

WIFI-Based Human Identification of gait recognition in multi-scenario

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ABSTRACT

With the development of 5G and the maturity of embedded technology, the Internet of Things has become the most promising technology at present, and human motion recognition and fingerprint feature recognition are hot research topics in the Internet of Things. At the same time, the way of human-computer interaction no longer satisfies the interaction only through screens and our computing devices. We hope to achieve human-computer interaction through simpler and more direct operations. For example, gestures, speech, etc., while the current methods of human recognition are mostly achieved through video or wearable devices, both of which have certain limitations. For example, when using video devices to recognize human bodies, it is necessary to ensure that there are no obstacles on the line of sight (LOS) in the video and sufficient ambient light is available. The Wi-Fi recognition method proposed in this article has the advantages of non-wearable, no light source restriction, and the ability to achieve human recognition using non-line-of-sight paths. Wi-Fi is ubiquitous in modern society, so using Wi-Fi signals for indoor human sensing has important research value. Based on existing Wi-Fi gait recognition work, this paper proposes a Wi-Fi-RSMID system for indoor human recognition. By analyzing the channel state information of Wi-Fi signals during human walking, the Wi-Fi-RSMID system extracts key feature information through PCA principal component analysis of thirty subcarriers of CSI. It collects 155 feature points from five principal components of PAC using a method that combines time-frequency domain information, and achieves human recognition through random subspace method. Experiments show that the system can effectively identify the identities of 15 people in different scenarios, with an average recognition rate of about 75.3% - 85.6%.

KEYWORDS

Wi-Fi CSI; Gait recognition; PCA; Random forest; Fingerprint feature recognition.

1. INTRODUCTION.

The research progress of identity recognition work has been more than ten years, and there are currently three mainstream recognition methods: computer vision, wearable devices, and wireless signals. These three methods have their own advantages and disadvantages. In this section, we will summarize these three methods.

The currently known and widely used technology is based on visual sensor methods [1]. Shotton et al. A method is provided to predict the position of body joints based on depth images. [2] Another example is the method of analyzing the principal components extracted from 122 time dimensions in the images. [3] Although using a camera to record silhouettes of individuals and extract gait patterns for recognition has good performance, this method poses privacy risks and is therefore not suitable for public places or personal homes. Simultaneously, the camera captures impressions, but it is

important to ensure that there are no obstructions within the Line of Sight (LOS) distance, and the recognition rate may be greatly reduced in low-light environments.

The second type of method uses wearable recognition devices such as floor sensors, smartwatches, smart collectors, etc. [4]. Wearable devices use accelerometers built into smartphones, watches, and other devices to collect motion information from the human body for identity recognition. Although devices like [5,6] solve the problems of LOS path obstruction and low-light environments, they have high usage costs and lack universality in terms of venues and personnel restrictions.

The method explored in this paper belongs to wireless signal identification technology, which includes various methods such as radar, laser, and WIFI for identification in this field. [7] Human movement can cause wireless signals to reflect and fluctuate, so we can use spectrum analysis to recognize human movement. In the field of radar gait recognition, researchers often use FMCW (Frequency-Modulated Continuous-Wave) radar to analyze the Doppler spectrum shift of the human body or the time-of-flight of the reflected signal. Although this type of method can provide higher accuracy, the cost of using radar devices is also high. The method of gait recognition using WIFI signals in this article has many advantages such as low cost, popularity, and privacy security. CSI contained in WIFI signals can be used in many fields such as action recognition, fall detection, and location determination.[8] In the field of gait detection, researchers achieved a recognition rate of 79% to 89% by conducting Doppler spectrum analysis on 50 individuals in a single scenario. [9] However, many studies on gait recognition have focused on the recognition rate in a single scenario, without considering performance in multiple scenarios. This paper will analyze and explore a universal recognition model based on human body data of different sizes in multiple scenarios.

2. METHOD OF WI-FI-RSMID

The Wi-Fi-RSMID system structure can be divided into three layers according to Figure 1. The first layer is data preprocessing: we read the CSI stream, remove outliers, perform interpolation, and use Kalman filtering to obtain the CSI signal with noise removed at regular intervals. Feature extraction at the second layer: In the first step, the processed CSI signals undergo PCA (Principal Component Analysis) to extract the top five principal components of the data and calculate the time-frequency domain features for each layer. The second step uses wavelet transform to extract the energy values of each layer after wavelet transform as features. The third layer performs feature training: all the extracted feature information from different scenarios is put into the classifier for training to obtain a model that can be applied to multiple scenarios. The classifier algorithm uses random forest for training.

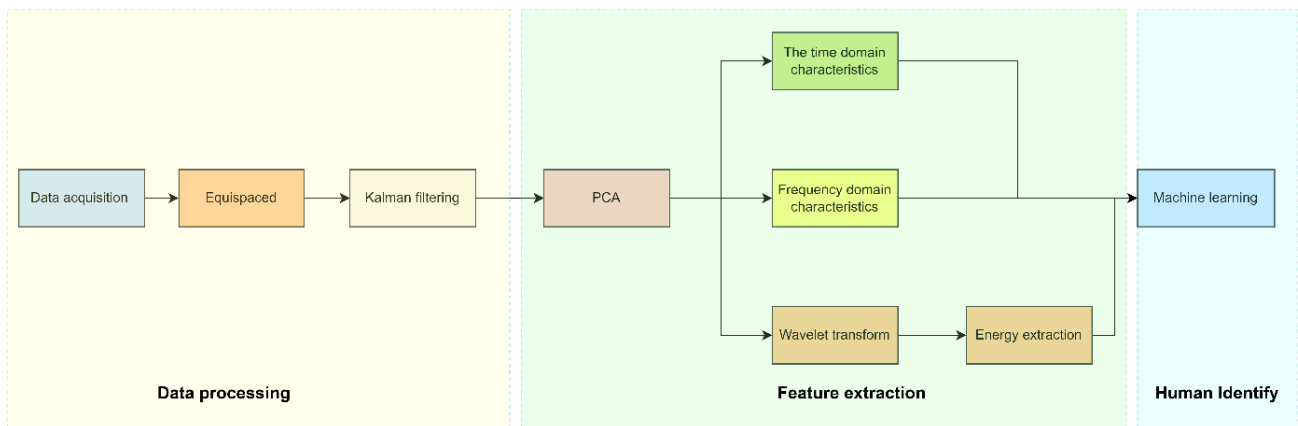


Figure 1. Wi-Fi-RSMID system flow

Subsequent articles will provide detailed descriptions of each layer's specific methods at the system level.

2.1. CSI Data Processing

The CSI stream collected by the receiving device has uncertainty and discontinuity in time. The intervals between each signal are not equal. This missing regularity has a significant impact on subsequent feature extraction and the construction of recognition systems. [10] Additionally, due to the adaptive transmission characteristics of Wi-Fi devices, the collected CSI signals contain a large number of outliers. Therefore, the first step in data processing is to filter out these abnormal values and interpolate the CSI stream strictly according to a sampling frequency of 1000Hz. Abnormal point removal selects Hampel identifier, and when the signal leaves the closed interval $[\mu - \gamma * \sigma, \mu + \gamma * \sigma]$, μ is defined as an outlier, where σ represents the median of a wave, γ represents the MAD of a wave, and selects an empirical value of 3. For interpolation, this paper chooses the method of cubic polynomial interpolation, which has the advantages of fast convergence speed and good smoothness of interpolation results.

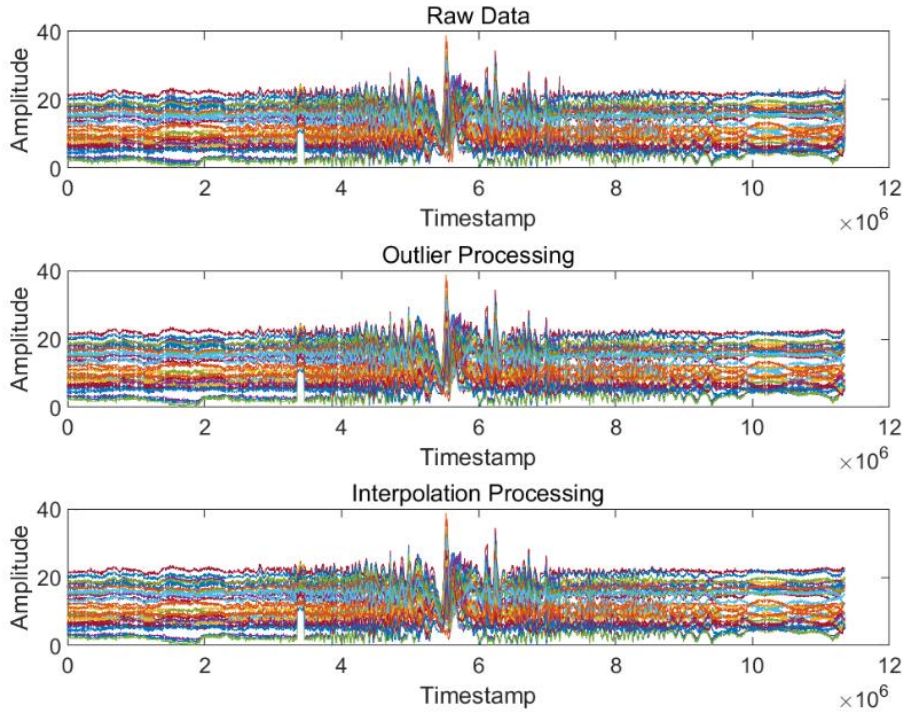


Figure 2. Metadata, removal of outliers, and interpolated results

Figure 2 shows that the signal after outlier processing eliminates spikes in the signal,[11] and the cubic polynomial interpolation fills in the signal sampling interval while preserving the original information. After analyzing the frequency domain information of the CSI signal, it is found that there is a lot of noise in the low-frequency part of the CSI signal. Therefore, we need to filter the CSI signal. In this paper, the Kalman filtering method is used to eliminate the low-frequency noise in the CSI signal.

2.2. Feature Extraction

2.2.1. PCA Principal Component Analysis

After preprocessing, the data needs to be filtered on 30 subcarriers of 3 antennas. Most previous studies select the most prominent subcarriers using entropy or variance methods. This method will discard a large amount of CSI feature information and reduce the recognition rate. In this paper, PCA principal component analysis method [12] is used. This method uses 30 subcarriers from 3 antennas of CSI as the feature matrix, uses PCA for principal component extraction, and calculates the contribution rate of each principal component. The formula for calculating the contribution rate is as follows:

$$\rho_i = \frac{\varphi_i}{\sum_{i=1}^m \varphi_i} \quad (1)$$

Where, φ_i representing the i -th feature value, we use the contribution rate to identify the principal components that contribute more than 5%. The advantage of using PCA for feature extraction is that it can fully utilize the information of each subcarrier. At the same time, due to PCA processing, it is an orthogonal subsystem that eliminates the mutual influence relationship between each subcarrier. The amount of data after extracting the first five layers is reduced, reducing complexity.

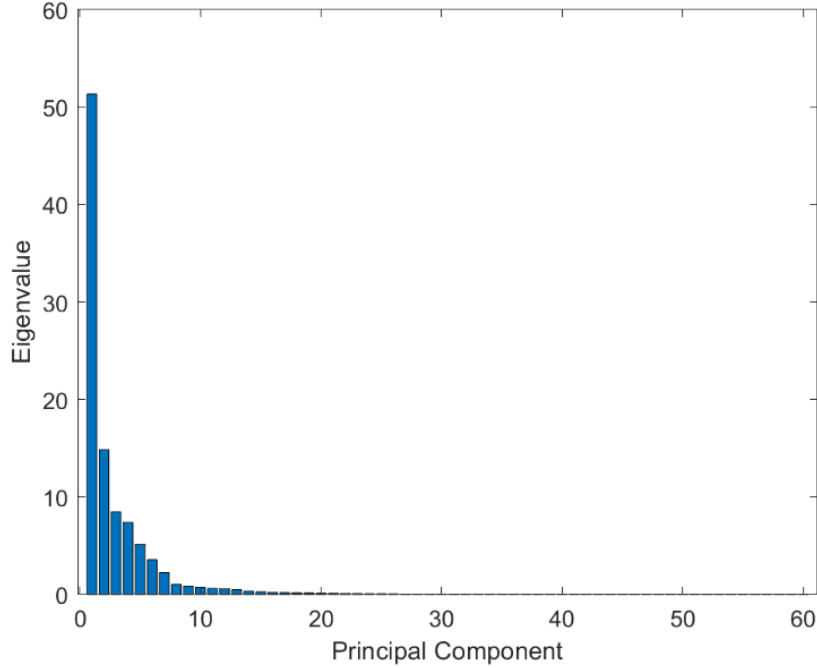


Figure 3. Contribution of PCA Principal Components

2.2.2. Extracting time-frequency domain features

In order to study the influence of human gait on the CSI stream, we extracted the temporal information of the first five principal components using PCA, including mean, root mean square value, root amplitude value, absolute average value, skewness, kurtosis, variance, maximum value, minimum value, peak value, wave index, peak index, pulse index, margin index, and kurtosis index as the temporal features of the CSI information. Then, the first five principal components were subjected to discrete Fourier transform to obtain the frequency domain representation of the data, from which frequency domain features were extracted, including average frequency, centroid frequency, sum of the first-level sideband amplitudes, sideband index, FMO, and sideband level factor. A total of 18 features. These constitute the basic required features of the system. Basic frequency domain information is not sufficient for training, so wavelet transform is introduced to add more feature information.

2.2.3. Wavelet Transform

After PCA extraction, the data needs to further extract the energy values of its wavelet decomposition as the features for the subsequent training of the support system. Based on the principles of discrete wavelet transform and the requirements for wavelet basis selection, and considering the orthogonality, support, and symmetry of the Haar feature, the Haar wavelet basis is fully capable of supporting our experimental needs. Table 1 shows the feature list after 12-layer wavelet decomposition of the data.

Through wavelet transform, we can separate the characteristics of high-frequency signals and low-frequency signals, and extract the energy values of 12 layers to represent the variation characteristics of CSI signals at different frequencies. The introduction of wavelet transform has improved the recognition rate of the system to a certain extent.

Table 1. Feature List

Time Domain Features	Mean	Frequency domain features	Average frequency
	Root Mean Square Value		Center of gravity frequency
	Root mean square amplitude		The first-level edge frequency band amplitude and
	Absolute Average		Edge Frequency Band Index
	Skewness		FM0
	Kurtosis		Edge frequency band grade factor
	Variance	Wavelet Transform Energy Feature	1 layer
	Maximum value		2nd floor
	Minimum Value		3 layers
	peak		4 layers
	Waveform indicator		5th floor
	Peak indicators	
	Pulse index		10 Layers
	Margin index		11th floor
	Kurtosis index		12 layers

2.3. Establish recognition model

In this paper, the random subspace method in machine learning is used to construct the recognition model. This method trains the classifier with randomly selected features, effectively reducing the correlation between classifiers. This method fits well with the training of 155 features for 15 individuals. When the data dimension is too high, using other classifiers can easily lead to overfitting, while RSM can avoid this problem. To train using random subspaces, it is necessary to normalize the feature vectors to ensure that the distribution of features during training does not become too scattered. At the same time, the model is evaluated using 10-fold cross-validation to ensure that the model does not overfit samples from specific scenarios.

3. EXPERIMENTAL SETTINGS

During the experimental stage, experiments were conducted in three environments: the lobby, corridor, and classroom, using an industrial computer with an Intel 5300 network card that supports the 802.11n protocol as the receiving device, and TP-link Wi-Fi as the transmitting end.[13] The data collection results in the three scenarios are listed as follows:

Table 2. Data collection situation

Environment	Number of subjects	Frequency band selection	Sampling frequency
Experiment Building Lobby	15	2.4GHz	1000Hz
Corridor	15	2.4GHz	1000Hz
Classroom	15	2.4ghz	1000Hz

The experiment needs to divide the collected data into two categories: one is used for training the model, and the other is used for testing the data. The experiment is conducted through detection rate and confusion matrix.

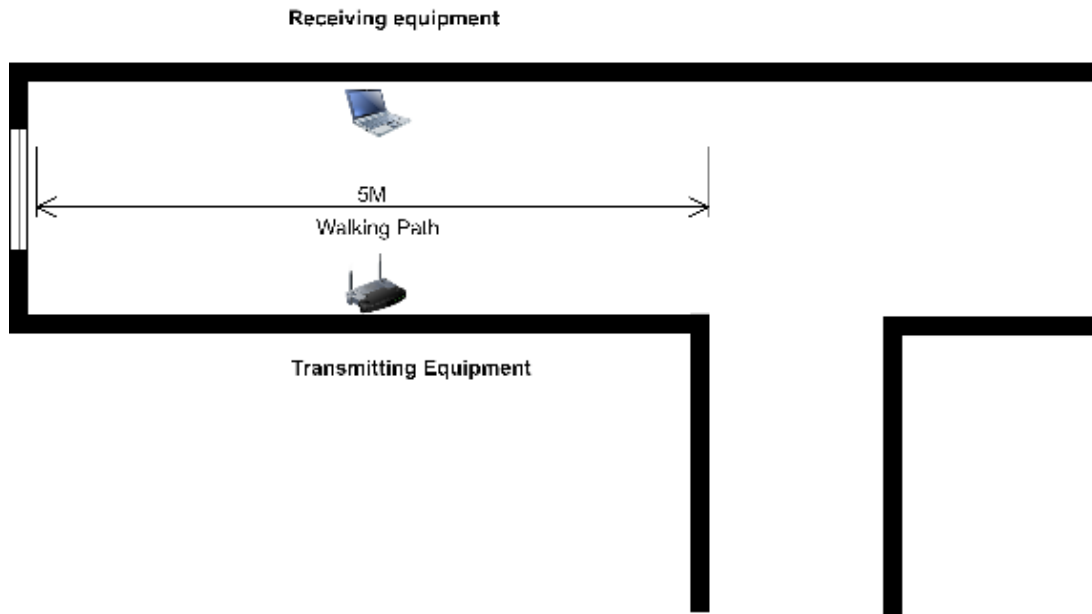


Figure 4. Corridor

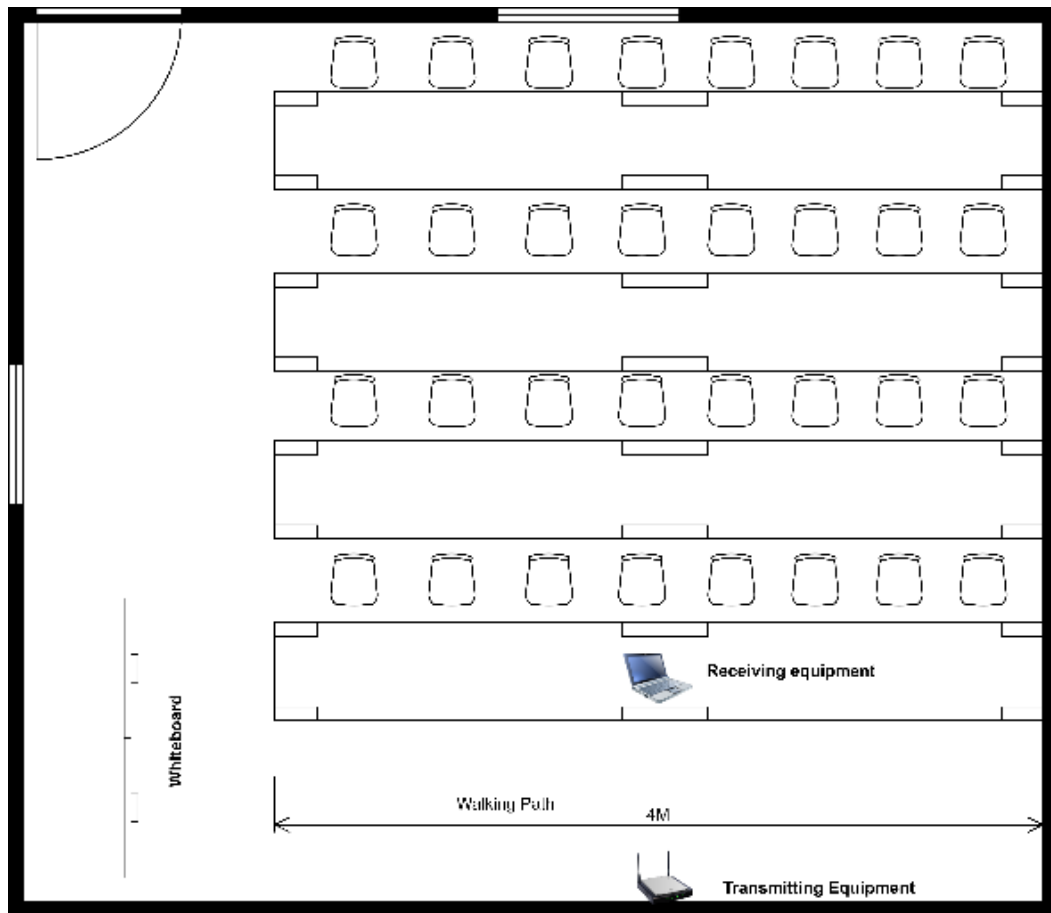


Figure 5. Classroom

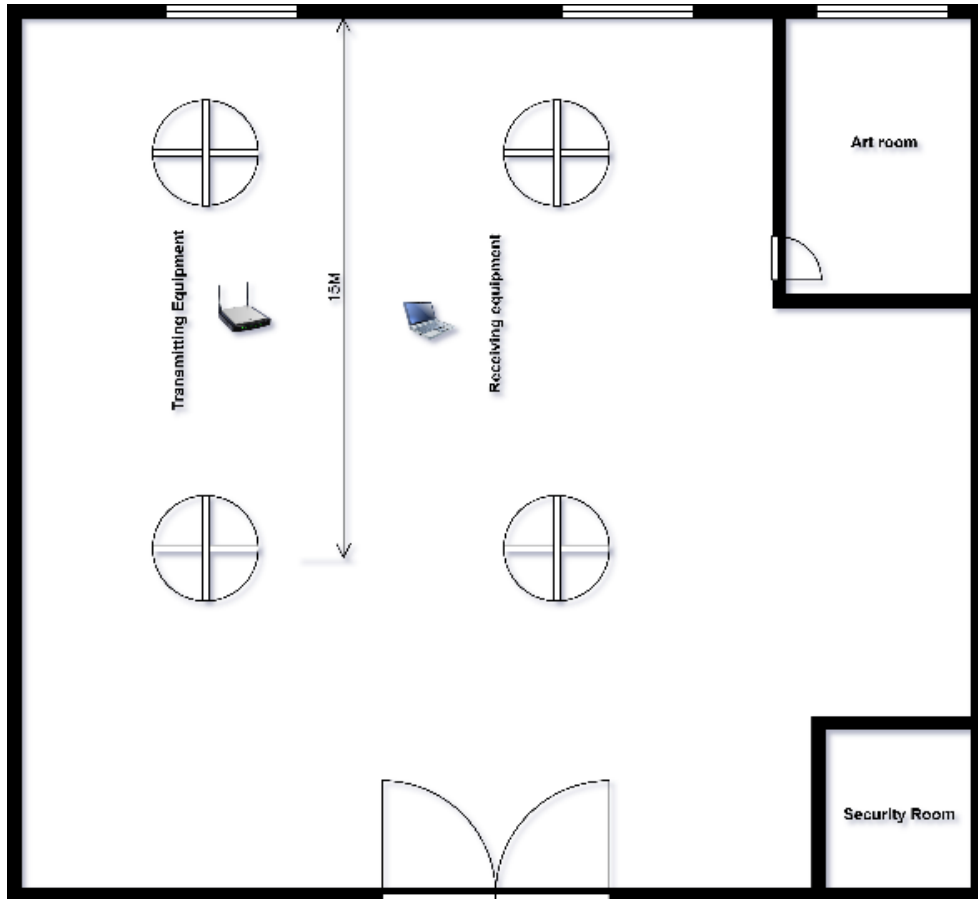


Figure 6. Laboratory Hall

The laboratory hall, as an open and spacious area, has the spatial configuration shown in the figure 6 Lobby. In this scenario, the WIFI signal is subject to external interference and is used as a typical dataset in this paper. The corridor has the spatial configuration shown in the figure 4 Corridor, and its narrow and elongated shape with multiple signal reflections ensures the diversity of our multi-scenario data. The final classroom in figure 5 Classroom, as a space with a wide but obstructed signal characteristic, has more complex differences in subcarrier information collected in these three scenarios. Therefore, it can be found that the physical environment of the experiment will have an impact on the final recognition rate.

4. LIMITATIONS

In this article, a multi-scenario identity recognition system is proposed, which still has some limitations. Some of the limitations recognized so far are as follows.

- 1). The flexibility In the current system we must assume that the recognized object is moving along a straight line and the direction of the movement does not change. Hence, the current system has good applicability for some corridors, aisles, and foyers. When the object to be recognized enters the house or passes through the corridor, it can be identified. In addition, this paper does not analyze the influence factors of the human body when its characteristics change, such as changing clothes or getting fat or taller.
- 2). This article has not analyzed the single-scene training and multi-scene application, the training mode is based on the gait information in different scenarios mixed training results. The square system program about single-scene training is the focus of the subsequent research work. Simultaneously, the recognition accuracy of other individuals in the non-training set is also yet to be explored.

3). The age of the recognized individuals in the dataset is between 20 and 25 years old, and the gait information of young and old people is not analyzed. This part of the dataset needs to be expanded in the follow-up work and the effect of age on the recognition rate and recognition model needs to be analyzed.

5. CONCLUSIONS

CSI data from 15 individuals, with 30 experiments per person per scenario. In this study, 20 experiments were selected as the training set and 10 experiments were selected as the prediction set, resulting in an identification rate of 87.2%. Figure 7 shows the scatter plot of the final prediction results, which satisfies the identification requirements in various scenarios. Figure 8 indicates that the predictions in this study follow a pattern rather than random probability.

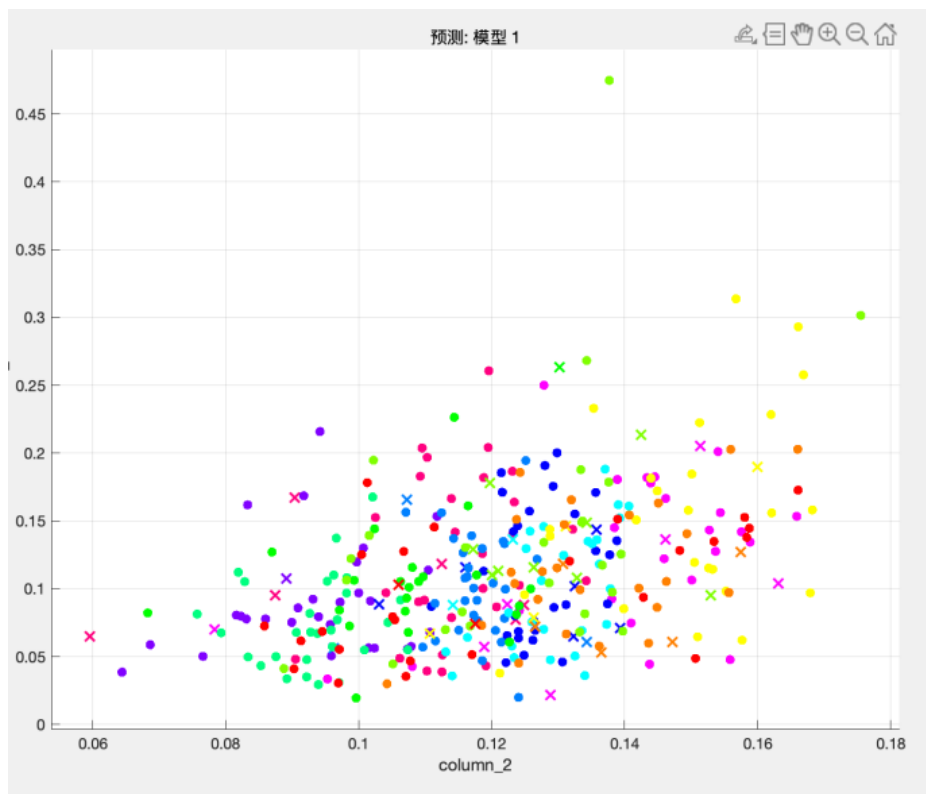


Figure 7. Scatter plot of experimental results

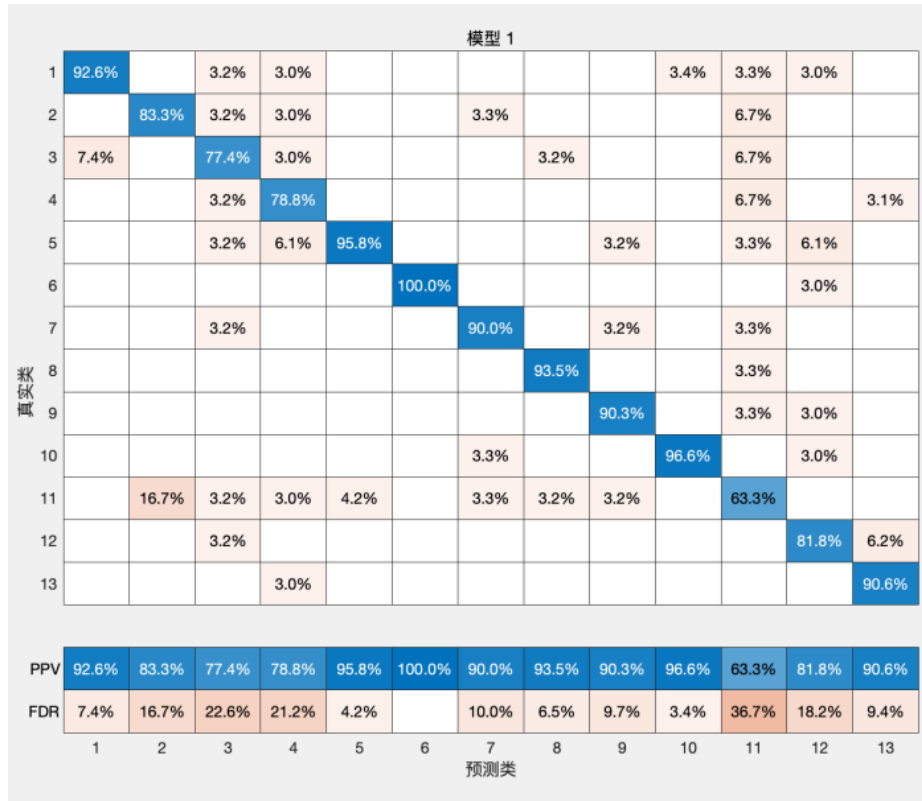


Figure 8. Confusion matrix of Model

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