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Device-free Gesture Recognition Technology Combining Radio Frequency Identification Method

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Abstract

With the development of computer technology, the methods of human-computer interaction (HCI) have also been innovated continuously. From the traditional mouse and keyboard to the popular touch screen, and the more advanced voice control, HCI technology has become increasingly humane. Compared with the conventional HCI methods, gesture interaction has the advantages of contactless operation, easy to learn, and massive information carried. Therefore, the study of gesture-based HCI technology is of great significance. Compared with the existing gesture recognition system based on radio frequency identification (RFID), the RFID-based device-free gesture recognition method can track the hand area during movement effectively by estimating and judging the position of the hand centroid when users are not required to carry any device. During dynamic gesture trajectory tracking, signal interference by gesture is considered as a fingerprint feature. Multipath is used to increase the matching difficulty and ensure the gesture recognition accuracy. The synthetic aperture radar (SAR) algorithm is used to obtain the fingerprint feature matrix corresponding to each gesture. The priori gesture fingerprint database is matched by the dynamic time warping (DTW) for gesture recognition. The experimental results suggest that the RFID-based device-free gesture recognition method has significantly improved the accuracy with excellent robustness.

Keywords: *Wireless Gesture Recognition; Radio Frequency Identification (RFID); Device-free; Synthetic Aperture Radar (SAR); Dynamic Time Warping (DTW);*

1. Introduction

Many intelligent instruments are available in the 21st century for more abundant and humanized ways of interaction. As an important part of human-computer interaction (HCI), gesture recognition has gained widespread attention and has become a research hotspot [1-2]. Gesture recognition makes many applications possible. For example, users can write, pay, and draw on smartphones, tablets, or laptops with touch screens and use gestures to control appliances in smart homes [3-4]. It is even proposed in some literature that mobile devices can be controlled by finger-writing-in-the-air to control sound volume or answer calls, making people's lives more convenient. With the rapid development of wireless technology, many documents point out that RF signals can pass through walls and are not subject to the effect of smoke, fog, and light [5-6]. According to the device-free wireless gesture recognition technology, the angle at which a signal reaches the receiving end is estimated in gesture recognition based on CSI (channel state information) or RSS (received signal strength) of multiple antennas, which usually requires a dedicated device. However, multiple paths can seriously affect RSS and CSI of RF signals in actual deployment [7-8]. As the result, the existing gesture recognition technology becomes less accurate and robust. As multiple paths have a relatively significant impact on RF signals, the previous solution was to eliminate the effect as much as possible. The accuracy of gesture recognition can be improved by combining fine-grained phase information of RF signals with signal strength and using gesture actions on multipath signals to increase the recognition difficulty in the matching link [9-10]. Meanwhile, based on RFID technology, not only the feature information of signals can be obtained easily, but it is also is convenient for popularization and practical

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application, with a broad industrial prospect. As RFID positioning technology matures, many researchers have begun to study the application of RFID technology for gesture recognition. Compared with the proposed gesture recognition method based on Wi-Fi, the cost of RFID-based gesture recognition is lower. As passive nodes, RFID tags generate signals according to the energy carried by radio waves, with a simple structure, large data storage capacity, small volume, and a relatively low price. Each device costs about 0.5 yuan, but most Wi-Fi devices cost above 100 yuan each.

To this end, an RFID-based device-free gesture recognition method is proposed in this paper. Multiple paths are used to improve the gesture recognition resolution and reduce the deployment cost. The main concept is that based on the different interference of signals at each moment of the gesture, the feature information of signals disturbed by the gesture is used as a fingerprint for gesture recognition. Combined with the RFID positioning and image recognition methods, the RFID gesture recognition classifies the collected data into pieces in time sequence, which is equivalent to classifying one gesture action. We conducted experiments to demonstrate the performance of the method. We established an experimental platform on a table (2.5 m × 1.5 m) in a classroom, with 4-antenna linear array, a reader (920.875 MHz), and 6 RFID tags. Firstly, experimental personnel made ten gestures to form a priori fingerprint database. Then, they made further gestures for recognition. The statistical results of the experiment suggest that a correct recognition probability of about 85% can be achieved by the method. Hence, the proposed method is feasible.

2. Key Technology of RFID-based Device-free Gesture Recognition

As RFID-based communication is discrete in the time domain, the traditional recognition method based on continuously changing signal features is not feasible. The data frame method is used to preprocess the interference information of gestures to signals based on data segmentation. For each frame of preprocessed data, the synthetic aperture radar (SAR) algorithm is used to obtain the feature matrix of gestures and form a priori knowledge base. Finally, the DTW algorithm is used to identify the feature matrix that best matches the prior knowledge base for gesture recognition.

Figure 1 shows the key technical components of the gesture recognition method. The priori fingerprint database includes two modules: data preprocessing and feature information extraction. The data preprocessing module mainly processes the data collected in frames, that is, gesture sampling at multiple points, which can be described by the multiple frames as 1 gesture. The feature information extraction module estimates the angle of arrival (AoA) of each frame based on the tag number, and obtain the feature matrix for gesture recognition; the corresponding feature points are determined, the physical coordinates of the data are divided into frames, and the SAR algorithm is used to estimate the AoA to obtain the signal features. The feature information matching module compares and rounds up the two-time series by the improved DTW algorithm to minimize the total cost. The matching gestures use the multipath effect to increase the matching difficulty and improve recognition accuracy.

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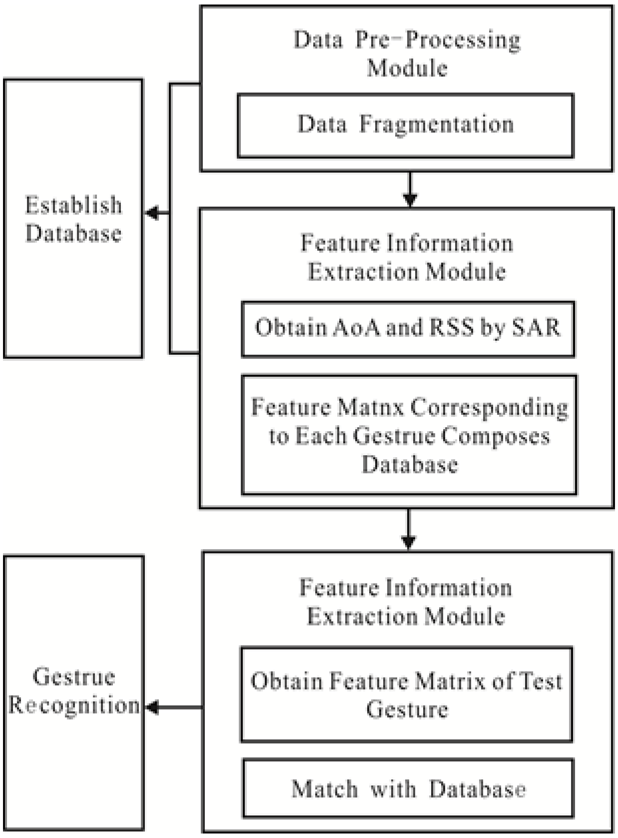

Figure 1. Key technology block chart

3. Device-free Gesture Recognition Core Algorithm Based on RFID

3.1. Extraction of Gesture Fingerprint Using RFID Phase Perturbation Features

A priori knowledge base is established for matching gestures to be recognized. Firstly, the phase and intensity data obtained from RFID signal disturbance by gestures are segmented. Subsequently, the feature vector corresponding to each frame of data is calculated, and a feature matrix of the gestures is formed. The same method is used to obtain the feature matrix of other gestures, and a priori fingerprint database is established by using the feature matrix of all gestures.

Due to the discrete time domain in RFID-based communication, the continuous signal of each gesture cannot be guaranteed. In the case of direct matching, there may be accidental errors. Hence, the conventional recognition method based on continuously changing signal features is not feasible. Based on the frame concept in image recognition (i.e., time-sampling complete continuous action), we propose that the data should be divided into slices in time sequence, i.e., processed into frames. The number of frames can be used to determine the number of sampling points. Framing is about dividing one gesture collected into discrete momentary positions. A sequence position describes one gesture, and each position corresponds to a data frame.

The data are collected in chronological order. The data of $Antenna_j$ are arranged in chronological order, and the order can be divided into an equal number of n portions. Thus, the data volume of each portion is $k = \frac{N}{n}$. Similarly, the data can be divided into n frames as follows:

$$Frame_q = \left(Antenna_{1q}, Antenna_{2q}, \cdots, Antenna_{jq} \right) \tag{1}$$

Where $q = 1, 2, \cdots, n$.

Similarly, multiple tags are taken as signal sources and isolated after framing. That is, Tag ID is used to separate and classify data in $Frame_q$. Hence, the data corresponding to each tag can be obtained:

$$Tag_d = \left(Antenna_{1d}, Antenna_{2d}, \cdots, Antenna_{jd} \right) \tag{2}$$

Where d is the Tag ID number, and the structure of $Frame_q$ at this time is transformed into the following

$$Frame_q = \left(Tag_{1_q}, Tag_{2_q}, \cdots, Tag_{d_q} \right) \tag{3}$$

Where Tag_{d_q} is the data of labels with d data in the q-th frame.

3.2. Construction of Priori Fingerprint Database

There is one label data for each gesture, with each gesture corresponding to vector B, forming a group that constitutes the feature matrix of one gesture in the q-th frame:

$$Action = \left(B_1, B_2, \cdots, B_l \right) \tag{4}$$

The above operation is performed on n frames separately to obtain a feature matrix of gestures:

$$W = \left(Action_1, Action_2, \cdots, Action_n \right)$$

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(5)

After the data of all gestures are input, the feature matrix corresponding to the gestures included can be obtained to constitute a knowledge base for gesture matching.

3.3. Feature Comparison of RFID-based Gesture Recognition

Gesture recognition is about identifying the feature matrix of the besting matching gestures in DB and recognizing gestures made by the user. For the matrix, each final column vector corresponds to a smooth curve, and matching is to find a similar curve. In the application of gesture recognition, various users may have different arm spans and gesturing durations when making the same gesture due to different personal habits, similar to voice recognition. DTW algorithm is commonly used in recognition. In the DTW algorithm, the core concept is about comparing and standardizing the time series of gestures on the time axis for non-linear mapping of the input time axis of gestures to the prior knowledge base, thereby minimizing the alignment cost. Subsequently, their similarity is determined.

In the DTW algorithm, the matrix of both curves is input and their similarity is output. For element pair $Action(\alpha)$ and $Action_x(\beta)$, $\alpha \in [1,u]$, $\beta \in [1,v]$ in the sequence, the alignment cost is the Euclidean distance between the elements:

$$C_{\alpha,\beta} = \left| Action(\alpha) - Action_x(\beta) \right| \tag{6}$$

The sum of sequence rounding cost © is $u \times v$ matrix. Assuming that Z is an aligned arrangement of element pairs in matrix C, $Z = (z_1, \cdots, z_h, \cdots, z_H)$, where $\max(u,v) \le H \le u+v-1$, and $z_h = (\alpha_h, \beta_h)$. The DTW algorithm is used to identify the arrangement Z and minimize C:

$$\min_Z \sum_{h=1}^{H} z_h = \sum_{h=1}^{H} C_{\alpha_h,\beta_h} \tag{7}$$

In addition, the following conditions are met:

1) Boundary conditions: $z_1 = (0,0)$, $z_w = (u,v)$;

2) Monotonic conditions:

$$\begin{cases} \alpha_{h+1} \ge \alpha_h, \beta_{h+1} \ge \beta_h, \\ \alpha_{h+1} + \beta_{h+1} \ge \alpha_h + \beta_h; \end{cases} \tag{8}$$

3) The window conditions are as follows: $|\alpha_h - \beta_h| \le Q, h = 1, 2, \cdots, H$.

When the difference between sequence pair elements is more significant than Q ($Q = H/6$), the sequence pair is considered to be corresponding to two different gestures. The window condition only requires the calculation of the elements in the cost matrix C with a diagonal width of 2Q, and the calculation complexity is significantly reduced.

4. Experiment and Result Analysis

4.1. Experimental Scene Establishment

We prepared the experiment on a 2.5 m × 1.5 m desk in a classroom (7 m × 10 m). The data reflected by the tag are collected by ImpinJ RFID reader (frequency set to 920.875 MHz), with the transmission distance of about 2 m. The following parameters are selected in the experiment: the number of antennas and tags. The data are divided into several frames to form a linear array, which is connected to expansion ports 1 ~ 4 of the reader. To improve accuracy and reduce array position errors, we place the 4 antennas in 1 element with a distance of 4 cm antenna fixed plate. The antennas are placed as straight as possible on the antenna fixing plate. During the measurement, the antenna center or antenna jack center of the fixed board is taken as the reference point.

We selected six tags and placed them in front of the array to ensure that the tags are directly facing the antenna at the half-height of the antenna, i.e., on the same horizontal line as the center of the half-height of the antenna), and placed scattered within the readable range of the reader as a signal source. The experimental devices are shown in Figure 2, and the scenario deployment is shown in Figure3 .

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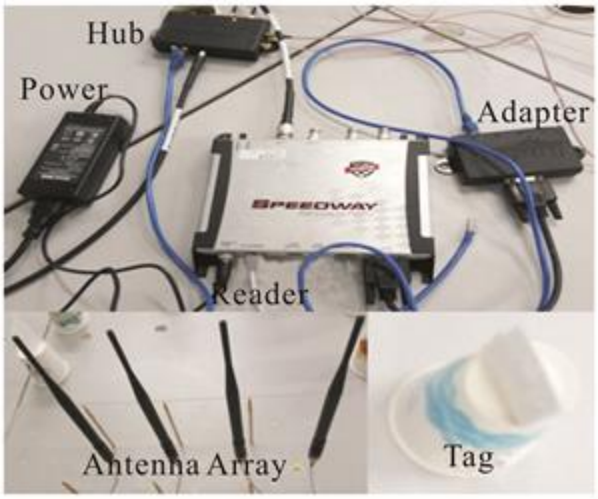

Figure 2. Experimental equipment

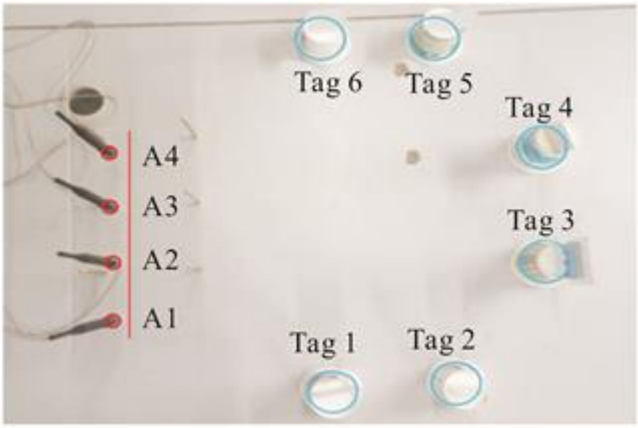

Figure 3. Experimental deployment diagram

4.2. Fingerprint Database Establishment

There are two options for establishing a fingerprint database: 1) Each gesture is made multiple times. Then loop matching is performed to remove error data that cannot be matched, and the rest data are used for the database. In the matching process, as long as the unknown gesture matches a specific data in the database, it can be considered as a match. 2) Each gesture is made multiple times, and loop matching is performed to identify a data group with a high degree of matching with each data as a knowledge base. The matching link only matches this group of data. Compared with Option 1, Option 2 has slightly lower accuracy. However, the calculation result of the matching link is much smaller. Hence, we choose Option 2 to establish the fingerprint database.

In the established experimental scene, the experiment personnel makes a total of 10 set gestures, as shown in Figure 4. Each gesture is made 10 times, and the obtained data are input according to the process described in Section 3 and Option 2 to get a priori knowledge base.

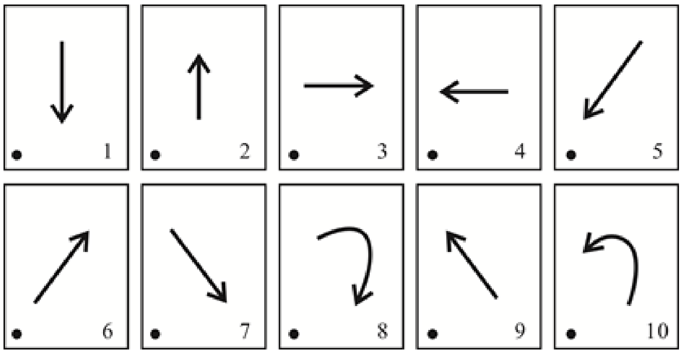

Figure 4. Ten preset gestures

4.3. Gesture Recognition

The experiment personnel randomly make gestures and use the algorithm described in Section 3.2, and the feature vector corresponding to each label is obtained. Figure 5 shows the characteristic curve obtained by three different motion data corresponding to the same label. The results show that characteristic curves of Frame 1 data in Figure 5 (a) and Figure 5 (c) are similar, which are significantly different from the Frame 1 curve in Figure 5 (b).

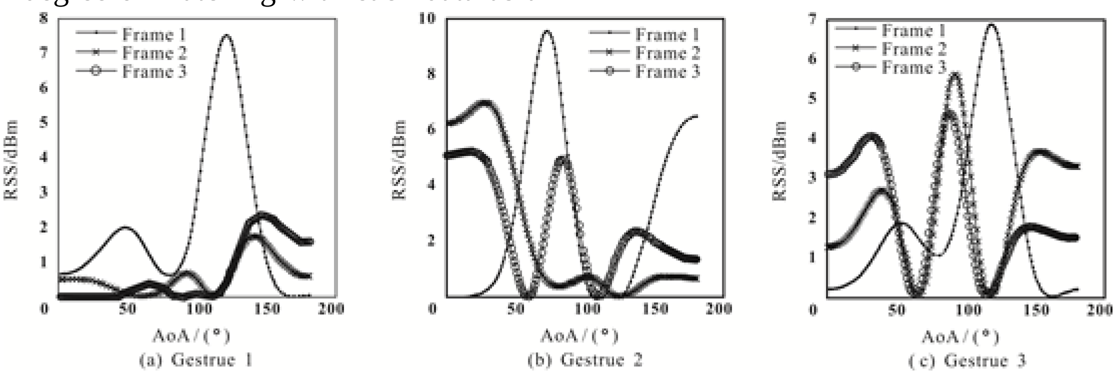

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Figure 5. Three different actions corresponding to the characteristic curve of Tag1

4.4. Performance Analysis

To further explore the scientific feature of the proposed method, experiment personnel make random gestures and repeat each gesture 10 times to obtain the corresponding data for statistics on the matching results based on the above method. Table 1 shows the cost matrix output during the matching of data in a specific experiment, which can be intuitively reviewed in Table 1: All groups can be correctly recognized except group 5. The statistical results of the experimental recognition suggest that a correct recognition probability of about 85% can be obtained by the method. It has proved that the proposed method is feasible.

Table 1. Matching cost matrix

Gesture Number	1	2	3	4	5	6	7	8	9	10
1	89.5206	242.463	178.2587	197.8908	326.4077	183.7775	235.6836	318.7997	184.3074	151.3221
2	152.766	210.1188	171.614	189.2444	304.9663	145.0399	275.598	336.8927	241.6214	188.4606
3	197.0855	262.0812	95.292	128.4139	140.2753	129.0623	189.615	267.3375	267.0573	193.427
4	172.0066	212.0365	171.9445	124.1742	241.9845	212.9868	232.6018	284.6376	194.7981	196.1069
5	150.8265	250.0855	316.012	229.098	343.3882	236.7288	274.9639	321.7592	321.2218	182.8407
6	128.8062	217.0948	211.046	136.3478	236.7895	128.4815	164.3106	252.7996	306.3499	228.7774
7	178.3137	224.7636	189.4095	199.5998	267.7354	199.2558	139.4626	237.6086	243.374	188.9232
8	282.5332	220.4231	183.0376	154.7879	246.2714	217.0199	158.6473	171.4237	260.7279	297.6817
9	250.6583	360.4447	152.758	179.8928	321.8409	221.2253	229.6961	283.4472	159.8501	190.9673
10	98.1395	329.7351	215.7167	259.3217	373.5191	193.7417	303.2005	255.3587	162.2184	96.3859

5. Conclusions

Gesture recognition is an essential part of device-free technology, which has a broad application prospect in smart homes and somatosensory games, making people's lives more convenient. The gesture recognition based on RFID technology proposed in this paper is low in cost and simple to implement. Based on the actual situation, a method of data slicing is proposed to preprocess the data. Subsequently, the SAR algorithm is applied to obtain the feature vector. Finally, the DTW algorithm is used for high-resolution gesture recognition. Practical experiments have verified that gesture recognition can be implemented by the proposed method. If the method matures, it will have a significant impact on smart home applications.

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