Gesture Recognition System Based on RFID

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Abstract. Gestures recognition as the main technology of human-computer interaction draws a great amount attention of researchers. Comparing to existing methods, the RFID-based passive gesture recognition requires no specialized equipment which makes it much easier to be used. To achieve the goal, we build a priori gesture database according to signal features caused by perturbation of different gestures. Then, the modified dynamic time warping (DTW) algorithm has been used to match with the priori fingerprint database. Besides, we propose a wireless phase calibration algorithm by utilizing the theory that the noise subspace and the signal subspace is orthogonal in multiple signal classification (MUSIC) algorithm to estimate and remove phase errors that may caused by equipment differences so that we can ensure the accuracy of angle of arrival (AoA) estimation. To evaluate the effectiveness of our gesture recognition system, the experiments in a real scene were carried out. And the experimental results show that we can achieve about 92% accuracy.

Keywords: Gesture recognition · Feature extraction
Phase calibration · AoA estimation · DTW

1 Introduction

In the 21st century, smart devices are gathered and the way of interaction is getting richer and more humane. Therefore, as an important part of human-computer interaction, gesture recognition has drawn extensive attention and become a hotspot of research [1–5]. Gesture recognition makes many operations that used to be hard to achieve become reality. For instance, users can write, pay, and even control the electrical appliances in smart home by gesture with our smart phones, tablets, laptops etc. Moreover, literatures [3,6] can even realize writing in the air by interacting with the smart devices. Obviously, our life become much more convenient if we can control the volume or answer the phone in a second.

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Nowadays, the RF signals that have been mentioned by many papers as they can pass through the walls and won't be affected by smoke, fog and light [7]. So device-free gesture recognition based on RF signals has become a hotspot [3,8–10]. The common device-free wireless gesture recognition technology mostly by using the CSI [11] or RSS [12] to estimate the angle that the signal arrives at the receiver, which always require dedicated equipment [12]. Moreover, RSS value and CSI amplitude of the RF signal are severely affected by the multipath when deployed in real environment, which will decrease the accuracy and the robustness of the gesture recognition technologies severely.

To reduce the impact of multipath on the RF signal, the previous method is to minimize the impact of multipath. But if we can implement gesture recognition by combining the fine-grained phase information of RF signals with the signal strength information and use the gesture influence on the multipath signal to increase the difficulty in the matching part of the recognition, the accuracy of the gesture recognition can be improved.

In the main while, the RFID can not only obtain the characteristic information of the signal easily, but have a broad industrial prospect as well because it can be easily popularized and deployed. As RFID positioning technology [13–15] becoming more and more mature, many researchers began to study how to use RFID technology for gesture recognition. Moreover, RFID-based gesture recognition is cheaper than the Wi-Fi-based gesture recognition methods [3,16,17]. RFID tags are passive nodes, which generate signals by the energy carried by the radio waves. The internal structure of the RFID tags is simple. Its data storage capacity is large and the volume is small. What's more, the price of it is about 0.5 yuan for each, while each Wi-Fi device is mostly at 100 yuan of the above.

Therefore, this paper proposes a device-free gesture recognition system based on RFID, which utilizes impact of gesture on multipath to improve the resolution of gesture recognition with minimal deployment cost. The main idea is utilizing the fact that each moment of the gesture will interfere with the signal differently, so that we can use the feature information of the signal perturbed by the gesture as the fingerprint to recognize gestures. To achieve the RFID-based gesture recognition system well, we have to handle the following key challenges:

– In actual wireless positioning, there are phase errors caused by hardware differences. The introduction of unknown phase offset to the received signal may cause array uncertainty and low accuracy of MUSIC direction finding technology so that estimate an incorrect AoA value. For this reason, this paper introduces a wireless phase calibration algorithm that does not require special equipment. In this algorithm, we will firstly construct an objective function by utilizing the orthogonal theory of signal subspace and noise subspace. After that, we can solve the phase error estimation value by Genetic algorithm.
– Since there are differences of starting time and speed among different users, the length of those two time-series which need to be matching in similarity may not be aligned on the time axis. Therefore, this paper utilizes the modified DTW algorithm which was used for speech recognition to compare and regulate two time-series and then judge the similarity between them.

To verify the performance of the proposed method, this paper carried out the corresponding experiment. We set up the experimental platform in a $7\,\mathrm{m} \times 10\,\mathrm{m}$ classroom. The main devices are a 8-antenna linear array, a reader with a frequency of 920.875 MHz and 6 RFID tags. We first make 10 gestures as priori fingerprint database. After that do gesture to identify freely. The experimental results show that this method can achieve a correct recognition probability of about 92%, which shows that the proposed method is highly feasible.

2 Related Work

The existing gesture recognition methods are mainly divided into three categories, which are method based on the sensor technology, the image recognition technology and method based on the RF signal.

Gesture recognition based on sensor mainly relies on MEMS (micro-electromechanical systems) sensors (accelerometers, gyroscopes, magnetometers, etc.) to extract the acceleration and angular velocity signal characteristics of the gesture, which requires users to wear sensors and other equipment. This method is inconvenient for users and has a limited application.

Gesture recognition based on image technology [18] mainly relies on the camera to capture real-time images of users with high precision, but the algorithm is computationally intensive and requires high light intensity and shooting angle.

Gesture recognition based on the RF signal mainly use the ubiquitous WiFi to recognize gesture. For example, WiSee [8] performs gesture recognition based on the Doppler shift caused by human motion measured by a WiFi signal. Since the RF signal can penetrate the wall, WiSee can break out the restriction on line-of-sight. However, this method requires the special equipment USRP, which has good effect but costs a lot and is not suitable for wide applications.

Gesture recognition based on RFID depends on the RFID tags mainly carried by targets to work. Receivers recognize the gesture by analyzing the change of amplitude or phase of the RFID tags. D.Katabi's RF-IDraw virtual writing [6], the recognition rate of which achieves 96.8%, is the most representative achievement of RFID gesture recognition. This achievement need users to wear RFID tags, and write English words or letters, then the receivers can analyze the tracks of spatial location and reconstruct the words.

In order to let users get rid of sensors and special equipment and obtain better experience, in this paper, we use machine learning method to recognize gestures. We obtain feature vector corresponding to every gesture by utilizing the gestures interference on signal obtained by reader. Then we match the database and utilize influence of the multi-path signal to increase the difficulty of matching to improve the identification accuracy.

Unlike Grfid [19], which is also a device-free gesture recognition system based on RFID phase information, we calibrate the phase error caused by hardware difference before feature extraction to improve the identification accuracy. Specifically, we firstly construct an objective function by using the orthogonal theory of signal subspace and noise subspace, estimating and removing phase error caused by equipment differences to ensure the accuracy of AoA estimation.

3 System Design

The critical techniques of our gesture recognition system are shown in Fig. 1. Establishing priori fingerprint database contains data preprocessing module and feature information extraction module. The data preprocessing module calibrates the obtained phases and then processes the collected data into frames, that is processing one gesture at multiple sampling points. Extracting feature information module is to estimate AoA (angle of arrival) utilizing MUSIC algorithm, and a feature matrix is obtained for gesture recognition. The feature information matching module uses the improved DTW algorithm in this paper to compare and sort two time series to optimal the sum of costs to match gestures. Difficulty of matching is increased by the influence of the multi-path so that we can improve the recognition accuracy.

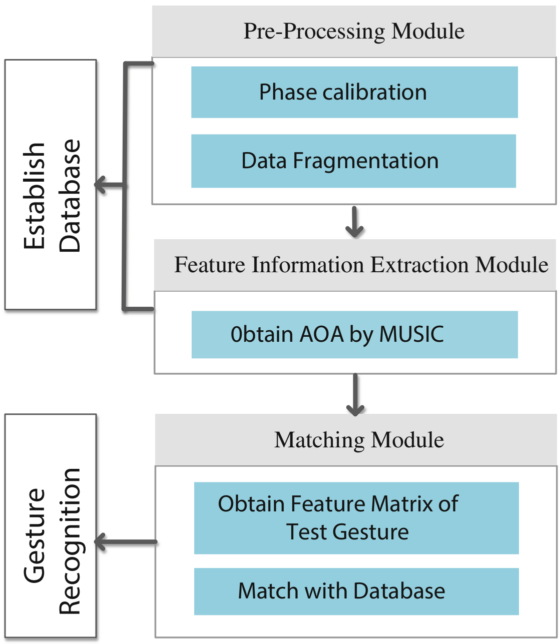

Fig. 1. Overview of the system.

3.1 Get RFID Signal Characteristics

RFID working under UHF has the farthest communication distance, so it is used for our gesture recognition. RFID uses 920 MHz electromagnetic carrier to communicate, and its communication signal as the ordinary wireless communication signal, which has three basic properties, namely, phase (ϕ), amplitude(A), frequency (f). The frequency is known, so the characteristics of the entire carrier signal can be known as long as the phase(ϕ) and the amplitude(A) of the signal are known.

The data obtained by the RFID reader are: phase (ϕ), amplitude(A), tag number (ID), time (T), then the obtained information can be expressed as:

$$antenna_i = (\phi_r, A_r, ID_r, T_r)$$

Here $r = 1, 2, \ldots, N$. $j = 1, 2, \ldots, M$. r is the packet number and j is the antenna number.

3.2 Extract Gesture Fingerprints

Create a priori fingerprint database and match the being recognized gestures with it. First, divide the phase and amplitude for gestures according to disturbance of RFID signal caused by gestures. Then split data into frames and calculate the eigenvectors corresponding to each frame to form the feature matrix of the gesture. Similarly, the feature matrices of other gestures can also be obtained, and then the feature matrixex of all the gestures constitutes a priori fingerprint databases.

Data Division. Because RFID communication is discrete in the time domain, there is no guarantee that there is a continuous signal for each gesture. If the matching is performed directly, errors may occasionally occur, so traditional identification methods based on continuously varying signal characteristics cannot be used. Inspired by the concept of frames in image recognition methods, this paper divide the data into frames in chronological order when analyzing the data. The number of frames depends on the number of sampling points of a gesture. This process is equivalent to dividing one gesture into several discrete moments that describes the gesture.

The data are collected in $Antenna_j$ is chronologically ordered. Divide it into equal parts of n copies, then the amount of data for each copy is $k = \frac{N}{n}$, so divide the data into n frames:

$$Frame_q = (Antenna_{1q}, Antenna_{2q}, \ldots, Antenna_{jq})$$

Here, $q = 1, 2, \ldots, n$.

In this method, multiple tags be used as the signal. That is to separate and classify each $Antenna$ data in $Frame_q$ according to the $TagID$ to obtain the data corresponding to each tag:

$$Tag_d = (Antenna_{1d}, Antenna_{2d}, Antenna_{jd})$$

d is $TagID$ number, so $Frame_q$ *is changed to* :

$$Frame_q = (Tag_{1_q}, Tag_{2_q}, \ldots, Tag_{d_q})$$

Tag_{d_q} represents the data corresponding to the tag with the data number d in the q frame.

Calculate the Feature Matrix Corresponding to the Gesture. After dividing the data obtained by each antenna into frames, we need to separate the corresponding data information for each tag. It is necessary to analyze the corresponding signal characteristics of each tag data of $Frame_q$. In this paper, the signal characteristics are obtained by using the method of AoA estimation. The method steps are as follows:

(i) Calculate the phase that arrives on each antenna.
The data processed in this step is a frame of data for each tag. The first column of data in $Antenna_j$ is the phase. Due to the environmental noise, the data may fluctuate. In order to make the data statistically representative, The highest frequency data is considered as real data, that is:

$$\phi_{antenna_j} = \phi \mid max(frequence_{\phi_r}) \tag{1}$$

(ii) Calculate the signal expression received for each antenna.
We have obtained the phase information of each antenna received data, according to the characteristics of the sine wave, the signal at time t can be expressed as:

$$S_{Antenna_j} = A_{Antenna_j} \cdot exp(i \cdot (2\pi ft + \phi_{Antenna_j})) \tag{2}$$

Calculate the signal received by each antenna to form the signal S.

(iii) AoA estimation.
Using the MUSIC algorithm to compute the matrix S, we can get AoA. The parameters are: antenna spacing Xd and step of angle value $\Delta\lambda$ (in degrees). The output data is

$$B = (P_m), \quad m = \Delta\lambda, 2\Delta\lambda, \ldots, \frac{180}{\Delta\lambda}$$

P is the AoA estimation.

3.3 Establish a Priori Fingerprint Database

Each gesture has data of l tags, so each gesture corresponds to 1 vector B, which forms a group, that is, the feature matrix corresponding to one gesture in the qth frame is formed:

$$Action = (B_1, B_2, \ldots, B_l)$$

Doing the above operations on the n frames of data respectively, we can obtain the feature matrix of a certain gesture:

$$W = (Action_1, Action_2, \ldots, Action_n)$$

Enter the data corresponding to all the gestures to build the feature matrix of collected gestures, then the feature matrices of all gestures constitute a knowledge database DB for gesture matching.

3.4 Use RFID Feature Comparison for Gesture Recognition

When recognizing the gesture x, the data of M antennas are acquired and processed according to the method of Sect. 3.2 to obtain the feature matrix Wx corresponding to B_x, $Action_x$.

Recognizing gestures, that is, to find out a feature matrix W which has the best matching rate with Wx in the DB. In the practical application of hand gesture recognition, due to different personal habits, different users have different gesture duration and starting time when making the same gesture, which has the same problem with speech recognition. Therefore, DTW is a good solution to solve this problem. The key idea of DTW algorithm is to compare and regress the time series of the data to be recognized on the time axis, map the input time axis of the gesture to be recognized to the time axis of the prior knowledge base nonlinearly, minimize the alignment cost of all the elements, using which to judge the similarity between the two series.

Using the DTW algorithm to calculate the matrix of two curves to be matched, the similarity of the curves can be output. For any element in the sequence pair, the Euclidean distance between $Action(\alpha)$ and $Action_x(\beta)$, $\alpha \in [1, \mu], \beta \in [1, \nu]$, is the alignment cost, that is:

$$C_{\alpha,\beta} = \mid Action(\alpha) - Action_x(\beta) \mid \tag{3}$$

Matrix with regular sequence and the sum of the cost C is $\mu \times \nu$. Let Z be the aligned arrangement of element pairs in matrix C, $Z = (z_1, \ldots, z_h, \ldots, z_H)$ where $max(\mu, \nu) \leq H \leq \mu + \nu - 1$ and $z_h = (\alpha_h, \beta_h)$. DTW algorithm is to find the arrangement of Z which make the cost of C smallest, that is:

$$\min_z \sum_{h=1}^{H} Z_h = \sum_{h=1}^{H} C_{\alpha_h,\beta_h} \tag{4}$$

Futher, we take the derivative of each pair of sampling point of the sequence as the second evaluation criteria. After we obtain the derivative of all pairs of samples $D = \{\frac{d\alpha}{dt}\}$, we need to calculate the cost of them C' based on the method described above. Therefore, matching cost here refer to the C' and C.

The sequence W_x of the gesture to be recognized with the characteristic matrix corresponding to each gesture in the DB. If each column in the characteristic matrix W_x has a smaller matching cost with the corresponding column of a gesture characteristic matrix W_y in the fingerprint database DB and the sum of the cost is the smallest, it is considered that the gesture is same as the corresponding gesture in the knowledge base, that is, the recognition is successful.

When the user makes a gesture, the user's limb may block a portion of the path from tag to reader or may reflect the signal to create a new multi-path. Figure 2 shows the AoA estimated characteristic curves generated from five data frames of the same gesture. The curve of Frame 2 shows that the tag forms a new signal path under the influence of the user's body. Therefore, in the matching process, multi-path will increase the difficulty of matching information, thereby improving the recognition accuracy.

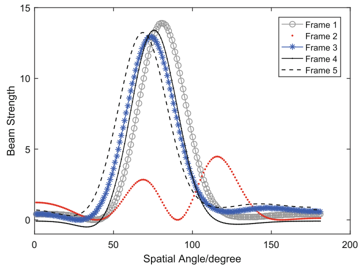

Fig. 2. Characteristic curve of AoA estimation.

3.5 Wireless Phase Calibration

Currently, there are multiple signal processing (MUSIC) algorithms [20,21], minimum variance non-distortion response (MVDR) adaptive beamforming algorithms [22], and ESPRIT algorithms [23] for array AoA estimation. Among them, the MUSIC algorithm has the advantage of high accuracy. Therefore, the MUSIC algorithm is widely used. However, the phase error caused by hardware differences often occur in actual wireless positioning, and an unknown phase offset is introduced into the received signal, which may causes array uncertainty. RFID positioning systems use MUSIC algorithm which assume that the array manifold matrix consists of all possible directions of the received signal. Due to the actual phase error caused by the hardware of the RFID system can not be ignored, such as cables, readers and antennas, signal transmission will have some loss. Literature [24] introduces a wired calibration method, and the traditional calibration method is through manual means, using special equipment, such as the Universal Software Radio Peripheral (USRP), a continuous wave is generated and input to the device to be calibrated as a reference source, and a group of devices including all the cables are measured at a time. The signal of the USRP passes through the device and the connection Line to reach the array. The hardware phase error can be directly estimated by observing the phase difference between the antennas, and then subtracting the phase error from the received signal, the influence of unknown hardware differences on AoA estimation can be eliminated.

However, this conventional method requires the use of a dedicated device, with the disadvantage of high hardware costs, and requiring an additional measurement of a set of data before the experiment to estimate the hardware error and then switch to the general-purpose device, which causes the operability poor.

So in this section we propose a wireless phase calibration method. As shown in Fig. 3, we assume the first antenna as a reference, in addition to the internal error, the i th antenna phase difference should also include the phase error caused by external hardware. Assuming that the phase error introduced by the first antenna is 0, the i th antenna phase error caused by the hardware difference relative to the first antenna is β_{i-1}, the antenna array is composed of the phase error vectors $\beta = \left[1, e^{-i\beta_1}, e^{-i\beta_2}, \cdots, e^{-i\beta_{\mathrm{M}-1}}\right]^T$.

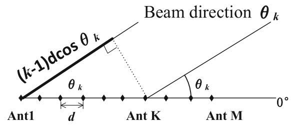

Fig. 3. Array signal model.

Let $\mathbf{B} = diag\{\beta\}$, the real measured signal should be $Rs = \mathbf{AB}x(n) + e(n)$, $\mathbf{U}_n$ is the noise subspace of Rs, $\mathbf{U}_s$ is the signal subspace of Rs, According to the above MUSIC algorithm, we know that the $\mathbf{U}_s$ and $\mathbf{U}_n$ of the actual measured signal are orthogonal, and $\mathbf{U}_n$ is the same as the subspace formed by the direction matrix $\mathbf{B}$, it can be seen that $(\mathbf{AB})^H$ is orthogonal to $\mathbf{U}_n$, that is $\mathrm{J} = \left\| (\mathbf{A} \odot \mathbf{B})^H \mathbf{U}n \right\|^2$.

The optimization process has two main points: first, using the information of one of the tags, to obtain the hardware error value that minimizes the objective function J; second, using the MUSIC algorithm to estimate the AoA values of other tags. Calibration algorithm specific process described as follows:

Step 1: Take the first tag for optimization, the parameter information is known (real AoA, phase, RSSI value), and then the signal s received by each antenna can be obtained. Find the autocorrelation matrix of $\mathbf{S}$, $\mathbf{R} = \mathbf{S} * \mathbf{S}'$. According to the above method, decomposing the eigenvalue of R can obtain the noise eigenvector $\hat{\mathbf{U}}_n$and the direction vector $\hat{a}$;

Step 2: Constructed the objective function for the phase error β as $Obj_\beta = \left(\hat{a} \odot e^{-i\beta}\right)^H \times \hat{\mathbf{U}}_n \times \widehat{\mathbf{U}}_n^H \times \left(\hat{a} \odot e^{-i\beta}\right)$.

Through the genetic algorithm to obtain the initial value of β, the one-dimensional search is used to obtain the optimal solution β_{opt} of β which minimizes the objective function;

Step 3: According to β_{opt}, the signal that the other tags arrive at the array after removing the hardware phase error can be obtained as $\mathbf{Rs} = e^{+i\beta_{opt}} \times \mathbf{S}$;

Step 4: The MUSIC algorithm is used to obtain the spatial spectrum. According to the value of the x-axis corresponding to the peak of the curve, the angle-of-arrival AoA can be obtained. Finally, the error can be obtained compared with the real measured AoA.

Step 5: By repeating the above operation, the error between the estimated AoA value and the true measured value can be obtained when each tag is used as a calibration source.

4 Experiment and Analyses of Result

4.1 The Construction of Experimental Scene

We deploy the experimental setting in a 7 m × 10 m classroom. To obtain data, we use the ImpinJ RFID reader with the with the frequency of 920.875 MHz. The actual transmission distance is about 5m. In the experiment, we choose these parameters: the amount of antenna $m = 8$, the amount of tag $l = 6$, the amount of data frame $n = 5$. A linear array, which is made up of 8 antennas, connects with the reader, the two with a distance of 4 cm. We choose 6 tags in front of the array, and make the tags face the array straightly to the greatest extent, and put them in the range of reader's readable area dispersedly as signal sources. The experimental equipment was shown in the Fig. 4, and the deployment was shown in the Fig. 5.

4.2 The Establishment of Fingerprint Database

We do each gesture circularly, and then we choose the data group which has highest similarity with other groups as the fingerprint for one gesture. In our experiment, we totally display 10 gestures which have been set in advance, as shown in the Fig. 6. So that we can obtain the priori fingerprint base.

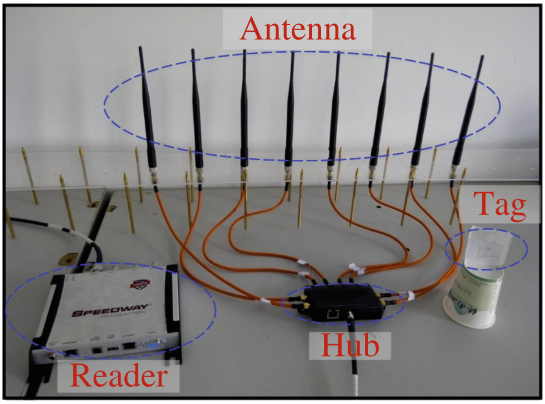

Fig. 4. Experiment equipment.

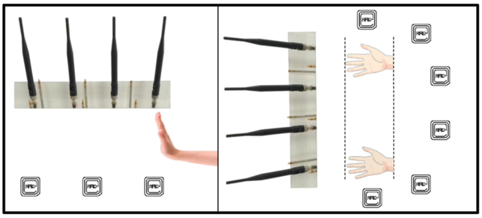

Fig. 5. Experiment deployment.

4.3 The Recognition of Gestures

User make gestures randomly. We use the algorithm introduced in the Sect. 3.2 to get each eigenvector of the tags corresponding to the gesture.

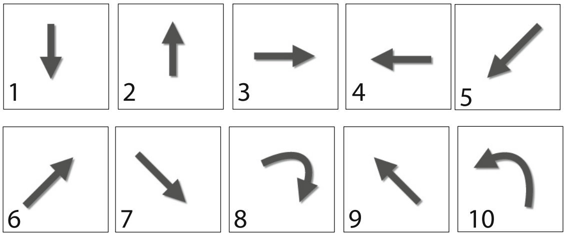

Fig. 6. Priori database of gestures set.

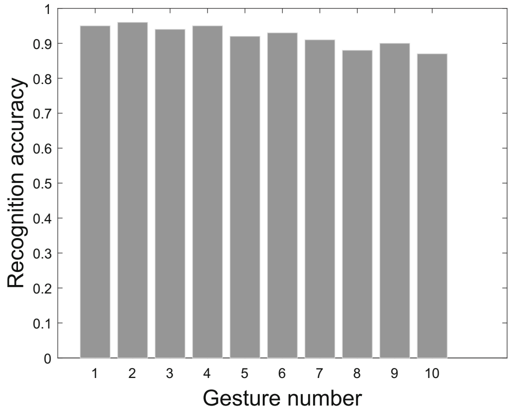

Fig. 7. Accuracy of our gesture recognition system.

In order to quantify similarity and diversity further, we input the data into our modified DTW algorithm to calculate regularly, the output data can quantify distance of each pair of corresponding points. From its output image we can explicitly see the matching rate.

4.4 The Analyses of Performance

In order to evaluate the system proposed in this paper, we repeat our each gesture 10 times. In this way we can get corresponding data. According to the aforementioned method, we obtain the gesture recognition results. Figure 7 shows that the correct recognition probability of our system can reach about 92%, it proves that this method has a quite high feasibility.

5 Conclusion

Gesture recognition is an important part of human-computer interaction. It has great application prospects in the fields of smart home and somatosensory games, which brings convenience to our life. The proposed gesture recognition technology is based on RFID, which is low cost, and easy to be deployed. This method preprocess the data by dividing data into fragment, and calibrates the phase to eliminate the phase difference caused by the hardware difference to improve precision. Then the MUSIC algorithm is used to obtain the eigenvector of each gesture. Finally, modified DTW algorithm is used to recognize the high resolution gesture. The experiment shows that the method proposed in this paper can realize gesture recognition well.

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