, infrared-based, and Wi-Fi-based.

2.1 Radar-Based

The radar emits electromagnetic waves to irradiate the human body's actions and receives the echoes, thus collecting the unique radar characteristics of the human body falling. Jin et al. [14] propose mmFall - a novel fall detection system, which comprises of millimeter-wave (mmWave) radar sensor to collect the human body's point cloud along with the body centroid, and a Hybrid Variational RNN Auto Encoder (HVRAE) to compute the anomaly level of the body motion based on the acquired point cloud. Experimental results show that the detection accuracy rate is 98% in 50 falls. Su et al. [15] proposed a fall detection method that integrates the fall characteristics collected by two Doppler radars installed in the center of the ceiling and the horizontal position of the torso. Experimental results show a 10-fold reduction in false alarm rate and a 100% correct detection rate compared to the radar at the ceiling position alone.

2.2 Infrared-Based

Infrared-based fall detection uses infrared to image the human body, which can meet the perception and recognition in low-light scenes. Chen et al. [16] proposed a fall detection method based on support vector machine-based infrared-ultrasonic sensor fusion, and experimentally studied the fall actions of standing, sitting, bending, falling forward, and falling sideways to simulate the daily activities of the elderly. Experimental results show that for discrete data recordings, the accuracy rate of fall detection reaches 96.7%. For continuous data recordings, the accuracy rate of fall detection reaches approximately 96.7%. Fan et al. [17] proposed a fall detection system using infrared array sensors and multiple deep learning methods (LSTM, GRU, etc.) is proposed.

2.3 Wi-Fi-Based

At present, there have been some research results of fall detection using Wi-Fi sensing technology. The WiFall [9] system uses amplitude transformation of channel state information in Wi-Fi signals, and then uses SVM and random forest algorithms to achieve single-person fall detection with accuracy rates of 90% and 94%, respectively. RT-Fall [10] uses the phase and amplitude of the channel state information to extract more effective features, achieving 100% accuracy and better than WiFall. Fallsense [11] uses the amplitude transformation of the channel state information and then uses the dynamic time warping algorithm to achieve 95% fall detection accuracy, and the complexity is lower than WiFall. Ramezani et al. [12] proposed a new type of Sensing-Fi system that uses Wi-Fi channel state information (CSI) and ground-mounted accelerometers to detect floor vibrations for fall detection. The test results showed that the fall detection accuracy rate of the system is 95%. PALIPANA et al. [13] proposed a CSI fall detection method, which used the traditional short-time Fourier transform (STFT) to extract time-frequency features, and used sequential forward selection algorithm to pick out features that were resilient to environmental changes. Test results showed that the system had a detection accuracy of 93%.

Compared with the first two wireless sensing technologies, Wi-Fi-based sensing technologies are more versatile and easier to deploy. However, the current research on fall detection based on Wi-Fi sensing technology is mainly focused on the daily life environment. There is no effective research result for fall detection in the special environment like bathroom. Therefore, this paper proposes a method for fall detection in bathroom scene using Wi-Fi sensing technology.

3 Preliminaries

3.1 Problem Definition

Under the premise that the Wi-Fi signal covers the bathroom environment, a fall of the human body will cause disturbance to the Wi-Fi signal, which in turn causes a change in channel state. The schematic diagram of bathroom fall detection based on Wi-Fi perception is shown in Fig. 1.

Fig. 1. Schematic diagram of bathroom fall detection

In widely used OFDM systems, CSI provides more multipath information than RSS, with different signal strength and phase in different subcarriers [18, 19]. Commercial Wi-Fi devices are usually Multiple Input Multiple Output (MIMO), and the CSI data of each antenna pair contains multiple subcarrier information [20]. If we use Nt and Nr to represent the transmitting and receiving antennas, and m as the number of subcarriers for each antenna pair, CSI can be constructed via the following equation.

$$H(f_k) = ||H(f_k)||e^{j\angle H(f_k)}k \in [1, K]. \tag{1}$$

where $H(f_k)$ is the complex number representation of the k-th subcarrier, $||H(f_k)||$ and $\angle H(f_k)$ represents the amplitude and phase respectively, and K is the number of subcarriers. Since the phase information is susceptible to interference, only amplitude information is used in this paper.

3.2 Feature Reconstruction

Accurate feature characterization methods can obtain features with a high degree of recognition, which in turn can improve the recognition performance of the model. Therefore, based on the feature reconstruction strategy of the previous frequency energy map [21], this paper selects Butterworth filter to remove noise. The complete feature reconstruction process is shown in Fig. 2.

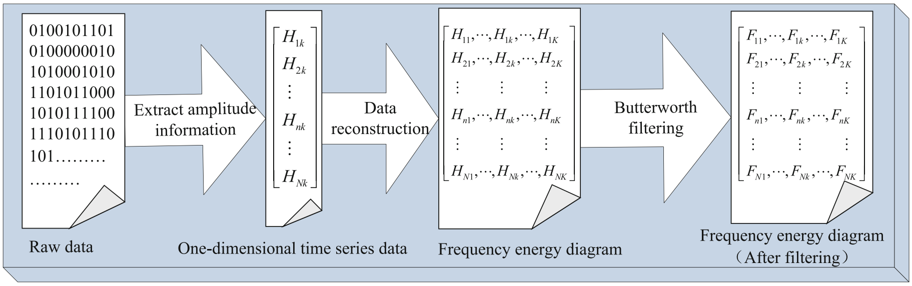


Fig. 2. Feature reconstruction process

Frequency Energy Diagram. In the existing Wi-Fi perception research, most of the CSI sequence is represented by one-dimensional data shown in formula (2) [22,23]

$$H_k = \left[H_k^1, \ldots, H_k^n, \ldots, H_k^N\right]. \tag{2}$$

where H_k represents the amplitude sequence value in the N time period, and H_k^n represents the amplitude of the k-th subcarrier at time n. The one-dimensional time sequence processing method can only extract the characteristic information in the sub-carriers and the disturbance of different sub-carrier amplitudes by human behavior is different [24, 25]. Therefore, in order to extract the characteristic information within and between subcarriers at the same time, this paper reconstructs the one-dimensional time series data in the N time period into the two-dimensional matrix form shown in formula (3), where Hnk is the CSI amplitude value of the k-th subcarrier at time n.

$$X = \begin{bmatrix} H_H, \ldots, & H_{1k}, \ldots., & H_{1k} \\ H_{21} & H_{2K} & H_{2K} \\ \vdots & \vdots & \vdots \\ H_{n1}, \ldots, & H_{nk}, \ldots, & H_{nk} \\ \vdots & \vdots & \vdots \\ H_{N1}, \ldots, & H_{NK}, \ldots, & H_{NK} \end{bmatrix} \tag{3}$$

According to the data reconstruction method shown in formula (3), the corresponding frequency energy map can be generated after proper coloring design.

Butterworth Filtering. The raw selected data may contain abnormal samples caused by background noise or hardware glitches and thus should be filtered [26]. The dynamic noise source of the bathroom scene is mainly shower water, and the frequency response curve of the passband of the Butterworth filter is smooth [10], it can effectively filter the bathroom noise. The signal fluctuations caused by human behaviors usually are at the low-frequency band, while the background noises induced by hardware and environment tend to focus on the high-frequency band [27]. Therefore, this article chooses it as the filtering method. In previous works, we found that the frequency f of CSI change caused by falling action is 10–40 Hz [10, 28]. In this article, the sampling frequency Fs of the

CSI data is set to 1000 Hz, and the frequency of the CSI time series change is set to 40 Hz. The construction process of the Butterworth filter is as follows:

First, calculate the cut-off frequency w_c by Eq. (4).

$$w_c = \frac{2 \times f}{F_s} \tag{4}$$

Secondly, the butter function in Matlab is called to calculate the coefficients b and a of the Butterworth filter, as shown in formula (5), where N is the order of the filter, *low* represents low-pass filtering, w_c represents the cut-off frequency. Then b and a represent the coefficient vectors of the numerator and denominator polynomials of the Butterworth filter system function.

$$[b, a] = butter\left(N, w_c, ' low'\right); \tag{5}$$

Finally, we use the filtfilt function in Matlab to construct a Butterworth filter, as shown in formula (6), where *Signal* represents the reconstructed perceptual information, and *Signal_Filter* represents the filtered perceptual information.

$$Signal\_Filter = filtfilt(b, a, Signal); \tag{6}$$

4 System Design

The flow chart of WiBFall is given in Fig. 3. There are mainly two modules in the process.

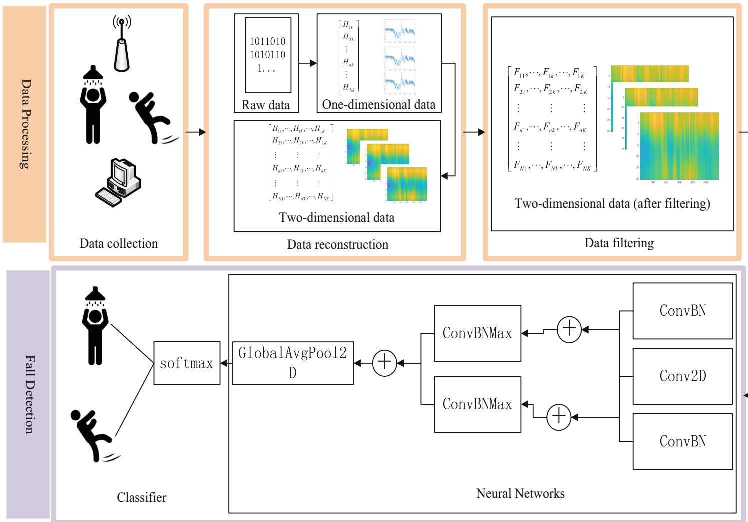


Fig. 3. System overview

Data Processing module mainly collects and preprocesses the perception data, including data collection, data reconstruction and data filtering.

Fall Detection module inputs the processed perception data into a designed neural network model to extract features. Then the detection result is calculated through the SoftMax layer. After training with a large amount of effective data, WiBFall can realize effective fall detection in bathroom scenes.

Table 1. The structure table of the neural network for fall detection

Layer	Output shape	Param	Connected to
input_1	[(None, 30, 400, 3)]	0	
conv2d_1	(None, 30, 400, 64)	640	input_1[0][0]
conv2d_5	(None, 30, 400, 64)	640	input_1[0][0]
batch_normalization	(None, 30, 400, 64)	256	conv2d_1[0][0]
batch_normalization_4	(None, 30, 400, 64)	256	conv2d_5[0][0]
conv2d_2	(None, 30, 400, 64)	12352	batch_normalization[0][0]
conv2d_6	(None, 30, 400, 64)	12352	batch_normalization_4[0][0]
batch_normalization_1	(None, 30, 400, 64)	256	conv2d_2[0][0]
batch_normalization_5	(None, 30, 400, 64)	256	conv2d_6[0][0]
conv2d_3	(None, 30, 400, 64)	36928	batch_normalization_1[0][0]
conv2d_7	(None, 30, 400, 64)	36928	batch_normalization_5[0][0]
conv2d	(None, 30, 400, 32)	128	input_1[0][0]
batch_normalization_2	(None, 30, 400, 64)	256	conv2d_3[0][0]
batch_normalization_6	(None, 30, 400, 64)	256	conv2d_7[0][0]
Concatenate	(None, 30, 400, 96)	0	conv2d[0][0] batch_normalization_2[0][0]
concatenate_1	(None, 30, 400, 96)	0	conv2d[0][0] batch_normalization_6[0][0]
conv2d_4	(None, 30, 400, 32)	27680	concatenate[0][0]
conv2d_8	(None, 30, 400, 32)	27680	concatenate_1[0][0]
batch_normalization_3	(None, 30, 400, 32)	128	conv2d_4[0][0]
batch_normalization_7	(None, 30, 400, 32)	128	conv2d_8[0][0]
max_pooling2d	(None, 15, 200, 32)	0	batch_normalization_3[0][0]
max_pooling2d_1	(None, 15, 200, 32)	0	batch_normalization_7[0][0]
concatenate_2	(None, 15, 200, 64)	0	max_pooling2d[0][0] max_pooling2d_1[0][0]
gap2d	(None, 64)	0	concatenate_2[0][0]
dense	(None, 3)	195	gap2d[0][0]

4.1 Network Structure

This paper builds a neural network module for fall detection based on the Keras Platform. For the methodology of this paper, it takes the filtered two-dimensional frequency energy map as input, and combines the characteristics of wireless sensing signals in bathroom scenes with the basic theory of image convolution. The sliding step length determines the overlap percentage between adjacent sliding windows, which increases the CSI data volume and as a result, enhances movement feature extraction [7]. Considering the instantaneous nature of the fall action, the sliding window size was set to 400 ms and the sliding step size to 100 ms when generating the frequency energy map. The detailed model structure is shown in Table 1.

4.2 Classifier

According to the problem definition, the input of the model is a filtered frequency energy map, denoted by X, and the output is a action category, denoted by Y. In a typical classifier, the sigmoid function is usually used for two classifications, while the SoftMax function is usually used for multiple classifications. Therefore, this article chooses the SoftMax function to distinguish the action categories. The expression formula is as follows:

$$p(y|X) = \frac{\exp(z_y)}{\sum_{y=1}^{r} \exp(z_y)}, y \in [1, \mathrm{r}] \tag{7}$$

In the formula, r represents the number of categories of y, z_y represents the result of global average pooling, and $P(y|X)$ represents the posterior probability of class y predicted by the model input X.

5 Experimental Results

In order to make the model more convincing, this paper designs comparative experiments using different filtering methods and models to comprehensively evaluate the recognition effect of the model, and analyze the experimental results in detail.

5.1 Experimental Setting

After investigation, there is no public Wi-Fi sensing bathroom fall data set at home and abroad currently. In order to verify the correctness of the model, this paper chooses the home bathroom environment for fall detection data collection. The actual environment of the home bathroom is shown in Fig. 4.

The experimental equipment is composed of TP_LINK AC1750 wireless router as transmitter (T) and ThinkPad X201 portable computer terminal as receiver (R) equipped with Intel 5300 802.11n Wi-Fi NIC network card. Among them, the opensource CSI Tool is installed on the receiving end device, which can realize real-time collection of CSI information. The transmitter has one antenna and the receiver has three antennas, forming three pairs (1×3) antennas, each pair containing 30 subcarriers. Therefore, the

Fig. 4. The exterior (left) and interior (right) of bathroom

data files collected by each receiving end contain 90 ($1 \times 3 \times 30$) sub-carrier CSI data [29].

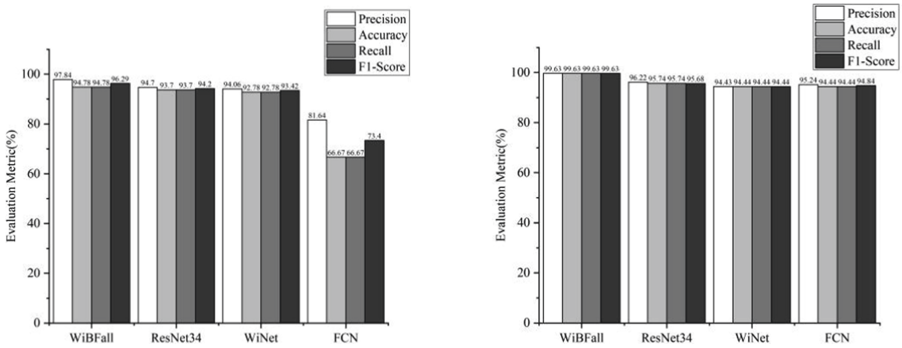
In the home bathroom environment, a total of 5 volunteers' normal bathing and falling motion CSI data and empty environment data were collected. The age of the volunteers is between 18 and 30, which can fully guarantee the diversity and representativeness of the data. In the data collection stage, one volunteer was invited to perform normal bathing and falling movements at a time. Due to the instantaneous nature of the falling action, each data acquisition was performed for 1 s and repeated 60 times to accurately obtain its characteristics.

For the collected data set, manually add no-action, shower, waterfall three action labels, and we divide them into training set and test set according to the ratio of 4:1.This experiment is based on a data set built by ourselves. The model focuses on the classification of predefined activities. There is no need to train different models for different people.

5.2 Comparison of Different Models

To verify the effectiveness of the model for fall detection in the home bathroom scene, the data before and after filtering was compared, and the classic methods like WiNet [21], FCN [30] and ResNet34 [31] were selected for model selection. WiBFall was compared with the experimental model and the results are shown as follows (Fig. 5).

It can be seen from the graphs that the area of the home bathroom environment is small, the signal propagation path is relatively simple, and there are fewer obstacles. On the dataset before filtering, the WiBFall model performed well, with a recognition accuracy of 94.78%. The frequency energy graph containing time and space information is used to accurately describe the action characteristics, but there is still some noise interference information that has not been removed. Therefore, to further improve the accuracy of the model, a Butterworth filtered frequency energy graph was introduced. Experimental results show that the model performs better on the filtered data set, and the recognition accuracy rate reaches 99.63%.



a. Before filtering   b. After filtering

Fig. 5. Comparison of evaluation indicators of different models

6 Conclusions

WiBFall proposed in this paper is a contactless fall detection model for bathroom. There are mainly two modules in WiBFall, data processing module and fall detection module. The filtered frequency energy map is used to reconstruct the CSI data to contain more kinds of features. Deep learning method is employed in fall detection module to accurately extract the features of target action. The experimental results show that t WiBFall has a high accuracy rate for fall detection in home bathroom scenes.

Future research work will start from the following aspects: (1) we will try to extract effective phase difference information to improve the accuracy of WiBFall. (2) We will enhance WiBFall's robustness to make it can adapt to different bathroom scenes.

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