基于 WiFi 的室内老人跌倒检测

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Fall Detection for Elders in Indoor Environment using WiFi Signals

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Abstract

Nowadays, China has become the country with the largest aging population. The increasing proportion of the elders inspires the development of related industries. Falling is extremely dangerous for the elders. Thus, it is of vital importance to detect it and send an SOS signal immediately when an elder falls.

Existing methods in fall detection include vision based, wearable sensor-based, ambinent device-based techniques. However, there are drawbacks in these existing methods. The video detection cannot guarantee the privacy of the elderly. Monitoring the changing of the environment requires high cost and its accuracy may be degraded by similar phenomena like strenuous exercise or a heavy object dropping down. The wearable sensors need to be worn all the time which is uncomfortable. In this paper, widely deployed Wi-Fi system is used for detecting a fall. It has little influence on the daily life of the elderly and can make up the drawbacks of the methods above.

Because human movements would affect wifi signal propagation, we could detect human behaviors, like falling, through wifi. We firstly extract Channel State Information(CSI) from the original wifi signals collected. After performing noise and dimensionality reduction via Principal Component Analysis (PCA), the characteristic data of the Wi-Fi signal is obtained. Then, the detection model is trained using Recurrent Neural Networks (RNN) based on the PyTorch deep learning. Finally, fall detection is achieved automatically based on the trained model. For further improvement of its function, a strategy based on Random State Reset (RSR) and RNN is brought up in this paper, called RSR-RNN.

Related experiments have been conducted to verify the feasibility of the method developed in this paper. Six types of fall scenarios are designed according to the data collected under different situations. The results of the experiments show that the RNN model can detect a fall effectively at an accuracy of 84.67%. The average accuracy of detection is further increased to 85.83% using RSR-RNN, which indicates that this strategy is effective.

Keywords: Fall detection, Activity recognition, Wi-Fi signal, Recurrent Neural Networks, Random State Reset

Catalogue

1. Introduction

1.1. Background and Significances

China has entered an aging society since the end of the twentieth century. According to statistics, the number of people over 60 reached 222 million in 2015, accounting for 16.15% of the population. It is expected that the aging population will reach 248 million and its proportion will rise to 17.17% by the year 2020. Among which, the population aged 80 and above will reach 3.067 million by then. By the year 2025, the population over 60 will reach 300 million. [1] Moreover, there are a large number of empty-nesters in China due to the implementation of the one-child policy. The number of the empty-nesters keeps increasing, but there is still a lack of solution about elderly care.

The elderly fall may be caused by multiple reasons, like the muscle weakness, balance disorder and stumble. It usually happens randomly in daily life and gives a big threat to the health and safety of the elderly. If there is no immediate treatment when falls occur, it may lead to the shock, paralysis, or even death of the elderly, especially those living alone.

Therefore, the technology of detecting the fall and sending the SOS signal can help reduce the health concern of the aged population and increase their independence. The significances of this research are introduced as below:

(1) It is beneficial to the elderly and their families.

According to the data published by U.S. Centers for Disease Control and Prevention (CDC) in 2006, there was 30% of elderly American aged 65 and above who had fallen. With the rapid growth of the aging population in America, the number of death directly caused by the falls increased from 13700 in 2003 to 15802 in 2006. The data from Disease Surveillance Points System (DSPS) shows that the falls resulted in the death of 49.56 of 100 thousand men and 52.80 of 100 thousand women in 2006 in China [2]. It can be seen from the data that the falls occur frequently and have become one of major causes of disability and death of the elderly. Therefore, the fall detection can not only help to avoid the death caused by the fall but also release the corresponding anxiety.

(2) It can help to reduce the national medical expenditure.

In America, the medical cost spent on the falls was over 20 billion dollars in 2002 and is estimated to reach over 32 billion dollars in 2020. In Australia, this cost reached 86 million Australian dollars in 2001 and will rise to 181 million Australian dollars in 2021 [2]. The immediate detection will reduce the medical expenditure on treatment and nursing effectively.

1.2. State of the Art

1.2.1. Related Works in Fall Detection

Fall detections for elders has been taken seriously in both health and academic industry. Analyzing the advantages and drawbacks of the existing technologies is necessary for further researches. N. Noury [3], X. Yu [4] and other researchers has summarized the principles and methods since 1990s. Fall detection technologies can be mainly divided into three categories: vision based, ambient device based and wearable sensor based.

Vision based fall detection systems capture images or videos using cameras installed and recognize human activities through algorithms and classification models. C. Yao et al [5] proposed a monitoring approach using an imbedded system and computer vision. N. Thome et al [6] detected the human behavior by Hierarchical Hidden Markov Model (HHMM) but the algorithms used were complicated. High brightness was required because cameras fails to work in darkness. Moreover, it required implementing the indoor cameras which may lead to the video given away and infringing user privacy.

Ambient device based fall detection techniques try to use the ambient information, including noises, floor vibration and infrared sensing data, to detect the behavior. For example, P. J. Rajendran [7 designed a fall detector according to floor vibration; Y. Li et al [8] detected the falls by distinguishing the sound. However, several special devices is required to be implanted indoors. The devices can be easily misled by a heavy object dropping down or strenuous exercise which can have similar influences with falling.

Wearable sensor based system recognizes human activities by sensors implemented on wearable devices such as belts, insoles, and watches. There are many types of wearable sensors including the gyroscope sensor [9], the pressure sensor [10] and the integrated accelerometer in a smartphone [11]. Nevertheless, it is hard for the elderly to wear those devices all the time, especially in the private environments like bathroom or bedroom.

1.2.2. Activity Recognition Using Wi-Fi Signals

Although human activity recognition using wireless network is a relatively new topic, there are already various related researches at home and abroad. The Received Signal Strength (RSS) of the Wi-Fi signal has been used for locating a person in previous research. P. Bahl et al [12] developed the indoor localization of people using RSS in 2000; S. Sen et al [13] divided the room into 1m x 1m boxes and then compared the RSS information with it of the Wi-Fi signals in the built database to localize users to the ccurate spot. However, RSS information from multiple data packages can easily be influenced by the paths and the obstructions so its accuracy is not impressive. Hence, Channel State Information (CSI) of the Wi-Fi signal has been harnessed instead. It contains the information of subcarriers and is sensitive to environments, providing more specific and more accurate information. Y. Liu et al [14] from Tsinghua University developed the indoor wireless localization based on CSI.

The activity recognition based on Wi-Fi system is a newly emerging research compared with the localization. Q. Pu et al [15] from the University of Washington are the first who identified various movements and gestures by Wi-Fi signal; F. Adib [16] used Wi-Fi signal to recognize activities behind walls; E-eyes [17] applied novel matching algorithms to compare the amplitude measurements against known profiles of the human activities; M. Ni et al [18] from Hong Kong University of Science and Technology monitored the sleep and sound by Wi-Fi signal.

A device-free fall detection by wireless networks called WiFall [19] has been proposed by C. Han et al in 2014. It classifies human activities to detect the fall based on the characteristics of CSI on IEEE 802.11n but there are still limitations. Firstly, it only analyzed the relationship between the distribution of CSI amplitude and human activities. Secondly, it can only distinguish the fall from four kinds of activities but the real movements are continuous and complicate, so it is not a practical solution. After that, Q. Zhang et al. [20] from Peking University further studied the correlation between CSI and human behaviors in 2016. They proposed the method based on the phase and phase difference of CSI to identify the unusual activities (the falls and similar activities), then compared both amplitudes and phases to distinguish the falls from the similar activities. It can be used for detecting the falls in real life. The related research based on it had been done by the team led by D. Zhang [21] from 2016 to 2017. They identified the phase difference of CSI as a better base signal than the widely used amplitude for the fall detection; they found the sharp power profile decline pattern of the fall in the time-frequency domain. It is currently the most comprehensive work of fall detection based on Wi-Fi signal.

In conclusion, although the fall detection has been taken seriously by various research institutions and companies at home and abroad, there is not an associated product that can detect falling conveniently and accurately in the daily life. Besides, compared with the widely used video analyzation and wearable sensors, the fall detection technology based on Wi-Fi system is still in its infancy and needs to be studied deeply in the future.

1.3. Outline of the Paper

There are five chapters in this paper, organized as follows.

The first chapter introduces the background and the significance of the research. It reviews state of the art of fall detection and activity recognition based on Wi-Fi system, then presents the outline of this paper.

The second chapter describes the characteristics of falls and the automatic detection. Analyze the internal and external causes for falling and classify the falls according to the movements before and after. The basic ideas of the automatic fall detection are also introduced.

The third chapter mainly talks about the deep neural networks (DNN) model based on Wi-Fi. Build the basic frame of the indoor fall detection in this paper. Descibe the feature extraction and dimensionality reduction of the Wi-Fi signal. The fall detection based on Recurrent Neural Networks (RNN) model is brought up and further developed to fall detection based on Random State Reset (RSR)-RNN.

The results of the experiments are analyzed in the fourth chapter. Related experiments are designed to prove the feasibility and effectivity of the research. The specific parameter setting, data preprocessing and training process is introduced.

The fifth chapter draws the conclusion and talks about future works.

2. Characteristics of Fall and Automatic Detection

2.1. Causes of Falls and Classification

There are multiple causes for the elderly falls including the poor eyesight, cardiovascular disease, imbalance of the body, side effects of long-term medication and uneven road surface. These causes can be roughly divided into internal and external ones.

The internal stability of human body relies on the coordination of sense organs, central nerves, and skeletal muscles [22]. The internal causes of the fall are as follows:

(1) Degeneration of sense organs: the degeneration of the vestibule may cause wobble, dizziness and easy fall.

(2) Central nervous system diseases: the stability of human body can be influenced by central nervous system diseases (hydrocephalus, stroke, etc.) and the drugs acting on the central nerves (hypnotics, antipsychotics, antidepressants, etc.).

(3) Skeletal muscles disorder: osteoarthritis of the lower limbs results in gait abnormality and muscle disorder and then leads to the reduced ability for the spine to control the lower extremity. Foot diseases impact the sensitivity of the sole, leading to the fall [22].

(4) Poor eyesight: the eyesight of the elderly declines with age. Those common eye diseases among the elderly including cataract, macular and glaucoma can affect the vision seriously. Thus, the fall is likely to happen on the elderly with poor vision especially in the environment with dim light.

(5) Cardiac-cerebral vascular diseases: the common elderly cardiac-cerebral vascular diseases like hypertension, cardiopathy, and arrhythmia may result in the insufficient blood supply to the brain. The coma caused by cerebral anoxia makes the elderly easy to fall during walking even sitting. Besides, some medicines for the treatment of the diseases above can also affect the elderly, leading to the falls due to dizziness [23].

There are also a lot of external causes for the elderly falls which are mainly related to the surrounding environments like the smooth floors, uneven roads, obstructions, etc.

Researches show that there are 9% of the falls due to the loss of consciousness; 20% occur on the stairs; 24% happen when standing from a chair or bed; 13% happen while turning around or reaching for something; 12% occur during difficult movements, such as standing in a chair, running or climbing. Thus, it can be seen that the causes mentioned above match the real situations.

In this paper, several typical falls are classified as follows:

- The fall during walking
- The fall during standing
- The fall during sitting

The falls are also classified based on their directions:

- Forward
- Backward
- Sideways

The experiments introduced below are also based on these typical scenarios.

2.2. Basic Ideas of Automatic Fall Detection

The automatic detection means that the computer collects the signals from the sensors and extracts the corresponding features, and then uses the trained model to detect these features of the signals automatically. The overall flow chart is shown below.

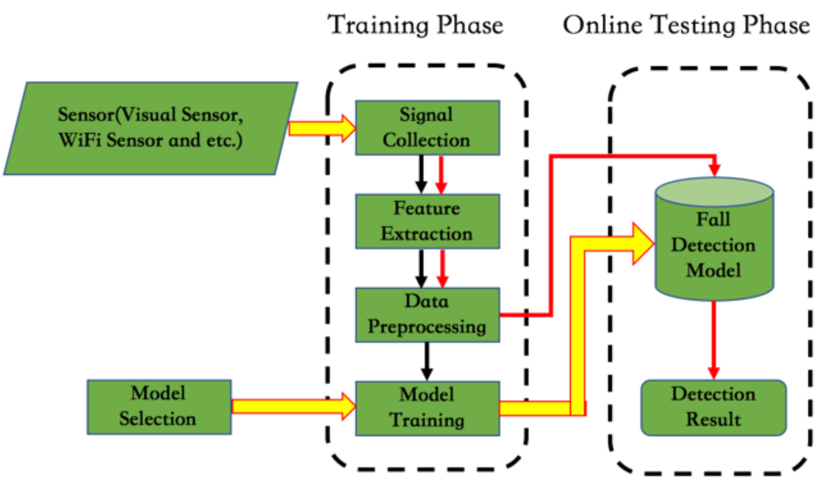


Fig 1. Overall flow chart of the automatic fall detection

The automatic detection is divided into two stages: training and detecting.

The training stage contains four steps:

Step 1, collect signal from the sensors while falling;

Step 2, extract features from the signals and preprocess the data;

Step 3, select a suitable fall detection model, such as the decision tree and the support vector machine;

Step 4, train the model by the preprocessed data of features.

The detecting stage contains three steps:

Step 1, collect signals of human behaviors in real time;

Step 2, extract features and preprocess the signal based on the same method used in the training stage;

Step 3, input the preprocessed data of features into the trained model to detect the fall online.

Based on the analyzation above, we have the following basic ideas:

Firstly, for data acquisition, we use the wireless card as the sensor to collect the Wi-Fi signals when a fall occurs because Wi-Fi is a widely used, contactless and privacy protected technology.

Secondly, for feature extraction, Principal Component Analysis (PCA) is used for reducing the dimensions of the high-dimensional original Wi-Fi data.

Moreover, for model selection, one of Deep Neural Networks (DNN) ——RNN is used because DNN has apparent advantages in representing the dynamic features of falling .

3. Deep Neural Networks Model Based on Wi-Fi

3.1. Feature Extraction and Preprocessing of Wi-Fi Signal

3.1.1. Wi-Fi Signal Propagation

The obstructions on the path including human body can impact the propagation of the Wi-Fi signal, which is the basic idea of the fall detection, as it shows in fig.2. There are a line-of-sight path and the other paths reflected by the ceilings, floors, and walls in the indoor environment. If a person moves in this room, the number of paths will increase.

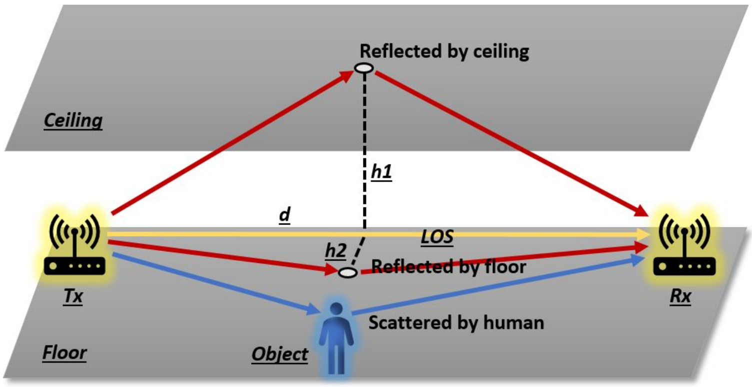


Fig 2. Wi-Fi signal propagation in the indoor environment

3.1.2. CSI Extraction and Preprocessing

CSI is an important and suitable feature for fall detection based on Wi-Fi signal according to the existing researches [19]、[21]. CSI is widely used in wireless communication, revealing the channel properties of a communication link. It describes the propagation of a signal from the transmitter to the receiver and represents the combined effect of, for instance, scattering, fading, and power decay with distance [25]. CSI contains the phase and the amplitude information for each subcarrier in the frequency domain.

CSI in the frequency domain can be shown as:

$$y = Hx + n \tag{1}$$

where y is the received vector, x is the transmitted vector, n is the noise vector, and H is the channel matrix. As noise is usually modeled as circular symmetric complex normal with $n \sim cN(0, S)$, H in the above formula can be estimated as:

$$\widehat{\mathrm{H}} = \frac{\mathrm{y}}{\mathrm{x}} \tag{2}$$

The Orthogonal Frequency Division Multiplexing (OFDM) system utilized in IEEE802.11 divides the channel into multiple orthogonal subcarriers in the frequency domain. It is a method of encoding digital data on multiple carrier frequencies. [26] CSI is represented at subcarrier level. CSI of a single subcarrier is represented by h.

$$\mathrm{h} = |\mathrm{h}|e^{jsin\theta} \tag{3}$$

where |h| is the amplitude and θ is the phase of each subcarrier.

The transmitter and the receiver of the Wi-Fi signal are equipped with antennas, respectively. The open source CSI tool is utilized to extract CSI from Wi-Fi signal [27] . Because there is a large amount of information and the change of each antenna in both phase and amplitude is similar, we have only analyzed the data from one of the receiving antennas.

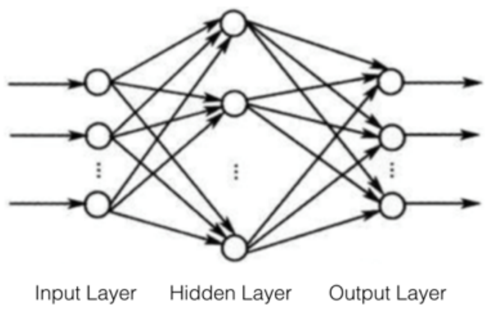
CSI of Wi-Fi signal is high dimensional with large data noise, so PCA is utilized to reduce the dimensions and remove the noise in the data. PCA is a statistical procedure for analyzing and simplifying the datasets. It is usually used for dimensionality reduction of a dataset while still retaining as much of the variance in the dataset as possible by concentrating much of the signal into the first few principal components. The first few principal components usefully capture the most significant features of the data while the later may be dominated by noise.

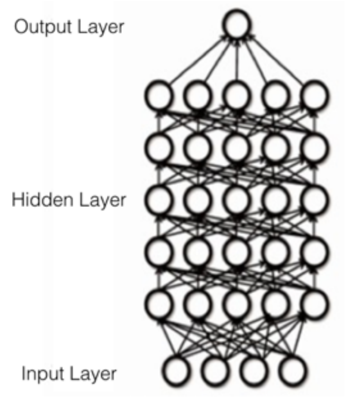
3.2. Wi-Fi Fall Detection Based on RNN

3.2.1. Neural network

As it shows in the fig.3(a), there are multiple units in all input layer, hidden layer and output layer of this three-layer neural network and each connection between units is assigned a weight. The input data to each unit in the input layer will be calculated by a weighting algorithm, and then the result will be inputted into the unit in hidden layer. Similarly, the output of the hidden layer will become the input of the output layer. Furthermore, the output of the output layer is the final output of this neural network. A neural network becomes a deep neural network when there are two more hidden layers, as it shows in fig.3(b).

The neural network can be used as a multi-classifier. The input and output are corresponding multi-dimensional vectors, representing the predicted probability of different varieties. The input is a Wi-Fi signal after dimensionality reduction by PCA and the output is a two-dimensional vector representing the predicted probability of the normal state and a fall.





(a) A typical structure of a neural network (b) The structure of a deep neural network

Fig 3. The structure of the neural network

3.2.2. Recurrent Neural Networks (RNN)

RNN is a typical deep neural network. Despite connections existing between layers, there is no connection between the units in the same layer in the conventional deep neural network. Hence, it is not suitable for processing time-ordered data. The input of the hidden layers of RNN includes not only the output of the last layer for the current moment but also the output of the same layer for last moment. This fully connected structure of layers can depict contextual dependency information well.

A typical RNN is shown below:

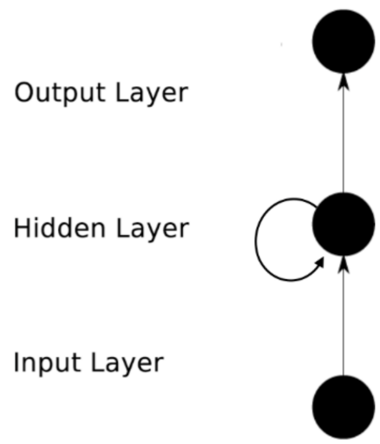


Fig 4. A typical structure of RNN

Unfold it:

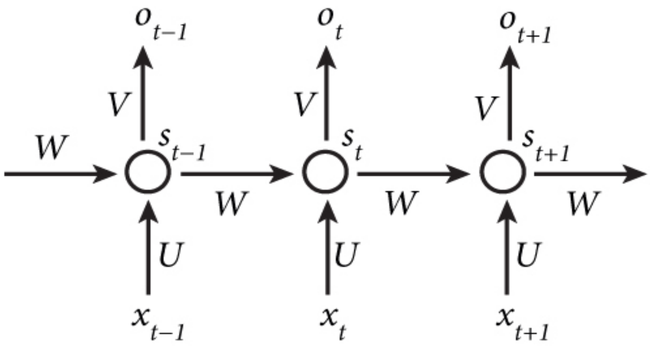


Fig 5. Unfolded RNN

As it shows in fig.5, x_{t-1}, x_t and x_{t+1} are inputs; o_{t-1}, o_t and o_{t-1} are outputs; s_{t-1}, s_t and s_{t+1} are outputs of the hidden layer; V,W and U represent the sharing parameters of different instants.

3.2.3. Frame of Fall Detection Based on RNN Model

The frame of the fall detection based on RNN is shown in fig.6.

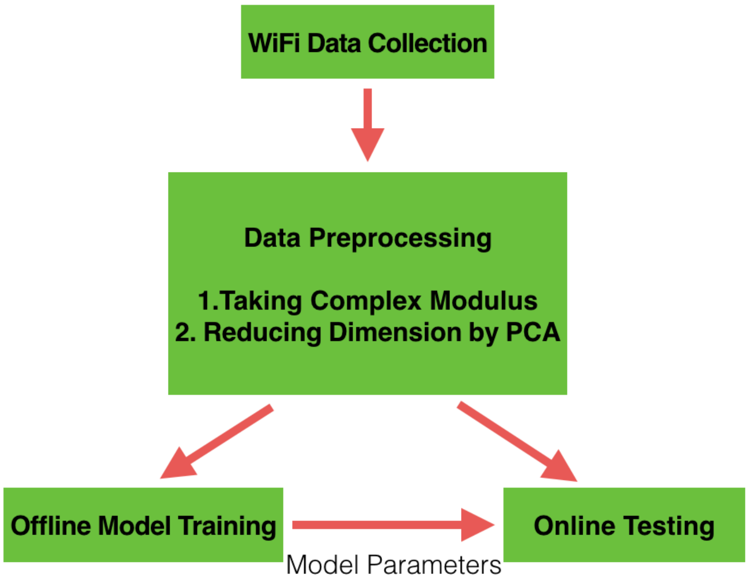


Fig 6. Frame of the fall detection based on RNN

There are four stages of this fall detection. Firstly, we gather the data by Wi-Fi, and then preprocess the collected data, which includes two steps: dimensionality reduction by PCA and de-nosing. After that, the preprocessed data is trained off-line as the input of RNN. Once the model training completed, the parameters from the off-line training and the RNN will be used for on-line prediction.

3.3. Fall Detection Based on RSR-RNN Model

3.3.1. Introduction of RSR

The state of the hidden unit S_t of the RNN at time t corresponds to not only the current input X_t but the state of the hidden unit S_{t-1} at last moment, as it shows in the formula (4).

$$S_t = f(S_{t-1}W + X_tU) \tag{4}$$

RNN can deal with long sequences because the state of the hidden unit can be passed in the same layer. However, when the behavior switching happens, the wrong history information contained in the hidden units will impact the behavior prediction.

RSR is adopted to reduce this influence of the wrong history information. At each moment t, there is a probability p for the state of the hidden unit S_{t-1} to be reset to zero, so the memorized information by RNN can be cleared to reduce the influence of wrong history information.

3.3.2. Frame of Fall Detection Based on RSR-RNN Model

The frame of the fall detection based on RSR-RNN model is shown in fig.7.

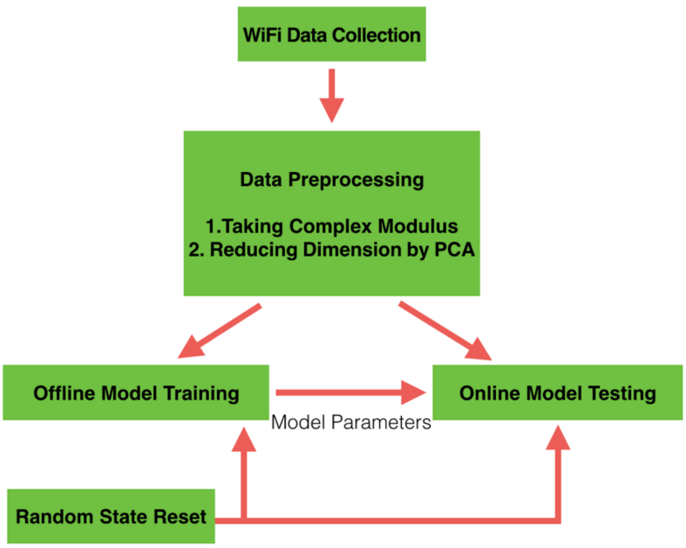


Fig 7. Frame of the fall detection based on RSR-RNN model

Compared with the frame based on RNN model, there is no difference in the stage of data acquisition and preprocessing. In off-line training of the model and the on-line prediction, there is a certain probability for the state of the hidden unit at last moment to be reset to zero after adopting RSR.

4. Results and Analysis

4.1. Experimental Design for Falling Related Behaviors

In this experiment, human behaviors are divided into two types—falling and the normal state. Fall contains the basic movement including forward falls, sideways falls, backward falls and unsteady falls. The normal state contains standing and walking towards different directions.

According to the daily life, six movement sequences composed of the behaviors above have been designed:

Movement Sequence A: walk forward –fall forward – stand up –walk forward

Movement Sequence B: walk forward –fall sideways – stand up –walk forward

Movement Sequence C: walk backward –fall backward – stand up –walk forward

Movement Sequence D: stand –fall forward – stand up –walk forward

Movement Sequence E: stand –fall backward – stand up – sit down

Movement Sequence F: sit on chair –fall sideways – stand up – sit down

4.2. Construction of Data Acquisition Platform and Experimental Setting

The specialized data acquisition platform and experimental environment have been built for research, as it shows in fig.8.

There are five parts for the data acquisition platform: the transmitter of Wi-Fi signals, the receiver of Wi-Fi signals, a PC for data recording, protection pad and a camera.

The PC for data acquisition is Toshiba laptop equipped with Intel 5300 wireless card, three antennas and Ubuntu 14.04 system; the router as the source of the signal is TP-LINK TL-WR742N, supporting 802.11n; the protection pad consists of 2 1m x 2m sponge pads to protect people when simulating the falls, located between the transmitter and the receiver. The camera is used for recording the process of the experiment and mark the following data for accurate data sequences.

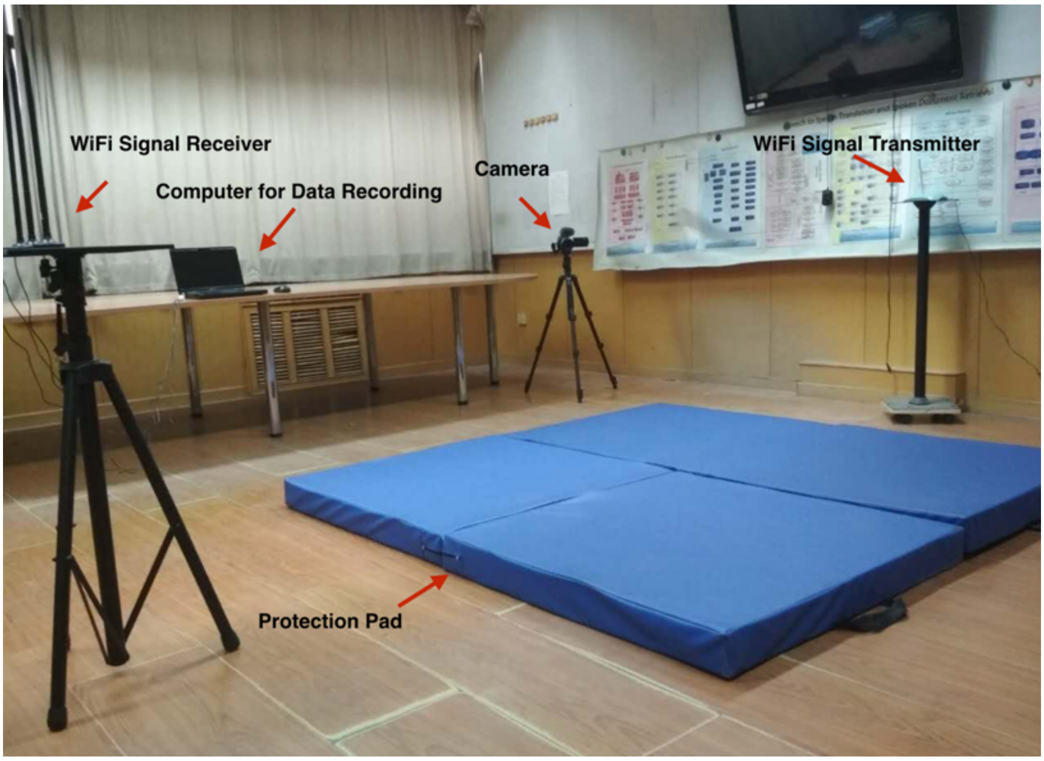


Fig 8. Experimental environment of data acquisition

4.3. Data Acquisition and Preprocessing

There are six volunteers doing the six movement sequences for three times to get 108 sets of related data sequences. The sample frequency is 25Hz and each movement lasts for six to eight seconds, thus, there are totally 150 to 450 sample points.

Each sample in the data sequences is a 90-dimensional complex number. Derive the modulus of this number to transform the 90-dimensional complex vector to a 90-dimensional real vector. There is large noise in the Wi-Fi signal so that PCA is used for reducing the dimensions of the original data and remove the noise at the same time. After many attempts, it was the found that the best performance appears when the dimensions of original data are reduced to 10. Therefore, each 90-dimensional sample point in the original data sequences has been transformed to 10-dimensional sample point after deriving the modulus of a complex number and dimensionality reduction by PCA.

To observe the features of data clearly, we visualized the sample points after reducing them to one-dimensional data, as shown in figure 9.

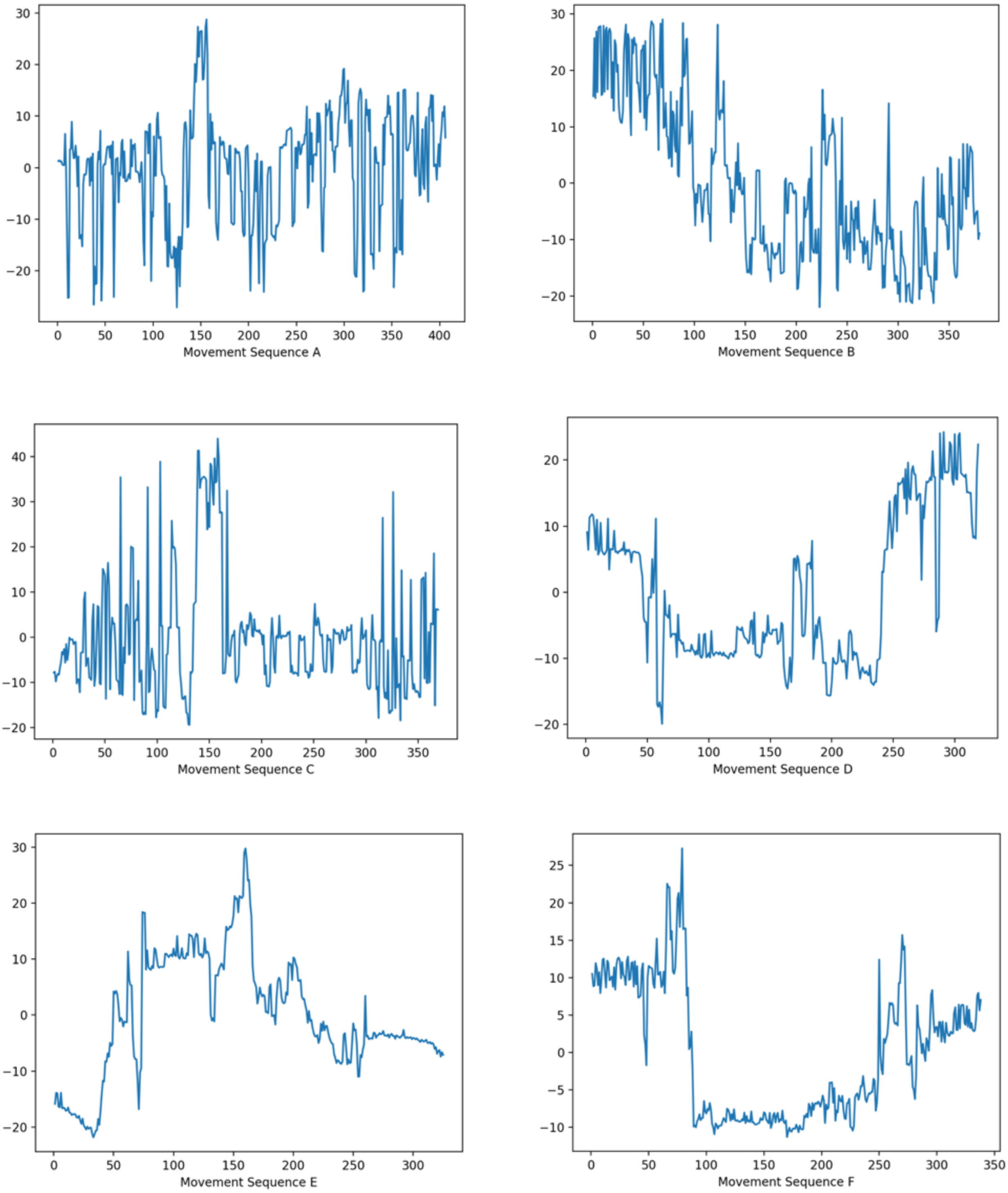


Fig 9. Data visualization of the movement sequences

4.4. Parameter Setting of the Experiment

Each movement sequence has been done three times and divided into two sets. The first and second time belongs to training set and the third time belongs to testing set.

RNN model introduced above is used for training. Two-classification model is adopted, where one is normal behavior and the other is the fall. We use the open source deep learning platform PyTorch of Facebook to build the neural network model [32].

The parameters of the network are set as follows: the number of iterations of training is 20; the number of input dimensions of the network is 10, which is the 10-dimensional feature after dimensionality reduction by PCA. There are two hidden layers, each containing 100 units; there are two units in the output layer since it is a two-classification problem. The backward step for gradient computation by RNN is 20. The loss function is the cross entropy; the Adam optimization is used for updating the parameters, and the learning rate is set to 0.001.

The model based on RSR uses the same parameters with the neural network. Only differ in the process of training and prediction, for there is certain probability for the state of the hidden unit at last moment to be reset to zero after adopting RSR.

4.5. Results and Analysis

4.5.1. Results of Fall Detection Experiment Based on RNN Model

In this experiment, the single sample point in the data sequences is used as input of the neural network in each moment. Due to the characteristics of the hidden states passing continuously in RNN, the input of the single unit in the unfolded network can also describe the time sequence of the movements.

In the training process of the RNN model, the cross entropy is used as loss function and the target of optimization. The gradient descent method is adopted to update the parameters. The experimental results are shown in table 1.

Table 1. Results of the fall detection experiment based on RNN model

Movement Sequence	Number of the Sample Points	Number of Correct Detections	Accuracy (%)
A	2050	1820	88.68
B	2299	1990	86.82
C	2209	1889	85.24
D	1814	1503	88.26
E	2047	1655	81.72
F	1415	1154	82.69
Average	—	—	84.67

As it shows in the table.1, the fall detection method based on RNN model can detect the fall correctly with probability over 80% for each movement sequence. The average accuracy of detection is 84.67% which indicates that the research of elderly fall detection based on the Wi-Fi signal is effective.

4.5.2. Probability of RSR

It is found that the detection of movement switching is delayed when using RNN model. RSR is used be solve this problem.

In this section, the results of experiments with different probabilities are compared to select the suitable probability of resetting the state, as shown in fig.10.

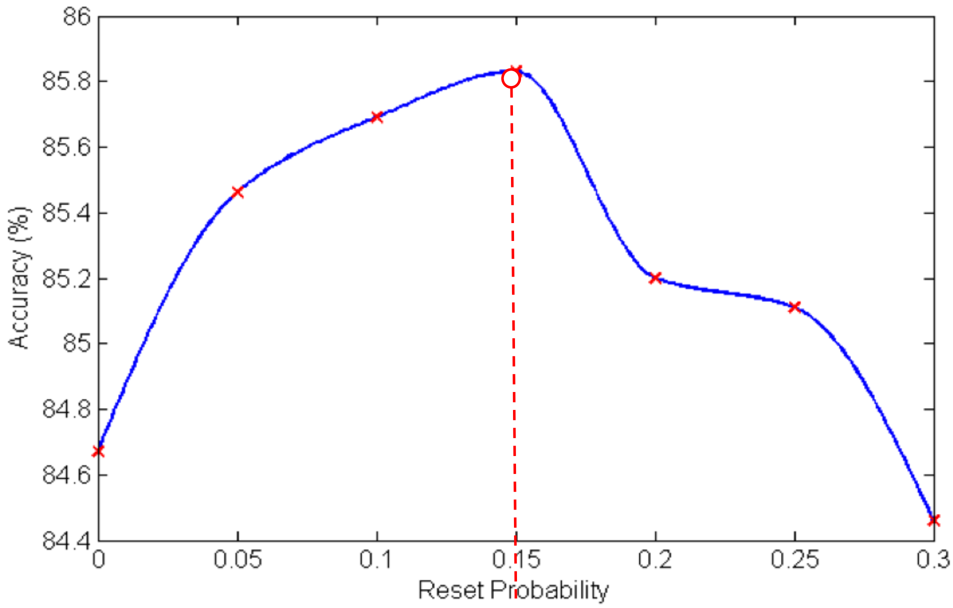


Fig 10. Accuracy of detection with different probabilities of resetting

As it shows in fig.10, the rate of correct detection increases as the probability of resetting grows from 0.00 to 0.15 and reaches the top at 0.15. After that, the rate falls as the probability of resetting further grows. When the probability of resetting increases to 0.3, the rate becomes lower than it without RSR.

When the probability of resetting is between 0.00 and 0.25, RSR reduces impact of the wrong history information on the detection so that it improves the rate. However, when it further increases to 0.30, the state transmission of RNN in consecutive time has been destroyed, thus affecting the accuracy of the detection.

4.5.3. Results of Fall Detection Based on RSR-RNN Model

The network parameters, targets of the optimization and the method of updating parameters of the RSR-RNN model are the same with the RNN model.

The probability of resetting is set to 0.15 since the detection accuracy reaches the top at this point according to the variation of the detection rate with different probabilities discussed in section 4.5.2. The results of the experiments under this probability of resetting is shown in table 2.

Table 2. Results of fall detection based on RSR-RNN model

Movement Sequence	Number of the Sample Points	Number of Correct Detections	Accuracy (%)
A	2050	1817	88.63
B	2299	1991	86.60
C	2209	1891	85.60
D	1814	1596	87.98
E	2047	1691	82.61
F	1415	1172	82.83
Average	—	—	85.83

As it shows in the table.2, the fall detection method based on RSR-RNN model can detect the fall correctly with probability over 80% for each movement sequence, which is similar with RNN model. The average accuracy of detection is 85.83% which further proves the significance of the research.

4.5.4. Results Comparison of the RNN Model and the RSR-RNN Model

To find out the actual performance of the RSR strategy, we compared the performance of fall detection based on RNN model and RSR-RNN model, as shown in fig.11.

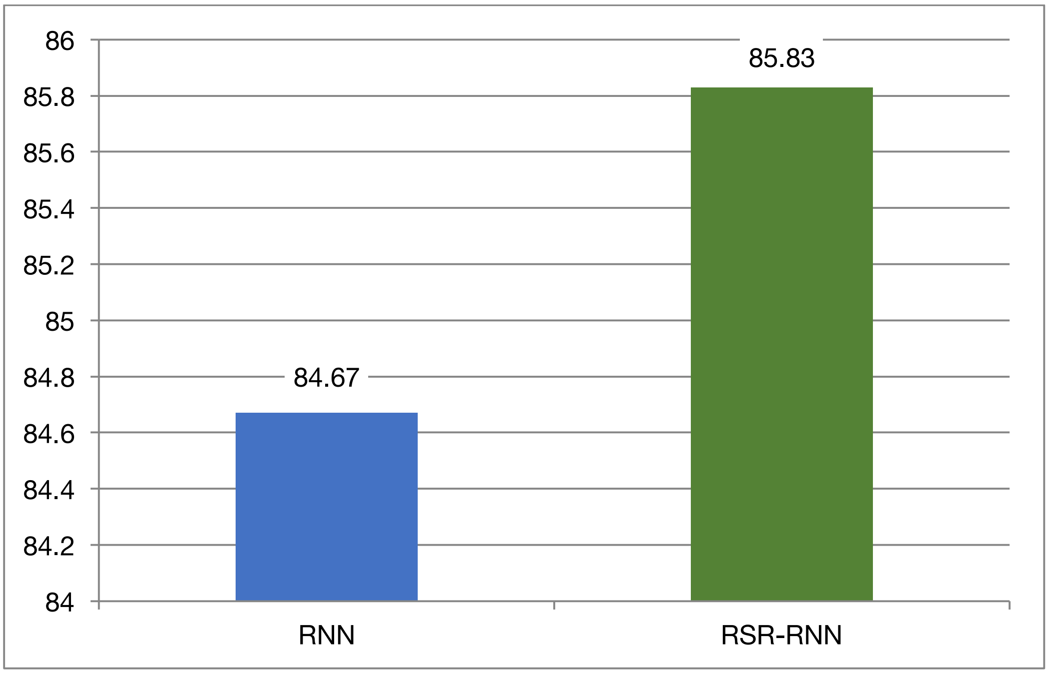


Fig 11. Comparison of the accuracy of the fall detection based on RNN Model and RSR-RNN Model

The recognition accuracy increases from 84.67% to 85.83% when using the RSR. The improvement of accuracy proves the effectiveness of our strategy.

The detection accuracies of two models on six different movement sequences have also been compared. As it shows in the table.1 and table.2, the detection accuracies on movement sequences A, B and C are almost the same. The detection accuracy of RSR-RNN model on movement sequences E and F are slightly higher than that of RNN model. The improvement is the most significant in sequence D.

The movement sequences A, B and C are composed of basic behaviors which are easy to distinguish when switching movements so the RSR strategy does not make any difference. The changes of movements from standing to forward fall, from stand to backward fall and from sitting to sideways fall in sequences D, E and F are hard to identify. The RSR strategy is more useful when the continuous movements are similar and more affected by the error history information.

5. Conclusions and Future Work

5.1. Conclusion

In this paper, an indoor elderly fall detection technology based on Wi-Fi signal has been addressed. The problems for the aging population brought by the fall have been summarized and the related researches about fall detections and Wi-Fi system have been introduced.

The concept and structure of RNN have been introduced. RSR is used for reducing the affection of the wrong history information contained in the hidden states of the RNN units.

The RNN model has been trained after setting up the data acquisition platform. RSR strategy is added on the trained model and the recognition accuracy has been further improved. It proves that RSR strategy is effective to reduce the affection of the wrong history information.

5.2. Future Work

There are still limitations in the current strategy. The RSR used in this paper resetting state of the hidden unit to zero with certain probability is a choice between keeping or discarding all. Although it can prevent the affection caused by the wrong history information when switching the movements, it impacts the regular transmission of the states without switching. We will try to multiply the coefficients between 0 and 1 obtained by the attention mechanism [31] to the hidden units.

The aging problem is becoming more and more serious today, and the loss to the individual and the family caused by the fall cannot be ignored. We hope to solve the elderly fall detection problem by further improving this system.

Ackonwlegments

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附录

罗定生老师、马阳学长、刘天林学长、参与实验的学长学姐们和我在实验现场的照片：