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Research on CSI Indoor Personnel Behavior Detection Algorithm Based on Adaptive Kalman Filter

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Abstract: In order to improve the accuracy of indoor personnel detection, we propose a channel state information (CSI) indoor personnel behavior detection algorithm based on adaptive Kalman filter in this paper. After collecting the original data package of CSI, the adaptive Kalman filter algorithm of variance compensation is used to filter the original data, and the dichotomous K-means clustering algorithm is used to classify the collected data and establish the fingerprint database. Then the k-nearest neighbor (KNN) matching algorithm is used to match the real-time data with the fingerprint database data to achieve the indoor behavior detection. The experimental results show that compared with the LIFS and FIMD methods, the method can recognize the action behavior of indoor people more accurately.

1. Introduction

With the precise demand of location service, indoor positioning system has become an increasingly hot technology field, and the indoor positioning method based on WiFi signal has drawn great attention to many researchers due to its openness and ease of use. As a kind of wireless network based on IEEE802.11 protocol, WiFi has been widely used in most families and office environments. Nowadays, most mobile devices have built-in wireless network card that conforms to IEEE802.11 standard, which makes it easy for users to access wireless local area network (WLAN), and its wide coverage significantly reduces the cost of indoor positioning technology.

Indoor location technology has good development advantages in many fields, such as indoor intrusion detection, campus security, personnel detection in shopping malls, patient monitoring, real-time detection of the elderly and children at home [1]. Literature [2] proposes a low-cost and high-precision passive target location method lifs based on CSI model, which effectively applies the characteristics of CSI to target location, but this method does not consider the relationship between detection area and detection rate. In the reference [3], FIMD system uses the stability of CSI to achieve more fine-grained personnel detection in static environment, but it does not achieve high detection rate, and the system performance will be affected by the experimental environment. In the reference [4], the CSI signal is effectively reduced by sparse representation in frequency domain, and the influence of signal multipath effect on positioning accuracy is solved to a certain extent. In the reference [5], Chengyue et al. Proposed to use multi-sensor location information to screen reference nodes of fingerprint database, retain effective reference nodes to improve the positioning accuracy.

In view of the shortcomings of the above methods, an indoor personnel behavior detection algorithm base on adaptive Kalman filter based for channel state information (CSI-AK) is proposed in this paper. After collecting the original data package of CSI, the adaptive Kalman filter algorithm of variance compensation is used to filter the original data, and the dichotomous K-means clustering algorithm is used to classify the collected data and establish the fingerprint database. Then the k-nearest neighbor matching algorithm is used to match the real-time data with the fingerprint database data to achieve the indoor behavior detection.

2. Personnel movements recognition algorithm

In this paper, CSI-AK algorithm mainly includes four modules: data acquisition, data processing, and fingerprint database establishment, feature information matching. The overall flow of CSI-AK algorithm is shown in Figure 1.

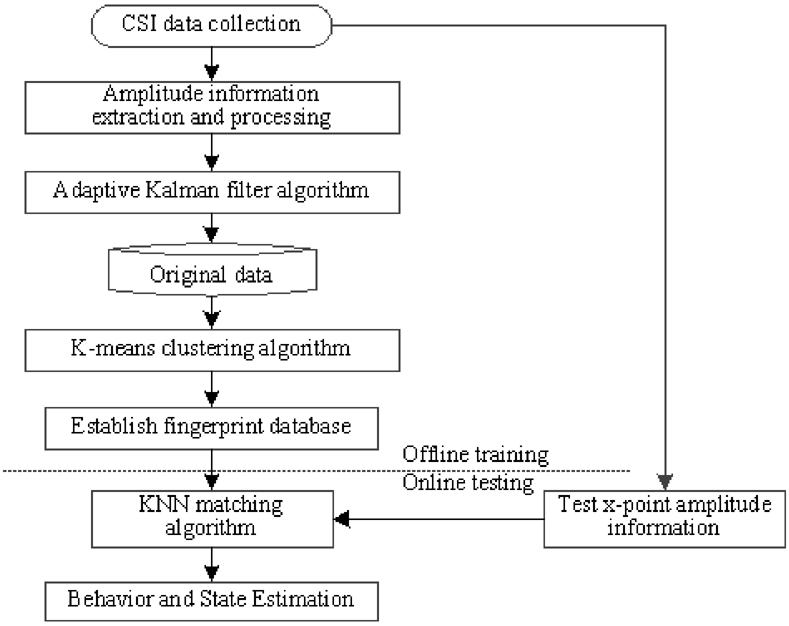


Figure. 1 Overall flow of CSI-AK algorithm

2.1 Data preprocessing

The adaptive Kalman filter algorithm [6] has the ability of dynamic data processing, that is, it can estimate and modify the unknown or uncertain system model parameters in the process of data filtering. By using the existing information to estimate the dynamic noise variance in real time, it can compensate the deficiency of dynamic variance or covariance in the filtering. This method uses the prediction residual to modify the original vector. The method of calculating the actual state vector is called the variance compensation method of adaptive Kalman filter. The basic ideas are as follows:

The Kalman filter state equation and observation equation of discrete linear system can be expressed as

$$\begin{cases} X_{k+1} = \varPhi_{k+1,k} X_k + \varPsi_{k+1,k} U_k + \varGamma_{k+1,k} \varOmega_k \\ L_{k+1} = B_{k+1} X_{k+1} + Z_{k+1} + \varDelta_{k+1} \end{cases} \tag{1}$$

In the statement, X_{k+1} and X_k are the filtering values of the state vector at time t_{k+1} and t_k, respectively; $\varPhi_{k+i,\,k}$ is the state vector coefficient matrix; $\varPsi_{k+i,\,k}$ is the control vector coefficient matrix; U_k is the control vector; $\varGamma_{k+i,\,k}$ is the coefficient matrix of the dynamic noise vector; $\varOmega_k$ is the dynamic noise vector; $\varDelta_{k+i}$ is the observation noise vector. If we considerate the system has deterministic input, the state equation and observation equation are

$$\begin{cases} X_{k+1} = \varPhi_{k+1,k} X_k + \varGamma_{k+1,k} \varOmega_k \\ L_{k+1} = B_{k+1} X_{k+1} + \varDelta_{k+1} \end{cases} \tag{2}$$

Suppose $\{\Omega_k\}$ and Δ_k are normal sequence and X_0 is a normal vector. And we define n-step forecast residuals as

$$V_{k+i} = L_{k+i} - \hat{L}_{k+i,k} \tag{3}$$

Where: L_{k+i} and $\hat{L}_{k+i,k}$ are the observation values of period $k+i$ and its best prediction value respectively. But

$$\hat{L}_{k+i,k} = B_{k+i} \varPhi_{k+i/k} X_k + \varDelta_{k+i} \tag{4}$$

Then the variance matrix of V_{k+i} is

$$D_{vv} = B_{k+i} \varPhi_{k+i/k} X_k + D_{\varDelta_{k+i} \varDelta_{k+i}} \sum_{r}^{k+i} B_{k+i} \varPhi_{k+i,r} \varGamma_{r,r-1} D_{\boldsymbol{\varOmega}_{r-1} \boldsymbol{\varOmega}_{r-1}} \varGamma^{\mathrm{T}}_{r,r-1} \varPhi^{\mathrm{T}}_{k+i,r} B^{\mathrm{T}}_{k+i} \tag{5}$$

Remember

$$B_{k+i} \varPhi_{k+i,r} \varGamma_{r,r-1} = A^{(k+i,r)} = \left[a_{hi}^{(k+i,r)} \right] \tag{6}$$

Where: $r = 1, \cdots, N$; $k = 1, \cdots, n$; The superscript $k+i,r$ indicates that it is related to k+i, r. It is assumed that $D_{\varOmega_{1-1} \varOmega_{1-1}}$ is a constant diagonal matrix over the observation period $t_{k+1}, t_{k+1}, \cdots, t_{k+n}$, and it is noted that

$$\mathrm{diag} \boldsymbol{D}_{\varOmega\varOmega} = \left(\sigma_{11}^2, \;\; \sigma_{22}^2, \;\; \cdots \;\; , \;\; \sigma_{rr}^2 \right) \tag{7}$$

According to

$$E\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1} \right) = \mathrm{tr} \left[E\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1} \right) \right] = \mathrm{tr} D_{vv} \tag{8}$$

Remember

$$\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1} \right) = D_{vv} + \eta_{k+i} \tag{9}$$

Where: η_{k+i} is the zero mean random variable, $i = 1, 2, \cdots, N$.

Order

$$E_{k+i} = V_{k+i}^{\mathrm{T}} V_{k+i} \operatorname{tr}\left[B_{k+i} \Phi_{k+i,k} D_{X_k} \Phi_{k+i,k}^{\mathrm{T}} B_{k+i}^{\mathrm{T}} \right] - \operatorname{tr} D_{\Delta_{k+i}\Delta_{k+i}} \quad (10)$$

Remember again

$$\eta = \left[\eta_{k+1}, \cdots, \eta_{k+n} \right]^{\mathrm{T}} \quad (11)$$

Then the wired equations are

$$E = A \operatorname{diag} D_{\Omega\Omega} \quad (12)$$

When $N \geq r$, the above formula has a unique solution. The least square estimation (Least Square, LS) of $\operatorname{diag} D_{\Omega\Omega}$ is

$$\operatorname{diag} D_{\Omega\Omega} = \left(A^{\mathrm{T}} A \right)^{-1} A^{\mathrm{T}} E \quad (13)$$

In this paper, we use the Atheros 9380 network card to obtain CSI information, which can be tested in 20MHz and 40MHz bandwidth, in 20MHz bandwidth, the number of subcarriers is 56, under the bandwidth of 40MHz, there are 114 subcarriers [7], 2 transmitting antennas, 3 receiving antennas, and 6 links in total, in that way, each CSI signal is a complex matrix, where is the number of subcarriers [8].

As shown in Figure 2, a person stands at a reference point in a static environment, sampled 20 times continuously at different times in 40MHz bandwidth, and filterd the CSI amplitude value of one link. It could be seen that the adaptive Kalman filtering algorithm is used to reduce the noise of the signal data collected from the original channel, which can reduce the abnormal value to a certain range, get a group of completely processed data the high-quality data and store it in the original database, which provides support for the next step of data classification.

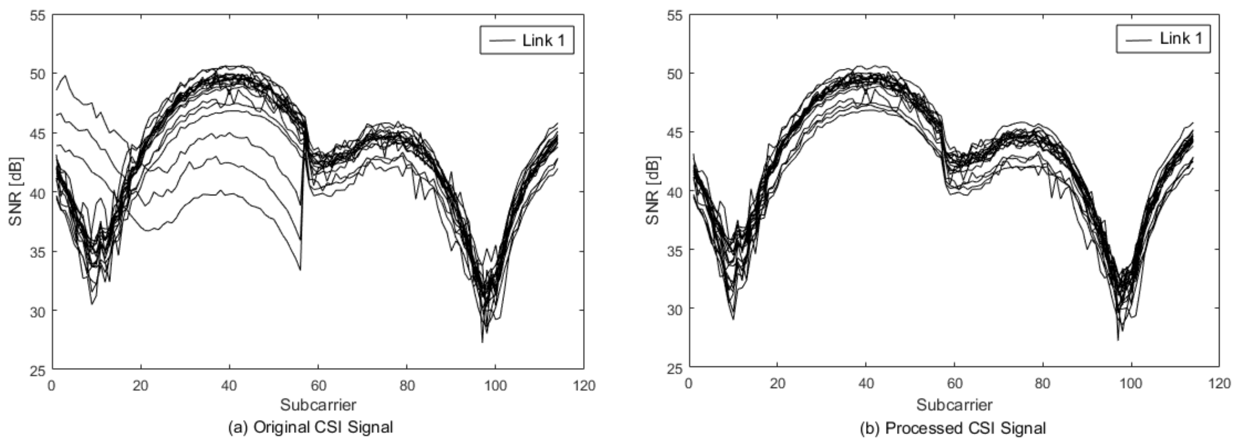


Figure. 2 Comparison of original data before and after filtering

2.2 Offline fingerprint database establishment

Firstly, collect the position coordinates of each test point, and process the received CSI original data. In the process of processing, first use the adaptive Kalman filter algorithm to filter the original data, and then use the binary k-means algorithm to classify the processed CSI data; Then, the processed data is stored in the fingerprint database, and the fingerprint database is updated in real time according to the changes of the environment. The specific steps are as follows:

Step 1: Preprocess the CSI data and find the frequency domain model of single channel state, the formula is as follows:

$$Y = HX + N \tag{14}$$

Where Y is the received signal vector, X is the transmitted signal vector, H is the channel matrix, and N is the Gaussian white noise vector [9].

Step 2: According to step 1, CSI of all subcarriers is expressed as:

$$CSI = Y / X \tag{15}$$

Step 3: The CSI of a single subcarrier is expressed as:

$$csi = |csi|^{e^{j \sin \angle csi}} \tag{16}$$

Then, $|csi|$ and csi Represent the amplitude and phase corresponding to the subcarrier respectively.

Step 4: The amplitude information in step 3 is filtered by the adaptive Kalman filter algorithm.

Step 5: Using binary k-means algorithm to classify the processed CSI data and store it in fingerprint database.

2.3 Online behavior detection

In the online behavior detection stage, the sending end is responsible for collecting the real-time data of CSI and the data when the tester's behavior changes, and then sending the collected data to the receiving end.

Step 1: Collect real time data in real environment.

Step 2: Select amplitude as characteristic value.

Step 3: If X_k represent the state vector of the system at time k, then the state transition equation of the system is as follows [10]:

$$X_{\mathrm{k}} = F_k X_{k-1} + B_k U_k + W_{\mathrm{k}} \tag{17}$$

If Z_k is the observation vector at time k, then the observation equation is:

$$Z_k = H_k X_k + V_{\mathrm{k}} \tag{18}$$

It is assumed that the noise follows the Gaussian distribution, i.e:

$$W_k \sim N_{(0,Q_k)}, V_k \sim N_{(0,R_k)} \tag{19}$$

Using Kalman algorithm to estimate the state of system at k time.

Step 4: Match the amplitude data collected in real time with fingerprint database.

Step 5: Let the characteristic value of the current amplitude obtained by the above steps be A, The offline phase threshold is B. If A>B, it can be judged that the current state is still, and then match again according to the change of amplitude.

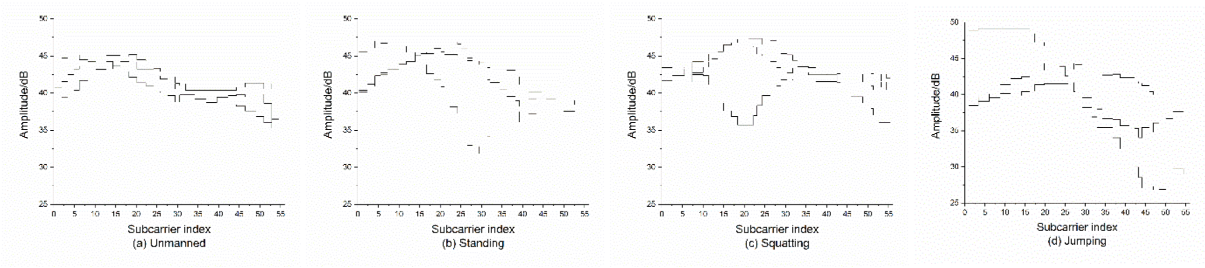


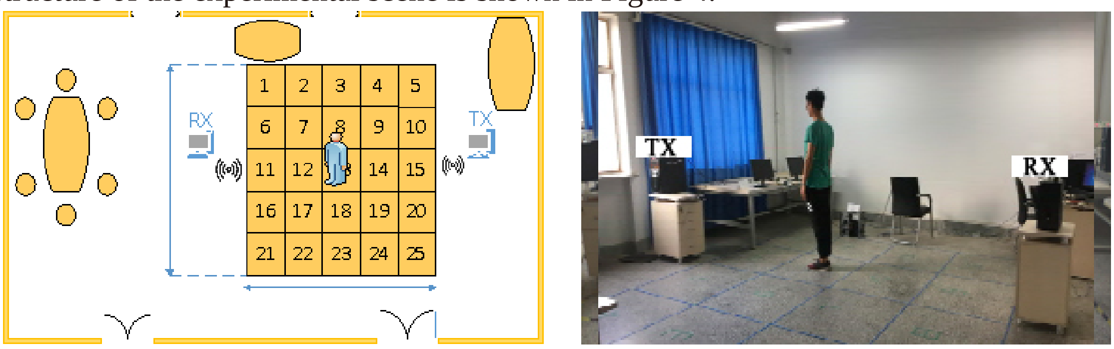
Figure. 3 Detection signal of personnel behavior state in laboratory environment

Figure 3 shows the detection signal of human behavior state in the laboratory environment. From Figure 3 (d), it can be seen that the amplitude fluctuates greatly at this time, indicating that the action amplitude is large, so it can be judged that the action is jump at this time. Figure 3 (b) and figure 3 (c) show small signal fluctuation, i.e. slow movement, so it can be judged that the behavior is standing or squatting at this time.

3. Experimental results and analysis

3.1 Experimental scenario

In this paper, we use the scheme of Atheros 9380 network card to obtain the CSI feature information. All equipments we need for the location algorithm are: Two desktop computers with atheros9380 network card, Intel Core i3-4150 CPU model and Ubuntu 10.04 operating system, one is the sender and the other is the receiver. The obtained data is processed in C program by using the CSI-AK algorithm proposed in this paper. The experimental scene is 7 m × 5 m laboratory, and the plane structure of the experimental scene is shown in Figure 4.



(a) Meeting room plan (b) Real view of conference room

Figure. 4 Deployment of experimental environment

3.2 Inspection probability analysis

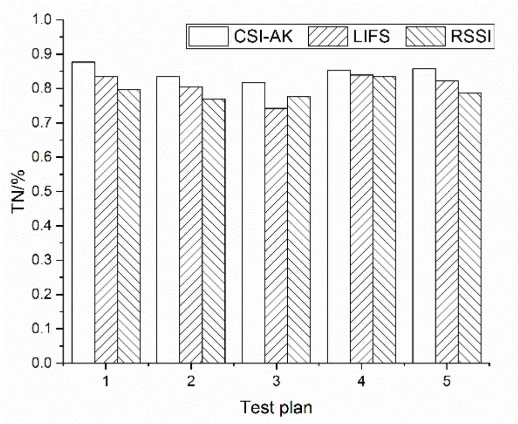


Figure. 5 TN comparison of different methods

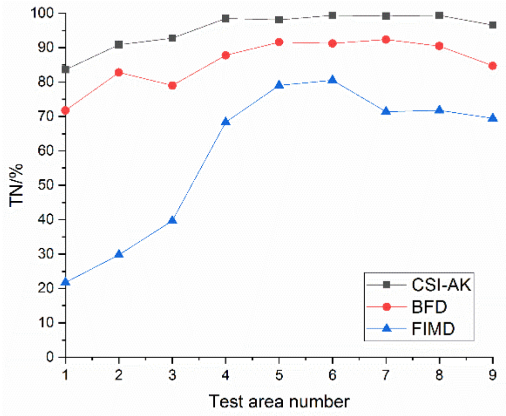


Figure. 6 Relationship of detection rate and test area

In order to verify the detection performance of CSI-AK method in this paper, it will be compared with LIFS, FIMD and traditional RSSI based system models. The detection probability is the correct classification probability, which is called TN rate. Figure 5 shows the TN rate detection results at different locations and time points, the TN rate of each method can reach more than 90%. However, the TN rate values of RSSI and LIFS methods will be affected by time, so their performance will be unstable. The results of CSI-AK method are stable and the overall performance is better than the other methods.

3.3 Impact of test area

In order to test the influence of the behavior state of the tester in different positions on the detection rate, the experimental area is divided into 20 squares, which are numbered in ascending order, and the grids numbered 1~9 are selected for testing. As shown in Figure 6, the detection rate of the system is high in the 4, 5, 6 and 7 grid areas, because these 4 areas are close to the transmitter and receiver, and there is no too much signal interference. The detection rate of 1-3 grids is low, because these three areas are far away from the receiving end and the sending end, and are interfered by multi-path effects such as tables and walls.

4. Conclusion

In this paper, a CSI-AK algorithm based on Adaptive Kalman filter is proposed. After processing the original data by using the adaptive Kalman filter with variance compensation, the classified fingerprint database is established, and match the data in the fingerprint database with the real-time collected data to achieve the purpose of indoor personnel behavior detection. The experimental results show that the CSI-AK method has good performance in sensitivity, robustness, detection rate and other aspects, and has strong practicability.

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