**KS-FALL: Indoor Human Fall Detection Method Under 5GHz Wireless Signals**

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**Abstract:** In modern society, it has become the main threat to the elderly fall's health or even death in the elderly. The real-time and reliable fall detection system can save the fall and hurt the elderly in time. In this paper, a human fall detection method KS-FALL based on Channel State Information and in 5G environment is proposed. KS-FALL uses Atheros commercial NIC equipment to map the amplitude information in the wireless signal to the human body's fall action, and does not require the user to wear any equipment. Compared with the traditional 2.4 GHz signal, the 5 GHz signal provides richer sub-carrier frequency domain information, which better reflects the relationship between human motion and wireless signals, thereby more effectively distinguishing and recognizing walking, squatting, falling, etc. action, filter the environmental interference through powerful denoising method, use K-means to cluster different action data, combine SVM classifier to construct fine-grained offline fingerprint database, and use SoftMax regression model to correct SVM classification in real-time detection stage. And real-time test in two different scenarios, and the detection accuracy of the fall reached 92.3%, realizing the device-free, non-invasive, high-precision human fall detection.

**1. Introduction**

As the population ageing process intensifies, the health problems of the elderly have become a hot topic of recent research. Especially for the elderly, falling is a kind of action that is harmful to the body and has unpredictable and preventive features. Most elderly people cannot stand up after falling, and if they are not treated in time, they may lead to some irreparable consequences, so it is important to study real-time indoor human fall detection systems.

The existing indoor fall detection systems are mainly divided into three categories: based on computer vision, wearable sensors and smart phones, and environmental equipment. The computer vision method mainly relies on the high-resolution camera to extract and recognize the action sequence of the human body fall. It is a mainstream method at present, but this method cannot work due to the low-light environment due to the dependence on the optical high-definition camera, and the user's privacy is easy to leak. Fall detection systems based on wearable sensors and smart phones generally use accelerometers, gyroscopes, air pressure sensors, etc. to detect abnormal changes in data caused by body measurements. However, for the elderly, it is unrealistic to wear these special sensors at home or to carry the phone at any time. The fall detection system based on environmental equipment mainly uses environmental information changes (such as audio information, vibration...
information, infrared information) caused by human fall to detect the risk of falling. These systems must deploy extra high equipment in the environment. Not suitable for popularization in the home environment.

The above systems all have problems such as high cost and high invasiveness, and are rarely applied to actual home indoor scenes. In recent years, the rapid development of wireless sensing technology has provided a new solution to overcome these limitations, especially the emergence of physical layer channel state information discovered from commercial WiFi devices, and subcarrier-level wireless display in OFDM demodulation. The channel characteristics have higher stability and finer-grained frequency domain information than the traditional MAC layer signal reception strength. At present, the research on the relationship between wireless signals and human activities using CSI has been widely used, and significant progress has been made in gesture recognition, vital sign monitoring, motion monitoring, and activity recognition [1]. The widespread popularity of WiFi devices in the home and its low deployment cost make it possible to detect indoor fall detection based on WiFi, which is in line with the detection requirements of elderly users, without wearing equipment or causing strong intrusion to users. It also enables high-precision real-time monitoring.

In this paper, we propose a KS-FALL method for indoor human body fall detection under 5GHz wireless signal, which realizes high-precision detection of human body fall by using commercial WiFi equipment with low cost and widespread popularity. The main contributions of this work are as follows:

- We use the TPlink WDR4310 router as the detection device to extract the amplitude information of the 5GHz wireless signal as a feature, and establish the correlation map between the amplitude characteristics of the subcarrier level and the human fall activity, and achieve a higher precision human body fall in multiple scenarios. Inverted activity detection.
- We built a powerful denoising method in the KS-FALL system. The wavelet function combined with the Chebyshev low-pass filter effectively filtered the multipath components and environmental interference to ensure the accuracy of the fall detection.
- In the data classification and fingerprint matching stage of KS-FALL system, we adopted a well-designed classification method. K-means clustered motion data and SVM to complete offline fingerprint design, and used SoftMax regression to improve the recognition accuracy of fall motion.

2. Related work
In this section, we introduce the work from two perspectives:

**Human fall detection:** Human fall detection has become the focus of research in the field of modern healthcare. Falling is more and more important because of its sudden and unpreventable nature, causing greater harm to the human body. Natthapon et al. [2] summarized and reviewed the existing indoor fall detection systems, which can be broadly classified into three categories: based on computer vision, based on wearable sensors and systems based on environmental devices. Firstly, the computer vision-based fall detection system separates the abnormal fall action from other activities by installing an optical camera to capture the video sequence of the fall motion in the detection environment, and by image classification [3], but exists work blind and privacy issues, in low light conditions (dark room), privacy environment (bathroom) does not work. The principle of the wearable sensor-based fall detection system is to embed a sensor that can detect the motion state of the human body into everyday objects that can be worn (such as clothes, watches, bracelets)[4], and the widely used sensors now have a gyroscope [5], MEMS [6], RFID [7], but these detection systems require the target to be worn to wear the device to work. The fall detection system based on environmental equipment utilizes the environmental audio [8]caused by the fall action, the change of the vibration [9] information and infrared data[10], realizes non-invasion, and does not require the fall detection of the human wearing device, but often such a system is expensive to deploy. And it is greatly interfered by the environmental source (the falling of the object will also produce detection data similar to the human fall), and the monitoring of the fall of the elderly cannot be effectively realized.
Human activity recognition based on WiFi: WiFi signal reception strength RSS has been widely used in indoor positioning [11], and has some research results in gesture recognition [12] and activity recognition [13], but because RSS belongs to MAC layer signal, there are inherent defects such as instability, coarse grain size, and vulnerability to narrow-band interference and multipath environmental influences. In order to overcome these shortcomings, CSI as a fine-grained, relatively stable PHY layer channel feature has been discovered from commercial WiFi network cards, and has been extensively studied in the human perception direction. Wi-Finger [14] recognizes finger gestures by establishing CSI signal changes caused by different gestures by the user doing numbers 1-9. The Wi-Sleep [15] system is able to monitor the user's respiration rate and heart rate through the CSI data of the commercial WiFi network card. E-eye [16] establishes correlation maps with 9 different daily activities through the CSI amplitude value to identify the daily activities of the human body.

The above work introduces the existing problems of the human body fall detection system and the application of WiFi human activity recognition. Based on this, this paper proposes a device-independent, non-invasive indoor human body fall detection system in 5GHz environment. Real-time monitoring of falls in the home environment.

3. KS-FALL Design
This section describes the KS-FALL method flow in three parts, namely data preprocessing, offline fingerprint library construction and online fall detection. The KS-FALL flow chart is shown in Figure 1.

3.1. Data preprocessing
We use the 5GHz wireless signal to sense the body's fall, squat and walking action. Due to the indoor multipath effect and the surrounding environment, as shown in Figure 2 (a), (b), (c) in this environment. The collected CSI motion data contains more or less noise, which will reduce the detection rate of the fall action and reduce the performance of the method. To this end, we have designed a more reasonable denoising process, using Chebyshev low-pass filtering to filter out high-frequency interference in the environment, and retain the low-frequency data of human motion. The results are as follows (d), (e), (f) show that, combined with the wavelet function to smooth the data, can better preserve the data integrity, and finally get the effective feature data of falling, deep, walking, as shown in (g), (h), (i).
3.2. Offline fingerprint construction

3.2.1. K-means clustering. The pre-processed CSI motion data is used as a sample data set to cluster CSI data of three different actions, and the cluster centers of falling, slow down and slow walking actions are found. The value of k is selected according to the number of actions to be 3, and 3 points in the CSI action data set are randomly selected as the initial cluster center, and the Euclidean distance from each sample in the data set to the initial cluster center is calculated. Set the CSI action sample set to

$$S = \{a_1, a_2, \ldots, a_n\}$$

Then the Euclidean distance between two samples can be defined as:

$$d(a_i, a_j) = \left[ (a_{i1} - a_{j1})^2 + (a_{i2} - a_{j2})^2 + \cdots + (a_{im} - a_{jm})^2 \right]^{1/2}$$

(1)

According to the difference of distance, the data is divided into three categories, and the center of each class is updated by calculating the average value of the CSI action data in each class until the square error of each class center reaches the minimum value and the class center does not need to change so far.

The average error function for each class is as follows:

$$Error_i = \sum_{i=1}^k \sum_{j=1}^{m_i} |a_{ij} - \text{avg}_i|^2$$

(2)

Wherein k is the number of clusters and assigned to 3, $m_i$ is the number of data samples in class i, $\text{avg}_i$ is mean of data samples in class i. K-means clustering results can be used as a basis to predict the classification of SVM classifier.

3.2.2. SVM classification. Establishing CSI fingerprint information for falls, slow walking, and squatting involves multiple classification of data. To solve this problem, we constructed a 2-layer SVM classifier. The first layer SVM classification uses the fall action data as the target class, denoted by $P$, and the other non-fall action data belong to the non-target class, denoted by $N$. Using the preprocessed CSI motion data $S$ as an SVM training sample, let $\varphi(x)$ be the kernel function of the
training sample mapped to the high latitude space $H$. In order to distinguish the target class from the original training data, it is necessary to find the regression function in the high latitude space $H$, that is, to solve the problem of the following quadratic minimization:

$$\min \frac{1}{2}\|c\|^2 + c \nu \mu + \frac{1}{k} \sum_{i=1}^{k} (\xi^* + \xi_i)$$

(3)

Where $\omega$ is the weight, $c$ and $v$ are the balance model complexity and training error weights, $\mu$ is insensitive loss function, $\xi^*$ and $\xi_i$ are upper bound relaxation factor and lower bound relaxation factor, through this problem, we can get the regression function of $H$:

$$f(x) = \sum_{i=1}^{k} (a_i - a_i^*)K(x, x) + b$$

(4)

Where $b$ is the offset, $K(x, x)$ is kernel function, as used herein, the Lagrange multiplier kernel $K(x, x) = \phi(x) \phi(x)$, this regression function is used to predict the training data $a$, if $f(x) > 0$, then $a$ corresponds to the fall. Similarly, the classified non-target sample data is used as the second-level SVM training set, and the slow walking action and the slow squatting action are taken as the target and non-target classes, and finally the classification result is obtained, and the offline fingerprint information of the three actions is established.

3.3. Online fall detection

In the online identification stage, the CSI data of human body fall, slow walking and underarm is collected, and data preprocessing is performed. The frequency domain amplitude value is selected as the action feature value, and the SVM classification model is used for training, and the SoftMax regression is used for the SVM classifier. The classification results are corrected. By constructing the SoftMax classification model, the data sample sets of different actions are input in turn, and each time the data representing different actions is selected, a one-dimensional matrix containing three categories is returned, and the probability of each selection is the largest. The classification of the SVM is further corrected by the SoftMax classification function to correspond to the three movements of the fall, the slow walking and the underarm to be classified, and the KS-FALL method has a high accuracy of the fall detection. Match the classified action data with the offline fingerprint to finally identify whether the tester falls.

4. Experiments and Evaluation

4.1. Experimental design

In order to verify the feasibility of the KS-FALL method in the actual scenario, the transmitting and receiving devices in this paper adopt the TPLink WDR4310 router supporting the 802.11n protocol and built-in Atheros AR9580 NIC, and use Openwrt technology to update the routing firmware so that the commercial router can obtain The CSI data, by adjusting the channel bandwidth by setting the routing kernel parameters, sets the transmission and reception bandwidth to 40 MHz to acquire a 5 GHz wireless signal. In the labs with large paths and relatively empty conference rooms, routers are deployed to simulate the fall of the elderly, slow walking, slow down and other actions to verify the performance of the KS-FALL method for fall detection. The experimental environment is shown in Figure 3. (a) is a multi-path laboratory, (b) is a relatively empty meeting room.
4.2. KS-FALL performance analysis

4.2.1. TR-RE(Transmitter-Receiver) distance analysis. The distance between the transmitting and receiving devices in the experiment will affect the accuracy of the fall detection. This is because when the human body action offline fingerprint information is established, different receiver and transmitter distance settings will result in different CIR (Channel Impulse Response). This affects the effect of CSI on fall detection. In order to explore the influence of the distance between TR-RE on the fall detection, this paper sets the distance between the transmitting and receiving devices of 1.2m, 2.4m, 3.6m, 4.8m and 6m when constructing offline action fingerprint information. The recognition effect of the fall detection.

![Figure 3 The scenario of fall detection experiment.](image)

As shown in Figure 4, as the distance of the TR-RE increases, the recognition accuracy of the fall action increases. When the distance is 4.8 m, the fall detection rate begins to decrease. This is because the signal matching strength between the transceiver routers is reached. A certain distance begins to decay, and it is unable to maintain strong signal matching and data transmission status. Therefore, a conclusion can be drawn that the TR-RE distance for the offline action fingerprint information is 3.6m, and the fall detection accuracy is the best.

![Figure 4 Effect of TR-RE distance on fall detection.](image)

4.2.2. Multipath environmental impact. In order to verify the robustness of the fall detection method proposed in this paper, we select two experimental scenarios that are closer to the complex indoor environment (labs with serious multipath interference and relatively empty conference rooms) for fall detection verification, in TR-The RE distance is 3.6 m. Under the other conditions, the same (falling) motion is sampled repeatedly in two scenarios, and the trend of the CSI amplitude as shown in FIG. 5 is obtained.
Figure 5 Falling contrast in different scenes. Figure 6 KS-FALL performance in two scenarios.

It can be seen from Figure 5 that the time domain characteristic information of the two is different due to the difference in environment. In a laboratory with severe multipath interference, due to excessive multipath components, large interference is caused to the wireless signal passing through the human body path, and the amplitude is increased. In the relatively empty conference room, the influence of the wireless signal after the human body falls is not significant due to the weak multipath interference. Although the state of the CSI signal is different when the action occurs in two different multipath scenarios, it can be seen that the basic trend of the signal change remains the same. Figure 6 shows the comparison of the multi-path scene and the empty conference room motion recognition rate. After the features are extracted, the SVM is classified and the SoftMax correction is used. Although the motion recognition rate is reduced, it can still maintain a higher interval. Therefore, the proposed KS-FALL has better robustness and can maintain better performance in multipath scenarios.

5. Conclusion

In this paper, we propose a non-invasive, highly robust human fall detection method KS-FALL based on 5GHz wireless signal. The experiment imitates the elderly’s fall, slow walking and slow kneeling. By constructing a powerful denoising method and a reasonable classification method, the CSI signal is used to effectively perceive the target whether it falls, and the effective perceptual distance is found. The performance of KS-FALL is evaluated in two different environments through comparative experiments. The experimental results show that KS-FALL has great potential as a practical and non-invasive fall detection solution.

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