Research on the Recognition of Abnormal Behaviors in the Elderly Based on Wi-Fi Signals

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Abstract. Wandering behaviour is an important diagnostic indicator for patients with Alzheimer's disease, and falls are the main threat to the health of the elderly. Effective detection of these two types of abnormal behaviours of the elderly and timely intervention are important for improving the quality of life of patients with Alzheimer's disease and related diseases significance. This study proposes and studies a method for detecting and identifying abnormal behaviours of the elderly based on Wi-Fi signals. First, the correlation between Wi-Fi signal changes and abnormal behaviours of the elderly was analyzed; secondly, this study applied general Wi-Fi equipment to obtain the status data of the abnormal behaviours of the elderly and preprocess the data through Hampel filtering; then, the effective features of the CSI sequence fragments were designed and extracted, a data set of 2243 samples including 7 types of abnormal behaviours of the elderly was constructed; finally, a BiLSTM-Based abnormal behaviour recognition model for the elderly was constructed, and the average classification accuracy reached 95.95%, which proved this experiment is feasible and effective.

1. Introduction
With the development of our society and the advancement of science, people's life expectancy is generally prolonged, and the aging situation is becoming more and more serious. As the country with the largest number of Alzheimer’s and the fastest growing rate in our country, the number of patients with dementia has reached 9.5 million[1], and the number is expected to reach 16.456 million by 2030[2]. In the early stage of Alzheimer’s disease, symptoms such as memory loss and decreased judgment will appear, and then psychomotor symptoms including aggression, wandering, hallucinations.[3], among which wandering is one of the diagnostic features of many mental diseases[4], psychiatric behavioral symptoms were present in 88.57% of patients[5]. When the judgment of the elderly declines, falls are also easy to occur. According to research, about 33% of elderly people over 65 will fall at least once a year[6], 4%-15% can cause serious injuries, and even 23%-40% of the deaths of the elderly related to injuries are caused by falls[7]. It is very important that elderly people can be detected and treated in time after falling[8]. In summary, the detection of wandering and falling movements is meaningful.

Human behavior perception technology has great research prospects in security monitoring, medical health, intelligent life, etc., and has become a core key technology in the field of computer applications[9]. The current technologies for human behavior perception mainly include computer vision[10-11], infrared[12], and wearable sensors[13-14]. However, the above-mentioned equipment has factors such as complex installation, high cost, and susceptibility to light, making the identification
task more difficult. In order to avoid the above problems, Wi-Fi-based behavior sensing technology came into being, and Wi-Fi equipment is low in cost, widely deployed, and has strong scalability. It can monitor the behavior of the elderly in real time and make timely responses, making it easier to apply. At present, there are many researches based on Wi-Fi at home and abroad, including positioning[15], gait[16], and human behavior recognition using different classification methods[17-19]. However, the above-mentioned research does not specifically focus on the elderly, so this article studies the abnormal behaviors of the elderly based on WiFi.

2. Basics principles of Wi-Fi perception

Wi-Fi signal is a kind of electromagnetic wave, which will be lost and changed due to various reasons during the propagation process. In the indoor Wi-Fi transmission environment, there is usually a LOS (Line of Sight) between the transmitter and the receiver of the signal and NLOS (non-line of Sight) is composed of multiple reflection paths and scattering paths generated by the ground, ceiling and walls. The basic principle of Wi-Fi perception is that the behaviour of the human body will disturb it during signal propagation. By analyzing the signal received by the receiver and detecting the change characteristics of the signal, the type of action can be further analyzed. The dynamic propagation model of indoor Wi-Fi signals is shown in Figure 1.

![Figure 1. Indoor dynamic Wi-Fi signal propagation model.](image)

The Wi-Fi signal currently used for research is mainly CSI (Channel State Information)[20]. CSI is the estimation of the channel state under the OFDM(Orthogonal Frequency Division Multiplexing) technology, which is fine-grained and easy to collect. In the research process, each subcarrier of each antenna link has a corresponding CSI value. For example, if the number of transmitting antennas is $N_t$, the number of receiving antennas is $N_r$, and the number of subcarriers is $m$, then each received transmission packet can be parsed into a CSI matrix of $N_r \times N_t \times m$, which can fully reflect the time delay, amplitude and phase of the output signal during the transmission process[10], as shown in formula (1):

$$y = Hx + n$$

Where $y$ is the received signal, $H$ is the CSI matrix, $x$ is the signal at the transmitter, and $n$ is the noise vector. This formula represents the process of transforming the transmitted signal $x$ into a signal $y$ through a series of interference. According to formula (2), the channel state can be estimated for $H$:

$$\hat{H} = \frac{y}{x}$$

3. Data collection and feature extraction

3.1. Signal acquisition and preprocessing

In order to recognize the behaviour of the elderly, it is necessary to obtain Wi-Fi data that can be analyzed. A Wi-Fi radar system with 3 antennas[21] is used as the receiver and Tp-link TL-WR742N router with 1 antenna acts as transmitter, constitutes a 1×3 MIMO wireless communication system.

As the memory and judgment of Alzheimer's patients decline, they are prone to wandering and falling. This study sets three types of wandering actions representing Alzheimer’s: ‘Walk’ (walking back and
forth in the transmitter and the receiver), ‘Turn’ (walking in a circle in the transmitter end and the receiver, the radius of the circle is variable), and ‘Freedom’ (no regular walking within the transmitter and the receiver) and ‘Fall’ as abnormal behaviors. In order to make a comparative analysis with these abnormal behaviors, data samples of three types of normal movements were collected: ‘Static’, ‘Sit’ (sitting and standing), and ‘Down’ (lying down and standing). As shown in Figure 3, the CSI amplitudes of the four abnormal behaviours set in this study received by the A antenna.

![Figure 2. Amplitude of abnormal behaviour.](image)

CSI and RSSI data are recorded in text (.txt) format. The data is an $n \times 183$ matrix, the first 3 columns are the signal strength RSSI of each antenna, the 30 subcarriers received by a receiving antenna are the real and imaginary parts. A total of 180 columns, and $n$ is the time of this data stream.

For the actions of ‘Fall’, ‘Down’ and ‘Sit’, which have shorter action cycles, the method of collecting only one action at a time and saving it separately is adopted. According to the symptoms of Alzheimer's disease, it takes a certain period of time for the wandering movement to prove its onset. Therefore, the data stream of several types of wandering movement is divided into fixed-length data every 30s.

Due to the changes in the device's internal transmission and reception power, signal transmission rate, etc., the signal will undergo abrupt changes, resulting in abnormal points. In order to make the data have better results, this study chose to use Hampel filtering to detect and replace the abnormal points of the signal. The principle of Hampel is to treat any point outside an interval as an abnormal point, and use the median to divide these points all are replaced to achieve the filtering effect.

3.2. Feature extraction

The basic principle of feature selection is to select category-related features and exclude redundant features, which can improve the generalization ability of the model while reducing data complexity. Each carrier received by each receiving antenna is a CSI value, the real and imaginary parts of the CSI value can calculate the corresponding amplitude and phase, but the amplitude and phase characteristics are not obvious and it is difficult to classify each action. Therefore, after many experiments, we selected 10 sets of amplitude calculation data in each action segment as the time domain characteristics of a set of transceiver antennas, and a total of 30 sets of data were obtained from 3 sets of transceiver antennas as the final feature data. These 10 sets of data describe different situations of CSI: Mean(the central tendency of CSI), Range(CSI fluctuations caused by an action), Mean Absolute Deviation(sample variability), Variance(the dynamic range of CSI), Third-order center distance(the skewness of random variables), Kurtosis(the level of confusion in CSI), Interquartile range(the degree of dispersion of CSI), Sum(the overall CSI fluctuation caused by the action segment), Root-Mean-Square(the average power of the CSI signal), Measure of Skewness(the level of confusion in CSI).
4. Human behavior recognition model

4.1. Recurrent neural network and its variants

The recognition of human behavior is essentially a classification problem. Since the human behavior studied in this study is time series data, each behavior has a strong local dependence in the neighborhood for a period of time, the recognition of these behaviors depends on the context of the signal on a time scale, and RNN (Recurrent Neural Network) is a neural network designed to better process time series data. It introduces state variables to store past information, and together with the current input determines the current output.

LSTM (Long Short-Term Memory) is a variant of RNN. Its characteristic is to add a "processor" that judges whether the information is useful, the structure of this processor is called a cell. In addition to the outer loop like RNN, it also has an internal "memory cell" self-circulation. The introduction of self-circulation can generate a long-term continuous flow path of gradient information, thereby solving the long-term dependence problem of general RNN, which is very suitable for the analysis and identification of long-length time series data.

![LSTM overall flow chart.](image)

The workflow of LSTM is shown in the figure above. There are three gates in LSTM, Input gate, Output gate, and Forget gate. First, the sigmoid function of the forget gate selects the information that can pass the cell. At this time, the input is composed of the input $x_t$ at the current moment and the output $h_{t-1}$ at the previous moment. The sigmoid function in the input gate determines the current value that needs to be updated, and the activation function tanh controls the information added to the current cell state. Finally determine the output of the model, use the sigmoid function in the output gate to control the information selected in the current cell, and then get the initial $o_t$. Then use the tanh activation function to control the value of the cell at the current moment in the interval (-1, 1), and finally multiply the above two values pair by pair to obtain the final output $h_t$.

LSTM can only train the network from the forward direction, and cannot encode information from the back to the front, and cannot grasp the overall changes in the data. The BiLSTM is based on the LSTM by a forward LSTM and a reverse LSTM training input data at the same time, you can learn the past features and future features of a specific time. Combine the output obtained from the forward and backward calculations at each moment and connect them to the output layer together. Finally, the prediction score Softmax obtained by training for each action category is first summed and then averaged to obtain the final classification result.

4.2. Introduction to the experimental model

The model used in this article is a deep learning model based on BiLSTM, The network structure diagram is shown below.
The first is the input layer, the extracted $n \times 30$ feature data constitutes the input of the classifier, and their combination reflects the signal changes that occur due to human actions. Then there is the hidden layer, the hidden layer is a three-layer BiLSTM, and the number of hidden units is 100, 125, and 150 respectively. The multi-layer neural network can better extract the depth features of the data. Then comes the fully connected layer, which converts two-dimensional data into one-dimensional output according to each action category. Finally, there is the decision-making layer, where the Softmax function is used to divide the one-dimensional output of the fully connected layer into seven categories: ‘Fall’, ‘Freedom’, ‘Turn’, ‘Sit’, ‘Down’, ‘Freedom’, and ‘Static’.

5. Experimental design and result analysis

5.1. Experimental design
In order to improve the generalization of the model, a total of 6 volunteers were invited to collect different actions in this experiment. After many experiments, the distance between transmitter and the receiver was set to 3 meters, and the signal frequency was 10Hz. Finally, 2243 pieces of data were collected, including 300 ‘Fall’, 308 ‘Turn’, 354 ‘Freedom’, 422 ‘Statics’, 268 ‘Sit’, 348 ‘Down’, and 243 ‘Walk’, the different actions of each person were placed in the training set and the test. In order to ensure the balance of the experimental results, the data of each action type in the test set is controlled to 60, and the rest are all used as the training set to train the model. This experiment is an experiment based on supervised learning, both the training set and the test set are labeled data. After adjusting the network structure and network parameters for a long time, this article sets the parameters as shown in Table 1.

| Parameter name                     | Parameter value |
|-----------------------------------|-----------------|
| Gradient descent                  | ADAM            |
| Execution Environment             | GPU             |
| The maximum number of iterations  | 150             |
| Batch size                        | 10              |
| Initial learning rate             | 0.001           |
| Shuffle                           | Every-epoch     |
In order to prove the capabilities of this model, a series of comparative experiments have been done for different aspects. First, a three-layer LSTM model with the same number of hidden units as 100, 125, and 150 is used, and the average accuracy is only 81.2%, this verifies the advantage of BiLSTM positive and negative simultaneous training timing data. The number of hidden units of the three-layer BiLSTM in this method is set to 150, and the accuracy rate is only 87.2%. This indicates that there is a gradient in the number of hidden cells, which can gradually amplify the data and better distinguish each type of action. Linear interpolation is used in the preprocessing, and the result was only 83.7%, indicating that there was almost no signal loss during the data acquisition process in this experiment.

5.2. Experimental results and analysis
The training time of this experiment was 26 minutes and 4 seconds, the average accuracy rate reached 95.95%, and the final loss value dropped to 0.0012. The confusion matrix was drawn according to the final classification and recognition. The three types of actions, ‘Sit’, ‘Down’, and ‘Fall’, are all vertical actions, the action trajectory is similar, and ‘Fall’ as an abnormal behavior can be completely identified correctly is very important for the feasibility of the model. The three types of wandering movements have similarities, and they all belong to the mental symptoms of Alzheimer's. Among them, only ‘Turn’ has some confusion with the other two types, ‘Walk’ and ‘Freedom’ are basically completely recognized correctly. These all prove the model's ability and feasibility.

![Figure 5. Confusion matrix.](image)

In order to further verify the pros and cons of the experiment and the model, this article uses 5 result evaluation indicators: accuracy, precision, recall, sensitivity, F1 score, and a model evaluation index Kappa coefficient as shown in Table 2.

| Fall   | Walk  | Turn  | Static | Sit   | Freedom | Down  |
|--------|-------|-------|--------|-------|---------|-------|
| Precision | 1.0000 | 0.9971 | 0.9699 | 1.0000 | 0.9886  | 0.9971 | 1.0000 |
| Recall  | 0.9528 | 0.9556 | 0.9833 | 0.9528 | 0.9639  | 0.9556 | 0.9528 |
| Sensitive | 1.0000 | 0.9833 | 0.8167 | 1.0000 | 0.9333  | 0.9833 | 1.0000 |
| F1 score | 0.9758 | 0.9759 | 0.9766 | 0.9758 | 0.9761  | 0.9759 | 0.9758 |
| Kappa   | 0.9531 |        |        |        |         |        |

6. Conclusion
It is of great significance to apply deep learning and Wi-Fi to identify abnormal behaviors of the elderly. In this experiment, a 7-layer BiLSTM-Based deep learning model was proposed to classify and recognize the feature data extracted by CSI amplitude information. The average recognition accuracy of
the seven types of actions reached 95.95%, which completed the initial goal. There is still a lot of work to continue. The artificial extraction of features is subjective, and you can try to use convolutional neural networks to automatically extract features. The analysis of different environments and multiplayer actions is also a future research direction. And for the data, I hope to have the opportunity to cooperate with medical units to collect more real data on elderly patients.

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