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Smart Attendance System Based on Frequency Distribution Algorithm with Passive RFID Tags

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Abstract: Staff attendance information has always been an important part of corporate management. However, some opportunistic employees may consign others to punch their time cards, which hampers the authenticity of attendance and effectiveness of record keeping. Hence, it is necessary to develop an innovative anti-cheating system for office attendance. Radio-Frequency IDentification (RFID) offers new solutions to solve such problems because of its strong anti-interference capability and non-intrusiveness. In this paper, we present a smart attendance system that extracts distinguishable phase characteristics of individuals to enable recognition of various targets. A frequency distribution histogram is extracted as a fingerprint for recognition and the K-means clustering method is utilized for more fine-grained recognition of targets with similar features. Compared with traditional attendance mechanisms, RFID-based attendance systems are based on living biological characteristics, which greatly reduces the possibility of false records. To evaluate the performance of our system, we conducted extensive experiments. The results of which demonstrate the efficiency and accuracy of our system with an average accuracy of 92%. Moreover, the system evaluation shows that our design is robust against differences in the clothing worn and time of day, which further verifies the successful performance of our system.

Key words: frequency distribution; Radio-Frequency IDentification (RFID); office attendance; K-means clustering

1 Introduction

Staff attendance information, which is closely related to salaries and bonuses, has always provided an important standard for company management, especially in large companies that employ a large number of people. Integrated-circuit card check-in is a common approach used to verify work attendance, whereby staff must punch a card when coming on and going off duty. However, this unsupervised approach can lead to false records for opportunistic individuals who consign others to punch their cards, which negatively affects the effectiveness of staff management. To reduce the occurrence of this phenomenon, a fingerprint attendance system has been proposed as an alternative, based on the high recognition accuracy and uniqueness of fingerprint identification[1–3]. However, the appearance of the fingerprint model made of silicon rubber has completely dashed the myth of the infallibility of attendance machines based on fingerprint identification technologies. The lack of living biological characteristics is the main problem with fingerprint attendance machines. Even worse, hygiene is also a problem since employees must directly touch the machine when checking in. Another technology known as face recognition[4–6] is attracting increasing attention, which combines computer image

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processing technology with biostatistical principles. Face recognition uses computer image processing technology to extract the feature points of each image from videos, and then establishes a face recognition model. However, there are many ways to invalidate this method, for example, the use of a prepared photo or video. Therefore, to guarantee the validity of attendance data, it is necessary to explore innovative and effective approaches to the development of an anti-cheating system for office attendance.

Recently, with the rapid development of Radio-Frequency IDentification (RFID) technology, RFID now has the potential to distinguish between different people. Compared with traditional attendance mechanisms, RFID-based attendance systems are based on living biometrics, which greatly reduces the possibility of cheating. Through the analyses of signals from Commercial-Off-The-Shelf (COTS) RFID readers, many valuable Radio-Frequency (RF) characteristics can be extracted, such as the relative Received Signal Strength Indicator (RSSI) and phase characteristics. The RSSI characteristic, although widely adopted due to its easy accessibility and simplicity, suffers from coarse features and poor time stability. The phase characteristic is more stable and demonstrates better anti-interference than RSSI.

In this paper, we present a device-free intelligent attendance system based on RFID, which is implemented by a commodity RFID reader and several COTS tags and uses the unique phase readings of different people to recognize various targets. To improve system performance, we extract RF characteristics by leveraging a statistical frequency distribution histogram to suppress the influence of signal contingency fluctuations on recognition accuracy. In addition, since this fingerprint may not work well when targets are in the company of those with similar features, multiple features are taken into careful consideration. We then use the K-means clustering method to realize an intelligent office attendance system. The contributions of this paper are as follows:

(1) To the best of our knowledge, we are the first to propose a device-free office attendance system based on RFID that can distinguish between different individuals based on their features.

(2) Instead of extracting a single phase value for target recognition, we extract multiple evaluation indicators from a statistical frequency distribution histogram of phase profiles that correspond to each volunteer.

(3) We develop a prototype of our system and use it to conduct extensive experiments. The results demonstrate the efficiency and accuracy of our system in target recognition, which has an average accuracy of 92%. Moreover, the system evaluations show that our design is robust against differences in the clothing worn and time of day.

The rest of this article is organized as follows. In Section 2, we present related work. In Section 3, we provide a detailed overview of the system. In Section 4, we mainly focus on the system methodology and design. We introduce the system implementation in Section 5 and present our evaluation in Section 6. In Section 7, we discuss our results and future work, and, lastly, we draw our conclusions in Section 8.

2 Related Work

In this section, we introduce state-of-the-art work on WiFi-based and RFID-based human detection technologies, which are relevant to our work.

2.1 WiFi-based human detection

Wireless signals can be used not only for data transmission but also for sensing. In a complex indoor environment, the signal is transmitted to the receiver through different paths, including reflection, scattering, diffraction, and so on, which means the received signal can be identified as the reflection of the environmental characteristics. Therefore, the presence of a person may cause interference to the wireless signals. By modeling the correspondence between the wireless signal and the person, the identification of the person based on WiFi may be realized. Traditional WiFi-based perception mainly uses RSSI as a fingerprint. Yang et al.[7] presented a joint intrusion learning approach which can detect both power of several complementary intrusion indicators and different intrusion patterns at the same time. RASID[8] combines different modules for statistical anomaly detection while adapting to changes in the environment to improve the detection accuracy. Radio Tomographic Imaging (RTI)[9], another famous Received Signal Strengths (RSS) based system, achieves high localization accuracy and dramatically reduces the energy consumption of the sensing units. However, RSSI has the disadvantages of weak anti-interference ability and poor time stability, which will challenge the accuracy of sensing. Due to the high variability of RSSI, previous works have tried to introduce Channel State Information (CSI) instead of RSSI, which can be easily extracted from off-the-shelf receivers and achieve better detection performance[10]. PADS[11] and DeMan[12] conduct research on wireless channel parameters and extract amplitude and phase as the detection metrics, achieving a more robust system based on CSI. WiFall[13] focuses on the anomaly change in wireless signal and proposes a corresponding detection algorithm based on a local outlier factor to further improve the accuracy of the system. Although CSI provides more possibilities for human recognition and makes the recognition more robust and fine-grained, the disadvantages of WiFi are still existed, which hampers the development of WiFi based recognition.

2.2 RFID-based human detection

To solve the problems of RSSI mentioned above, RFID is becoming more and more popular in the field of sensing due to its strong anti-interference capability and non-intrusiveness. Previous efforts have exploited phase changes of passive RFID tags to detect human/target motion. LANDMARC[14] is the first attempt of positioning system based RFID with RSSI which suffers from severe multipath problems. Yang et al.[15] presented a system which works even through walls and behind closed doors for tacking moving objects. An RFID-based human motion sensing technology, called RF-HMS[16], is presented to track device-free human motion through walls. A comprehensive localization and tracking scheme by attaching two RFID tags to one object instead of using per-tag localization pattern is proposed by Xiao et al.[17] Togoram[18] builds a differential augmented hologram according to the phase values and constructs a virtual antenna array to track mobile RFID tags with a high precision. In this paper, we mainly focus on levering distinguishing phase values to differentiate people, rather than tacking human/object motion.

3 Overview of System

In this section, first, we present more details regarding RF signal characteristics and the background of our RFID-based system. Then, we introduce the inspiration for and the feasibility of this design and highlight its attendant challenges.

3.1 Background

A complete COTS RFID system is composed of one RFID reader and several RFID antennas and passive tags. It mainly operates on a frequency band between 902 MHz and 928 MHz, and utilizes the backscatter radio link for communications. The RFID reader communicates with the passive tags in full duplex mode, continuously sending signals to the tag and simultaneously detecting the tag response. By analyzing the signals from COTS RFID readers like the Imprinj Speedway reader, we can extract many valuable RF characteristics such as RSS, phase, and Doppler shifts, which offer more opportunities for human recognition.

(1) RSSI reflects the power of a received radio signal, which characterizes the attenuation of radio signals during propagation, and has been adopted by many indoor localization systems. RSSI satisfies the pass loss relation of the distance d between the reader and tag, as follows:

$$RSS = RSS_0 - 10\lambda \log(d) \tag{1}$$

where RSS_0 is the transmitting power, and λ is the pass loss exponent, which changes with changes in the propagation characteristics.

(2) Phase is a measurement of the offset of a received radio signal. Since phase shifts change periodically over propagation distances, they are more robust than an RSSI. It is a periodic value with a period of 2π. Since the antenna works in full duplex mode, the transmission distance of backscattered signal is twice the distance between the antenna and the tag. The measured phase ϕ can be calculated as follows:

$$\phi = 2\pi \frac{2d}{\lambda} \text{mod}(2\pi) \tag{2}$$

where $\lambda = c/f$ denotes the wavelength of the signal and d is the distance between the antenna and tag.

3.2 Feasibility and challenges

The aim of the proposed office attendance system is to correctly distinguish between different people. RFID signals can convey information about the environment through which they pass, which means that the signals differ when different people block the Line-Of-Sight (LOS) transmission link. This difference makes it possible to realize human detection and recognition. As such, it can satisfy the requirements of an attendance system, thus providing a new solution to the problems associated with office attendance systems.

3.3 Preliminary experiments

However, there are still some challenges. First, how can we distinguish different people who have similar features? From the perspective of RF characteristics, the differences in phase values presented by people with similar body sizes may not be obvious, which may challenge the detection accuracy. Second, how can we eliminate RF signal differences for the same person? Our experiments have shown that, due to the volatility of the signal, the phase characteristics extracted for one person are not exactly the same even when that person stands in the same position, which can cause mistakes, especially when the targets are of similar size. In the null case, the key to realizing a smart RFID-based attendance system is to extract the distinguishable characteristics of RFID signals that can maximize the differences between different people while weakening the small differences of the same person.

We conducted a series of preliminary experiments using a COTS Impinj reader, an 8-dBi linearly polarized antenna, and an Impinj H47 omnidirectional tag. Five volunteers were asked to stand still at a specified location between the antenna and tag for 3 seconds at a time and to simulate punching card. The extracted phase value, as shown in Fig. 1, enables some valuable observations. First, people with different body sizes have different blocking effects on the LOS link, which results in different phase values and suggests the feasibility of their use. Second, people with similar body shapes, like B and C in Fig. 1, also have similar phase profiles. Therefore, to translate this idea into reality, we must devise an effective method for distinguishing between people with similar body sizes.

The schematic diagram in Fig. 2 shows that our system contains three basic functional blocks for performing data preprocessing, feature extraction, and target recognition. In the first step, data preprocessing, the system purifies raw phase readings reported by the

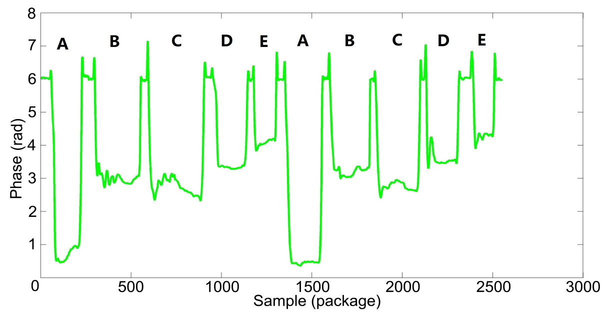


Fig. 1 Results of preliminary experiment.

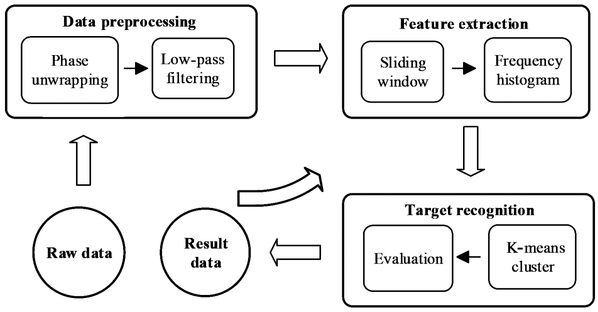


Fig. 2 System workflow.

standard API. This step involves phase unwrapping and low-pass filtering. In the next step, feature extraction, we extract valuable RF fingerprints and then analyze the data by leveraging statistically significant frequency histograms. The results obtained in this block serve as the cluster samples for the next step. In last step, to improve system performance, we apply the K-means clustering method to recognize unknown targets. In the following section, we further detail the specific techniques applied in each functional block and describe our obtained results.

4 System Design

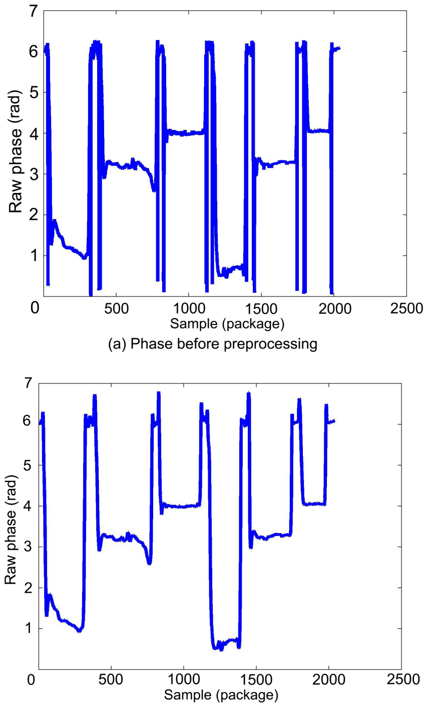
In this section, we give a detailed description of the system design, which is based on the three blocks mentioned above, including the problems that must be solved, the methods we applied, and an analysis of our experimental results.

4.1 Data preprocessing

The phase reported by the standard API is a periodic function ranging from 0 to 2π, which is called the wrapped phase, as shown in Fig. 3a, and cannot indicate actual phase characteristics. To achieve accurate phase differentiation, we must first unwrap the original phase. In addition, as shown in Fig. 3a, we find that the signal will carry some random noise during the signal transmission process. Hence, we introduce a demising method and smooth the phase values to recover the actual phase information. Since the part with a low rate of change corresponds to the low-frequency component, and that with a high rate of change corresponds to the high-frequency component, we use low-pass filtering to filter the random noise introduced during transmission. Figure 3b shows the phase profile after preprocessing.

4.2 Feature extraction

Given the phase profile after preprocessing shown in Fig. 3b, it is obvious that when someone is present in the



(a) Phase before preprocessing

(b) Phase after preprocessing

Fig. 3 Phase profiles before and after preprocessing.

LOS link between the antenna and the tag, their body will have a blocking effect on the link, which results in a sharply dropped phase value. In contrast, when the person walks away from the link, this blocking effect disappears and the phase returns to its original value. This is due to the difference their body shape causes in the occlusions of the received signal. Figure 3b shows the phase profiles of five volunteers who are standing still in the same position in the LOS link. To separate the accurate phase fingerprint of each volunteer and thus improve recognition accuracy, we use the sliding window method to extract every phase fragment. Here we note that the size of sliding window is discretionary.

An appropriate window size can improve the accuracy of feature separation. Too large a window size can result in not being able to obtain each stable phase segment and still satisfy the variance. Too small a window size can make the phase segment too fragmented, which is disadvantageous to the subsequent feature extraction. In our experimental scenario, after many trials, we selected a size of 60 for the sliding window.

After phase segment extraction, rather than extracting a single phase value for target recognition, we further improve the accuracy by extracting multiple evaluation indicators from the statistical frequency distribution histogram of a phase section corresponding to each volunteer. We asked one of the volunteers to enter (exit) the specified position in the link six times, and used the sliding window method to extract a relatively stable phase waveform, as shown in Fig. 4. The corresponding frequency distribution histogram is shown in Fig. 5. We can acquire three meaningful measurements from the frequency distribution histogram: (1) the phase value with the highest frequency, (2) the average phase along the X-axis in the frequency distribution histogram, and (3) the weighted phase. These three measurements also play a very important role in target recognition.

4.3 Target recognition

4.3.1 Coarse-grained target recognition

As a unique basis for target recognition, a simple matching method can be used to obtain the phase indicator corresponding to each volunteer from the X-axis in the frequency distribution histograms. Figure 6 shows the frequency histograms of five volunteers (A, B, C, D, and E). When identifying a target, the phase with the highest frequency on the frequency distribution histogram is selected as the indicator of a specified target. If it falls within the phase range corresponding to A, the target is determined to be A, and so on.

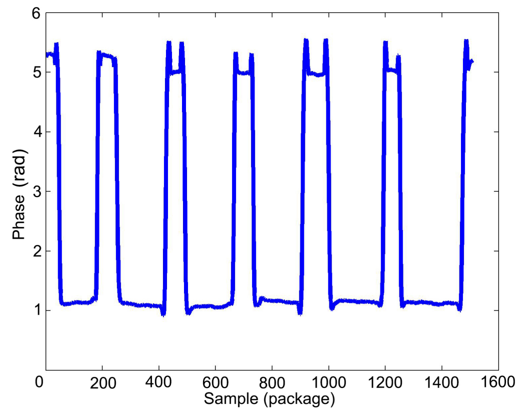


Fig. 4 Segmented phase through sliding window.

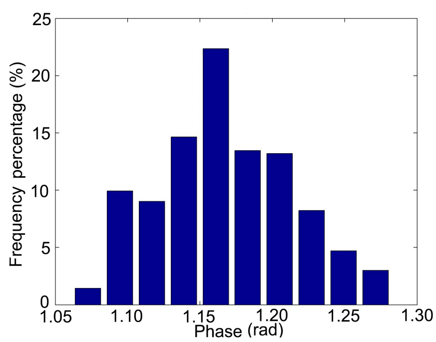


Fig. 5 Phase distribution results.

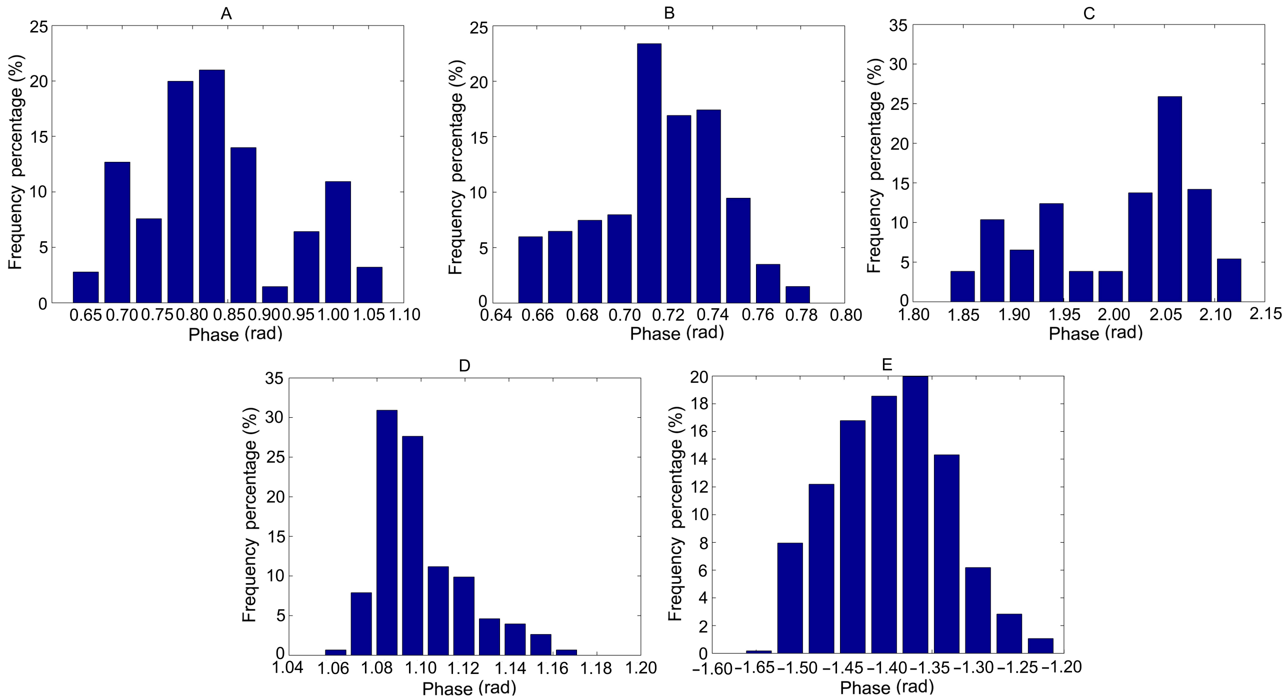


Fig. 6 Frequency distribution histograms of five volunteers.

Unfortunately, this method is not sufficiently accurate when the volunteers have similar body sizes. So, a more fine-grained target recognition method is needed to improve system performance.

4.3.2 Fine-grained target recognition

For fine-grained target recognition, we improved the matching method of the coarse-grained algorithm. Instead of simply obtaining the phase indicator corresponding to each volunteer from the X-axis in the frequency distribution histograms, we extract three meaningful fingerprints from each frequency distribution histogram and codify the phase characteristics of the received signals into quantitative fingerprints: (1) the phase value with the highest frequency, (2) the average phase value on the X-axis in the frequency distribution histogram, and (3) the weighted phase. We then introduce a K-means algorithm to achieve more precise feature differentiation to thus realize more robust human recognition. Of course, there are many other clustering methods such as the Density-Based Spatial Clustering of Application with Noise (DBSCAN) and the K-MEDOIDS[19]. However, these methods are restricted by their higher computational complexity, so their real-time capability is insufficient, which rules out their use in this attendance system. In addition, by adjusting the k value based on different scenarios, we can obtain more accurate detection results.

The purpose of the K-means algorithm, which was originally used in signal processing, is to cluster samples into k clusters according to their fingerprint features. The difficulty in applying K-means clustering lies in the computation, since K-means clustering is essentially a Non-deterministic Polynomial (NP) hard problem. Many solutions, such as the use of heuristic algorithms, for example, have been proposed to obtain a local optimum as quickly as possible. We can use K-means clustering for human recognition based on the above three fingerprints. The specific algorithm steps are as follows:

Step 1: Randomly select k-cluster center points that are assumed to be as: $\mu_1, \mu_2, \ldots, \mu_k \in \mathbf{R}^N$.

Step 2: For each sample point, calculate the distance between it and the k-cluster center points. Then, select the cluster with the shortest calculation distance and assign it to this cluster. Here, we use the Euclidean distance formula to calculate the distance between two points. The shorter the Euclidean distance, the higher the degree of similarity. For example, for two sample $x^{(1)}(x_1, y_1, z_1)$ and $x^{(2)}(x_2, y_2, z_2)$, the Euclidean distance between $x^{(1)}$ and $x^{(2)}$ is $d = ((x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2)^{\frac{1}{2}}$.

Step 3: After all samples have been assigned, recalculate the center of each cluster to obtain the arithmetic mean of the respective dimensions of all the samples in each cluster.

Step 4: Re-cluster all samples according to the new center.

Step 5: Repeat Steps 3 and 4 until the clustering results converge, i.e., they no longer change.

5 Experiment Implementation

In this section, we provide details about system implementation, including the hardware and software used and the experimental scenarios. (1) Hardware: we developed a system prototype using COTS RFID devices, including a commodity Impinj R420 as the RFID reader, an Impinj H47 omnidirectional tag, and an 8-dBi linearly polarized antenna. The reader is connected to a local server via an ethernet cable. We fixed the default operating frequency to 920.625 MHz. In this case, the corresponding wavelength is 32.587 cm. We set the antenna parallel to the tag at a distance of 1 m and a height of 1.2 m. Targets should stand in the middle of the LOS link. (2) Software: the software of this system is implemented in C♯ language and runs on a personal computer with a low level reader protocol. During data collection, the software is integrated with the Octane SDK and continuously interrogates the tag at a rate of 340 readings per second to acquire physical layer information, such as phase, RSSI, and Doppler shift.

6 Evaluation

In this section, we describe our experiments and evaluate the system performance from various aspects. To guarantee system robustness, we conducted two preliminary experiments to evaluate system performance, considering that the office attendance system should be able to correctly recognize the same target wearing different clothes or arriving at a different time.

6.1 Impact of clothing

To consider system robustness, we took into consideration the number and the material of the clothes worn, which may generate RFID signal interference. In the experiment, the volunteers were asked to simulate office attendance in summer and winter by wearing a thin T-shirt and then several layers of thick clothing, respectively. Figure 7 shows the results of one volunteer, in which the green line indicates the phase when the volunteer was wearing several layers of thick clothing, and the red when the volunteer was wearing fewer and thin clothes. We can clearly see that the number of clothes worn or their material has little effect on the extracted phase characteristic and thus can be ignored. The reason for this is that the body, rather than clothing, strongly reflects electromagnetic waves.

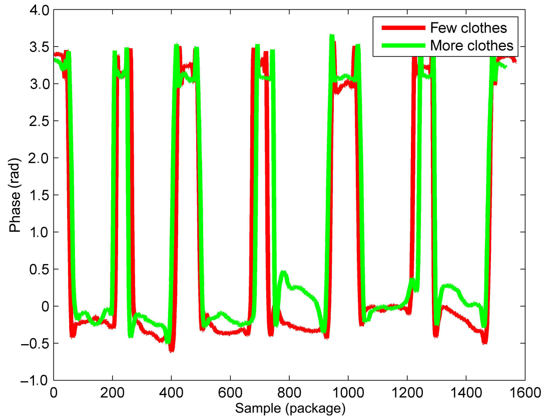


Fig. 7 Impact of clothing.

6.2 Impact of different times of day

Signal collection at different times of day can present different characteristics. Hence, we also asked one of the volunteers to simulate office attendance while standing in the same position in the morning, at noon, and in the evening. From the results shown in Fig. 8, we can draw two conclusions. First, the phase profile is not exactly the same when collected at different times of day even when the target is the same person. Second, the difference in the phase characteristics obtained for the same person at different times of day has a negligible effect on the results.

6.3 System performance

As noted earlier, our proposed intelligent RFID-based office attendance system contains three basic functional

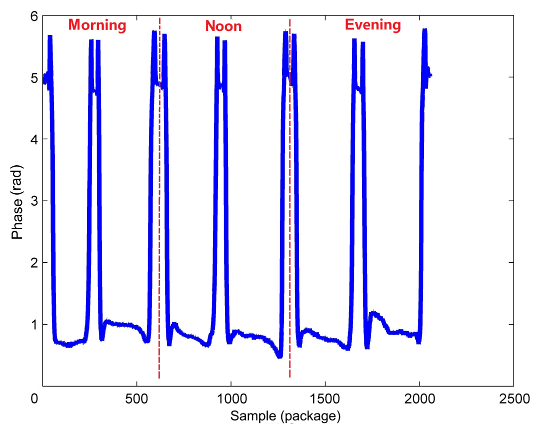


Fig. 8 Phase of the same person at different times.

blocks: data preprocessing, feature extraction, and target recognition. The system purifies raw phase readings reported by the standard API in the data preprocessing step. In the next step, feature extraction, we extract valuable RF fingerprints and then conduct a data analysis by leveraging statistically significant frequency histograms. The results obtained in this block serve as fingerprints for clustering in the next step. In the last step, we apply K-means clustering to improve system performance in the recognition of unknown targets.

To evaluate the system performance, we invited five volunteers to perform multiple tests at random times, and then used a K-means clustering algorithm for target recognition. The clustering results are shown in Fig. 9, in which each point represents one test for one volunteer. Each color corresponds to one volunteer, for a total of five volunteers. From the results, it is obvious that the K-means clustering algorithm can achieve high efficiency and accuracy in target recognition, with just a few exceptions that can be ignored.

To quantify the experimental results of our system, we used the following two metrics to evaluate its accuracy: (1) False Acceptance Rate (FAR): whereby the sample does not belong to the person but the algorithm identifies it as that person. (2) False Rejection Rate (FRR): whereby the sample belongs to a person but is not correctly identified.

The FAR and FRR results for each volunteer are shown in Fig. 10. We collected a total of 200 data sets and found only 16 to be incorrectly justified. As such, the efficiency and accuracy of our system demonstrated an average accuracy of 92%. In addition, we can see

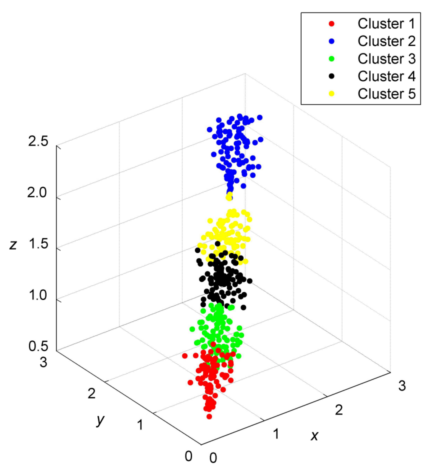


Fig. 9 K-means clustering results.

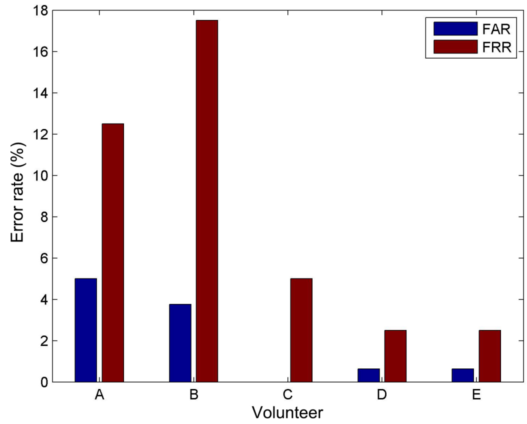


Fig. 10 System accuracy levels.

that the FAR and FRR values of all five participants are relatively small. It is remarkable that the FRRs of volunteers A and B are higher than those of the other volunteers, since A's body shape is very similar to B's, which indicates that our algorithm can achieve robust human identification, thus verifying the performance of our system.

7 Discussion and Future Work

In this section, we identify some limitations and discuss future plans for our system. For this prototype, due to laboratory limitations, we invited just five volunteers to participate in our experiments and evaluated the system performance on this basis. However, when the number of people is increased, the detection accuracy may be affected. This is because the more people there are, the more likely they are to have similar body features, which will require that we obtain more refined features. In addition, real-time capability may also be a key consideration for further enhancing the robustness of our system.

8 Conclusion

In this paper, we proposed a device-free office attendance system and presented our key motivation, design methodologies, implementation, and evaluation of this system, which can distinguish various targets according to the unique phase signals of individuals in the LOS link, as collected from an RFID reader. To improve system identification accuracy, we used a frequency distribution histogram and a K-means algorithm to extract phase fingerprints. We conducted extensive experiments and the results show that our system performs very well, with an average accuracy of 92%. In future work, we will mainly focus on taking into consideration more phase features to achieve higher recognition accuracy in the identification of more targets.

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