Human fall recognition based on WiFi CSI with dynamic subcarrier extraction of interference index

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Abstract Recently, human fall recognition based on channel state information (CSI) were emerging technologies. However, the widespread deployment of WiFi may cause wireless interference problems for such WiFi CSI recognition, which will reduce the accuracy of human fall activity recognition. So, the paper proposed a dynamic subcarrier extraction method based on interference index (CII-DSE). It used the interference index to divide the interference level and determined the corresponding weak correlation subcarrier combination to reduce the presence of channel interference. Experiment results shown that in the WiFi overlapping channel interference environment, the accuracy of CII-DSE was 95.8%, which effectively improves human the fall recognition influence.

1. Introduction

Recently, researchers have extracted channel state information (CSI) from commodity WiFi devices. CSI contains the amplitude and phase information of subcarriers. By using subcarrier amplitude and phase information, researchers have made certain progress in the field of wireless sensing[1], such as activity recognition [2 3 5], and gesture recognition [4], fall detection recognition [6-11], and human tracking[12]. J. Liu et al. [2] proposed the behavior recognition system of E-eyes, which collected CSI data through WiFi devices and extracted CSI amplitude for the identification of walking and in-situ activities. E-eyes achieved an average recognition rate of over 95% in two different environments. In [6] Zhang and Wang proposed an indoor fall detection system based on WiFi. The system uses CSI information to provide reliable salient features under a single WiFi device. In [10], Wang et al. proposed the RT-FALL system, which used the CSI phases difference as the basic signal for the first time for activity segmentation and fall detection. In [5], AbdelNasser proposed a WiFi-based gestures recognition system (Wigest). The system uses the change of WiFi signal strength to perceive the change of human gestures and does not require additional equipment. Chen et al. [6] proposed an attention-based two-way long and short-term memory method. This method is proposed based on the basis of using BLSM to realize automatic feature learning and selection. In [9], M. Huang et al. proposed the FallSense system, which is based on dynamic matching and constantly updates the use conditions to reduce the impact of the environment. Yue et al. [13] showed a device less activity recognition system with radio frequency interference (RFI), which can recognize 4 behaviors (such as, lying down, sitting, standing and walking). Based on this system, the author found that the CSI signal was severely affected, and RFI obviously changed the measurement data. Therefore, the accuracy of behavior recognition is reduced due to electromagnetic interference.
However, when commodity WiFi devices coexist, we observe that WiFi subcarriers change due to channel overlap. Due to the WiFi overlapping channel interference environment, the performance of human fall recognition based on CSI decreases. Therefore, in this paper, we use WiFi channel state information (CSI) to propose a dynamic subcarrier selection method based on interference index (CII-DSE). CII-DSE can effectively improve recognition performance.

In summary, the main contributions of this paper are as follows:

- By analyzing the CSI interference intensity and the CSI active ratio, we construct a WiFi interference feature mapping matrix, and then use the matrix to calculate the channel interference index to realize WiFi interference discrimination.
- We propose a dynamic subcarrier extraction method based on interference index (CII-DSE). The CII-DSE mainly uses the interference index to divide the interference level, and selects and outputs weak correlation subcarrier combinations according to the interference level.
- Combining the characteristics of OFDM multi-antenna transmission, a multi-link data fusion method CSI-MLDF is propose to aggregate time-domain feature information of multiple data streams in undisturbed data to improve data reliability.

The rest of this paper is organized as follows. Section II describes the overall architecture of the human fall recognition. Section III describes WiFi interference detection and interference processing method. Section IV describes the experimental environment and performance evaluation. The last section is the summary of this paper.

2. System Architecture

The system structure of the human fall recognition method under the WiFi channel interference environment is shown in Fig. 1. It mainly includes four parts: interference identification, interference processing, feature extraction and activity classification.

![Fig. 1 The system structure](image-url)

In the first part, we set the interference index to judge the existence and magnitude of interference. In the second part, according to the size of the interference index, we divide the data into two types: non-interference data and interference data. In the case of interference-free data, a multi-link data...
fusion method is used to aggregate the time-domain characteristic information of multiple data streams in the interference-free data. On the contrary, in the case of interference data, we designed a WiFi interference processing algorithm for interference filtering processing to reduce the impact of interference data. In the third part, we extract features from the prepossessed data. The fourth part uses classification algorithms to classify and identify activities.

3. Algorithm Design
In this section, we introduce the WiFi interference detection method, WiFi interference processing algorithm and multi-link data fusion method respectively. We can effectively improve the data in the WiFi channel interference environment by using the above method.

3.1 WiFi Interference Detection
In an environment without WiFi channel interference, each channel is exclusive. When the access point (AP) sends data packets, we found that the number of data packets received within the same time will not decrease. However, in the WiFi overlapping channel interference environment, the number of data packets received within the same time would be reduced, and the signal strength would be reduced. Therefore, by collecting signal reception strength, noise threshold and CSI packet reception rate, we analyze CSI interference strength and CSI activity rate to construct a WiFi interference feature mapping matrix. Using the matrix to calculate the interference index can determine whether there is WiFi interference.

Define $H_{\text{rem}}$ as the vector composed of the received signal strength value (RSSI) in the CSI data collected by the periodic $T_i$. Use $|H_{\text{rem}}|$ to represent the number of RSSI collected. Use the noise threshold $\text{Noise}_{\text{thr}}$ to determine whether the extracted RSSI value is noise. Therefore, when the RSSI value is less than or equal to $C$, the value is regarded as channel noise. $H_{\text{rem,rem}}$ is the vector after $H_{\text{rem}}$ removes noise, then the interference strength is:

$$ P = \sum_{i=1}^{\text{rem,rem}} \frac{|H_{\text{rem}}|}{|H_{\text{rem,rem}}|} $$

(1)

$H_{\text{active}}$ is a 0/1 vector. When $H_{\text{rem}}(i) > \text{Noise}_{\text{thr}}$, $H_{\text{active}}$ is 1. Otherwise, the $H_{\text{active}}$ is 0. $|H_{\text{active}}|$ is the length of $H_{\text{active}}$. The active ratio is:

$$ A = \sum_{i=1}^{\text{rem,rem}} \frac{|H_{\text{active}}(i)|}{|H_{\text{active}}|} $$

(2)

Firstly, let $P_{\min}$ and $P_{\max}$ be the minimum and maximum interference levels respectively, and $A_{\max}$ be the maximum active ratio that may occur. The value space of parameters $P$ and $A$ is divided by a grid. The value range in the $P$ axis direction is $[P_{\min}, P_{\max}]$, and the unit width is $\Delta P$; The value range in the $A$-axis direction is $[0, A_{\max}]$, and the unit width is $\Delta A$; let each grid point correspond to an interference feature, and establish a feature mapping matrix $S$ to store all interference features $(P, A)$ corresponding $PRR$ estimates; given a set of measured values $(PRR_1, PRR_2, \ldots, PRR_s)$ for feature $(P, A)$, the corresponding $PRR$ estimates for this feature are:

$$ \frac{PRR_s}{S} $$

(3)

Secondly, calculate the interference index of each channel according to the feature mapping matrix $S$. The interference characteristic of the current WiFi channel is $(P, A)$, the interference characteristic of channel $i$ is $(P_i, A_i)$, and the distance between the interference features $(P_i, A_i)$ and $(P, A)$ is:

$$ d((P, A), (P_i, A_i)) = \sqrt{\frac{(P - P_i)^2}{\Delta P} + \frac{(A - A_i)^2}{\Delta A}} $$

(4)

The estimated $PRR$ of the interference state corresponding to the interference feature $(P, A)$ is:
Where $K$ represents the number of WiFi interference sources.

Finally, assume that the WiFi interference source channel is $m$ and the sender channel is $n$. Calculate the interference index $I_{\text{index}}$ as:

$$I_{\text{index}}(m,n) = 1 - \text{PRR}(P,A)$$

(5)

The interference index $I_{\text{index}}$ can reflect the WiFi interference level of the channel, and the interference index can be used to perform interference detection on CSI data.

### 3.2 WiFi interference processing algorithm

In the coexistence of commercial WiFi devices, channel overlap between devices will cause channel interference. In the WiFi channel interference environment, there is a competition relationship in the overlapping part of the channel, which causes the corresponding subcarrier power to increase. On the contrary, there is no competition in the non-channel overlapping part, and the subcarrier power is not increased. The power difference between the two will cause the amplitude of each sub-carrier to be different, thereby affecting the correlation between the subcarriers.

To facilitate the description of the correlation between subcarriers, we introduce a channel state matrix $H$. The formula is as follows:

$$H = [H_1, H_{v+1}, \ldots, H_{i=v+1}]$$

(7)

Where the channel state matrix $H_i$ represents the channel matrix of the $i$-th CSI data packet.

The Pearson correlation coefficient is used to represent the sequence correlation between subcarriers, so as to describe the fine granularity of the correlation between subcarriers. By analyzing the cross-correlation between the 30 subcarriers in the CSI data sequence, the correlation coefficient matrix $C$ is calculated as follows:

$$C = \begin{bmatrix}
C(H_1, H_2) & \cdots & C(H_1, H_{v+1}) \\
\vdots & \ddots & \vdots \\
C(H_{v+1}, H_2) & \cdots & C(H_{v+1}, H_{v+1})
\end{bmatrix}$$

(8)

$C(H_i, H_j)$ is the correlation coefficient between $H_i$ and $H_j$, as shown in the following formula:

$$C(H_i, H_j) = \frac{\text{cov}(C(H_i), C(H_j))}{\sqrt{\text{D}(H_i)\text{D}(H_j)}}$$

(9)

The size of the $C(H_i, H_j)$ value indicates the correlation between $H_i$ and $H_j$. The smaller the value of $C(H_i, H_j)$, the lower the correlation coefficients between the two columns of $H_i$ and $H_j$ in the matrix H. The larger the value gap, the more pronounced the changes in the environment.

Fig. 2. Correlation matrix of subcarrier in an no-interference environment
Fig. 3 depicts the subcarrier correlation matrix diagram in an interference environment. These two figures reflect the correlation of 30 subcarriers in different environments. The blue area indicates weak correlation, and the red part indicates strong correlation. Compared with Fig. 2, we found that the blue area in Fig. 3 is significantly increased, indicating that channel interference weakens the correlation of subcarriers.

On this basis, a dynamic subcarrier selection method based on interference index (CII-DSE) is proposed to deal with interference data. This CII-DSE uses the interference index to divide the degree of interference into two interference levels: severe interference and general interference. According to the interference level, the corresponding weakly correlated sub-carrier combination is selected and output. Using the characteristics of the selected subcarriers to represent the characteristics of all subcarriers can reduce the data dimension and information loss.

The CII-DSE is as follows:

Step1: Set the sliding window size \( w_f \) to partition the disturbed CSI data stream. The total number of sliding windows \( N \) is as follows:

\[
N = \left\lfloor \frac{L}{w_f} \right\rfloor
\]

Where \( L \) is the length of the data stream, \( w_f \) is the size of the sliding window, and \( i \) is the number of data streams. Determine the number of cycles according to the total number of windows \( N \); The number \( k \) of subcarrier selections is determined according to the interference index \( I \)-index. When the interference level is severe interference, the number \( k \) is set to 6, and when the interference level is general interference, the number \( k \) is set to 9;

Step2: According to the CSI correlation coefficient matrix feature model, the correlation coefficient between the 30 subcarriers in the \( f^\text{th} \) window is calculated, and a matrix \( R_{xy} \) is generated;

Step3: Arrange the values in the matrix \( R_{xy} \) in ascending order to generate the array \( I_f \);

Step4: According to 1, let the minimum value in the array \( I_f \) be \( m_f \), select the two subcarriers \( (a,b) \) with the weakest correlation, and add the subcarriers \( (a,b) \) to the set \( C_f = \{a,b\} \);

Step5: Let the number of existing subcarriers in \( C_f \) be \( n \). When \( n < k \), perform correlation analysis between the existing subcarriers in \( C_f \) and the remaining 30-\( n \) subcarriers, and select a correlation coefficient with the existing subcarriers each time. The subcarrier with the smallest sum is added to \( C_f \). After performing \( k-n \) times, add \( C_f \) to the set \( C \);

Step6: Number of cycles \( f = f + 1 \), slide to the next window and repeat the above steps, until the
cycle number $f = N$ ends the cycle. Find the mode of the data in the set $C$ and arrange them in descending order. Take the first $k$ subcarriers and add them to the combination $C_k$. Determine whether the subcarriers in $C_k$ are in [1,10],[11,20],[21,30] have distributions in the interval. If the above conditions are met, let $C_i = C_k$ output the result; otherwise, reselect subcarriers for judgment until the above conditions are met.

3.3 Multilink Data Fusion Method (CSI-MLDF)

In the previous research, most of the methods simply processed the data links, and did not fully understand the relationship between the data links, resulting in poor recognition results. We use the multi-link data fusion method CSI-MLDF to process undisturbed data.

Firstly, the right to all data streams are a first operation of reset to 1, and then calculates an average value of the final data acquired, where $N$ represents the number of data streams, as follows:

$$k(t) = \frac{[k(t) + k_i(t) + \cdots + k_m(t)]}{N}$$

(11)

Secondly, the feature value $e_0$ corresponding to the center point of the original data set is used as the standard of the action. After the action classification is performed, the feature value $e_m$ of the group of actions is obtained. Use $e_0$ and $e_m$ to calculate the Euclidean distance $L_m$ of the data stream, $L_m$ is:

$$L_m = \sqrt{\sum_{i=1}^{n} (e_m^{(i)} - e_0^{(i)})^2}$$

(12)

$$e_0 = \left( e_0^{(1)}, e_0^{(2)}, \ldots, e_0^{(n)} \right)^T$$

(13)

$$e_m = \left( e_m^{(1)}, e_m^{(2)}, \ldots, e_m^{(n)} \right)^T$$

(14)

Finally, we calculate the timing sequence $k(t)'$ of the aggregate CSI, and $k(t)'$ is expressed as:

$$k(t)' = \frac{\sum_{i=1}^{n} L_m k_i(t)}{N}$$

(15)

We use Euclidean distance to perform weighted voting on the CSI data stream in each link. While maintaining the integrity of each link information, we increased the proportion of volatile links in the final aggregated CSI data stream, and reduced the impact of performance on bad links.

3.4 Activity identification

Choosing an appropriate activity recognition algorithm is beneficial to improve the accuracy and efficiency of system recognition. Based on the comparative analysis of the advantages and disadvantages of various activity recognition algorithms, this paper uses the most widely used and mature support vector machine (SVM) algorithm to classify the constructed feature data set.

4. Experiment Evaluation

In this section, we analyze and evaluate the performance of the proposed human fall recognition method in the context of WiFi interference. Firstly, the experimental platform and environment required in the real scene are introduced. Secondly, several groups of tests of different dimensions are carried out in different scenarios. Through the collection of a large number of CSI data, the activity data set required for simulation is constructed. The simulation verification is compared with the traditional identification method WiFall, and the results show that the proposed method has better identification performance. Finally, the influence of different factors on the recognition performance in the interference environment is analyzed experimentally, and the stability of the CII-DSE is verified.
4.1. Experimental scheme plan
We chose the empty student dormitory on the campus of Chongqing University of Posts and Telecommunications as the experimental environment. We built a complete set of test equipment for data collection in the actual scene. The experimental scene is an indoor environment of a typical living room. The experimental scene is shown in Fig. 4.

The indoor environment contains two routers and two computers. We use two wireless routers TP-WR842N as the access point (AP) and interference source, and use a computer equipped with an Intel 5300 network card as the monitoring point (MP) and interference receiver. Among them, point A represents the data sending end. Point B represents the source of WiFi signal interference. Point C represents the data receiving end. Point D represents the computer communicating with the interference source. The distance between point 1 and point 2 is 3 meters. The distance between computer C and computer D is 1m. The distance between computer C and router B is 1m. The operating system of computer C is Ubuntu 12.04, equipped with an Intel 5300 (i-wl5300) wireless network card, and three receiving antennas for receiving CSI data sent by router A. The operating system of computer D is Ubuntu 12.04, equipped with Intel 5300 (i-wl5300) wireless network card, which is used to receive the signal from router B. The former is placed at point A as the data transmitter, and the latter at point B as the source of interference.

In the experiment, we selected 5 common situations in daily life: no activity, falling, sitting, standing, and walking. Each activity was repeated 10 times. Each test lasted 30 seconds and sent 40 times per second.

4.2. Performance evaluation

4.2.1. With or without interference environment
For the Default channel mode, we analyze its impact on recognition performance. We set both the AP channel and the WiFi interference source channel in the automatic channel mode, and analyze the WiFall system and the CII-DSE in this mode. And give their activity recognition rate confusion matrix diagram.

| predicted | None | Fall | Sit | Stand | walk |
|-----------|------|------|-----|-------|------|
| Actual    |      |      |     |       |      |
| None      | 1.00 | 0.00 | 0.00| 0.00  | 0.00 |
| Fall      | 0.00 | 0.95 | 0.04| 0.00  | 0.01 |
| Sit       | 0.00 | 0.00 | 0.94| 0.05  | 0.01 |
| Stand     | 0.00 | 0.00 | 0.01| 0.96  | 0.03 |
| walk      | 0.00 | 0.11 | 0.02| 0.03  | 0.84 |
Table 2. Recognition rate of WiFall system in interference environment

|               | None | Fall | Sit  | Stand | Walk |
|---------------|------|------|------|-------|------|
| **Predicted** |      |      |      |       |      |
| None          | 1.00 | 0.00 | 0.00 | 0.00  | 0.00 |
| Fall          | 0.00 | 0.86 | 0.11 | 0.01  | 0.02 |
| **Actual**    |      |      |      |       |      |
| Sit           | 0.00 | 0.00 | 0.90 | 0.07  | 0.03 |
| Stand         | 0.00 | 0.01 | 0.03 | 0.91  | 0.05 |
| walk          | 0.00 | 0.12 | 0.05 | 0.08  | 0.75 |

Table 3. Recognition rate of CII-DSE in interference environment

|               | None | Fall | Sit  | Stand | Walk |
|---------------|------|------|------|-------|------|
| **Predicted** |      |      |      |       |      |
| None          | 1.00 | 0.00 | 0.00 | 0.00  | 0.00 |
| Fall          | 0.00 | 0.96 | 0.04 | 0.00  | 0.00 |
| **Actual**    |      |      |      |       |      |
| Sit           | 0.00 | 0.00 | 0.97 | 0.03  | 0.00 |
| Stand         | 0.00 | 0.00 | 0.01 | 0.97  | 0.02 |
| walk          | 0.00 | 0.06 | 0.01 | 0.03  | 0.90 |

Table 1 shows the recognition effect of WiFall system in a non-interference environment. Table 2 shows the recognition rate of the WiFall system in an interference environment. Table 3 shows the recognition rate of CII-DSE in interference environment. The abscissa of FIG. 6 represents the predicted activity type, and the ordinate represents the actual activity type. There are five types of activities: no activity, fall, sitting, standing and walking. Compared with WiFall in the WiFi interference environment, the CII-DSE proposed in this paper increases the fall recognition rate by 10%, seat recognition rate by 7%, standing recognition rate by 6%, and walking recognition.

Fig. 6. Comparison chart of recognition rate
We use SVM, KNN, RF and DT four algorithms to conduct experiments. In the presence of interference, we found that the average recognition accuracy of CSI-DSE reached 95.8%. Compared with WiFall, the recognition accuracy of CSI-DSE was increased by 8%. Experiments show that our method can improve the recognition rate under different algorithms.

4.2.2. Different factors in interference environment

4.2.2.1. Different interference channels

In order to better explore the influence of the channel on the channel transmission channel, we fix the channel source and construct the Overlapping channel interference environment. In the experimental scenario, we fixed the WiFi channel source, set the AP channel to 1, and set the WiFi interference source to 1, 4, and 7 for data collection. In an environment with overlapping channels, we analyze the effect of the CII-DSE method.
In the Overlapping channel, the average recognition accuracy rate of the five methods of activity recognition using the traditional method WiFall is only 85.8%. For the above situations, the average recognition accuracy rate after processing by this method can reach 95.2%, and the recognition performance is obtained. Significantly improved, an increase of 9.4% over the previous. For the Partially overlapping channels environment, the average recognition accuracy of WiFall using the traditional method is 87.9%, and the average recognition accuracy after processing by this method can reach 96.1%, which is 8% higher than before processing. Using the method of this paper can solve the above problems well, and can steadily improve the accuracy of activity.

4.2.2.2. Packet rate
Considering the impact of the data transmission rate of the interference source on the accuracy of activity recognition, it is an objective problem that must be considered. Therefore, in this paper, the AP data transmission rate is kept at 40pkt/s unchanged, and the interference source is allowed to use 40pkt/s, 200pkt/s, and 500pkt/s data transmission rates were tested and the impact of interference sources on the recognition performance at different transmission rates was analyzed. Fig.9 shows the recognition accuracy of interference sources at different transmission rates.

It can be seen from Fig. 9 that as the data transmission rate of the interference source gradually increases, the average recognition accuracy of WiFall using the traditional method also gradually decreases. Only when the transmission rate of the interference source is 1pkt/s, the degree of interference caused is weak, and the average recognition accuracy can reach 93%; while when the transmission rate is 40pkt/s, 200pkt/s, 500pkt/s, with the degree of interference The enhancement, the average recognition accuracy rate also fell below 90%. In addition, when using this method for activity recognition, the recognition performance at the data transmission rate of the four interference sources has been greatly improved and more stable, and the average recognition accuracy rate has reached more than 95%, and there is almost no change in transmission rate.

5. Conclusion
In order to solve the problem of serious WiFi wireless interference in CSI human fall activity recognition, which leads to a greatly reduced accuracy of fall activity recognition, a channel-based dynamic subcarrier extraction method proposes an interference index. Experimental results show that the accuracy of activity recognition has been significantly improved compared to the existing human fall recognition methods in WiFi channel interference environment. In future work, we will conduct more in-depth research on wireless interference, hoping to bring more help to CSI-based identification systems.

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