

# Activity Recognition Using RFID Phase Profiling in Smart Library

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**SUMMARY** In the library, recognizing the activity of the reader can better uncover the reading habit of the reader and make book management more convenient. In this study, we present the design and implementation of a reading activity recognition approach based on passive RFID tags. By collecting and analyzing the phase profiling distribution feature, our approach can trace the reader's trajectory, recognize which book is picked up, and detect the book misplacement. We give a detailed analysis of the factors that can affect phase profiling in theory and combine these factors with relevant activities. The proposed approach recognizes the activities based on the amplitude of the variation of phase profiling, so that the activities can be inferred in real time through the phase monitoring of tags. We then implement our approach with off-the-shelf RFID equipment, and the experiments show that our approach can achieve high accuracy and efficiency in activity recognition in a real-world situation. We conclude our work and further discuss the necessity of a personalized book recommendation system in future libraries.

**key words:** *RFID, activity recognition, smart library, wireless sensing, internet of things*

## 1. Introduction

Today, the Internet of Things (IoT) has created changes in various industries. With the help of perception, the core of the IoT, an increasing number of services have become intelligent and efficient. For example, personalized recommendations have been applied to improve consumer services. In most cases, only knowledge from online interaction is used, which is not sufficient. However, more offline activities such as reading in the library can be utilized to promote this kind of application, especially with the development of a large-scale RFID system [1]. Reading activity can be inferred by monitoring the state of books, providing more accurate book recommendations to the reader and assisting the library in book management.

The concept of a smart library had been put forward several years ago. Research has been conducted both in industry and academia. Min proposes his conceptual model of a next generation library information service, which is an all-encompassing infrastructure utilizing cloud computing [2]. Toivanen introduces a book-finding system based on RFID, consisting of a portable handheld reader and customized tags [3]. Markakis designs an RFID-enabled library

management system using a fixed low specific absorption rate antenna [4]. Shangguan uses spatial-temporal phase profiling collected by a mobile antenna to detect the misplacement of books in the library [5]. Liu proposes an RF-Scanner which is a robot with an RFID antenna that can localize the book and detect the book if it is lying down [6]. Among these studies, the Min study pays more attention to information communication [2], the Toivanen and Markakis efforts only help the reader find a specific book [3], [4], and the Shangguan and Liu proposals lay special emphasis on book misplacement [5], [6]. None of these studies involve recognizing reader activity.

Our long-term goal is to develop a context-aware system that can automatically recognize reader activity in real time and provide personalized services to the reader according to the specific activity in the smart library. Several technologies can be utilized to build such a system, e.g., RFID, computer vision, and Wi-Fi. In this study, we focus on reading activity recognition based on the phase profiling of passive RFID. RFID phase is a physical attribute of the return signal from a passive RFID tag. It is collected by the RFID reader in every query of a tag. The detail of the RFID phase is introduced in Sect. 2. We analyze the feasibility for detecting activity in the library using RFID phase in theory. Then, we find that the variation of RFID phase can reflect the interaction between the reader and the book. We can determine the state of the book through the variation of phase in a sliding window. So, we process the phase signal of tagged books and distinguish different activities with thresholds. Furthermore, to evaluate the effectiveness of our approach, we implement the approach on a bookshelf in which there are 50 books in total, and the COTS reader and UHF tags are used to obtain the phase.

There are several challenges in such a system. The first is that the external size and behavioral characteristics are different for each reader. This makes it impossible to train the model for a specific reader. To address this challenge, we use different features to describe the phase profiling rather than use it directly. The second challenge is that the system should operate in real time. We put the antenna on the top of each bookshelf and kept scanning the tags on the books continuously. The computational complexity is low enough to guarantee real-time operation. The third challenge is versatility. According to [6], book misplacement detection should be considered. Our approach can not only detect the activity of the reader but also has the ability to detect the misplaced book, without any other equipment.

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There are three main advantages to our approach over the prevalent waveform-based activity recognition, such as described in [7]. First, only when the distance between the reader and the bookshelf is short enough is the phase waveform identifiable while the reader walks before a book. According to the verification experiment, our approach still works even for a distance greater than 80 cm. Next, the computation complexity of our approach is significantly much lower, because our approach does not have to generate a particular waveform for each activity. Last, but not least, people may pick up a book in different ways, causing totally different phase waveforms.

## 2. Preliminaries

The basic idea of our approach is to recognize activity based on the amplitude of the variation of RFID phase. This section provides a detailed analysis of factors that can affect phase value. We suggest that the phase of a tag is determined by three aspects: distance, angle, and multi-path effect.

### 2.1 RF Phase Values

In a typical RFID system, the reader transmits a continuous-wave signal to the tags and then receives a backscattered signal from the tags. The phase value of the RF signal describes the offset between the transmitted and received signal, which depends on the round-trip ( $2d$ ) and hardware-specific factors [8]. Parameter  $d$  is the distance between the antenna and tag. For a standard phase-distance model, the hardware-specific factors include three parts:  $\theta_T$ ,  $\theta_R$ , and  $\theta_{TAG}$ , which represents the transmission circuit, receiver circuit, and tag reflection characteristic of the reader. Furthermore, the RF phase is a periodic function ranging between 0 and  $2\pi$ . Thus, the phase value  $\theta$  of a tag measured by the reader can be expressed as:

$$\theta = \text{mod}(2\pi \frac{2d}{\lambda} + \theta_T + \theta_R + \theta_{TAG}, 2\pi) \tag{1}$$

where  $\lambda$  is the signal wavelength [9]. The phase value is a common attribute that is supported by most COTS RFID readers, e.g., ImpinJ R420 [10]. Note that the hardware-specific factors are constant since the devices are produced. Phase measurement contains random errors in real-world situations, and different tags have different levels of random

errors following a Gaussian distribution, with a standard deviation of 0.1 radians. As denoted in Eq. (1), the phase is linear to the distance between the antenna and tag, ignoring the random error.

For example, ImpinJ R420 can be set to work at 920~926 MHz with 16 channels. Thus,  $\lambda$  is approximately 320 mm, and  $\theta$  will repeat if the distance is larger than 160 mm. In particular, when the  $\theta$  is near 0 and keep decreasing,  $\theta$  jumps from 0 to  $2\pi$ , and vice versa. This is called the “phase jump”.

Equation (1) only considers distance, ignoring the phase deflection caused by the rotation of tags. For most phase-based application, Eq. (1) works well. However, the rotation of devices has to be considered in our situation to distinguish different activities, which will be discussed in the next subsection.

### 2.2 Rotation of Tags

The phase of a tag is affected by the relative orientation to the reader antenna. This observation is mentioned in the Wei study, published in 2016 [11]. To reinvestigate this phenomenon, we conduct an experiment as illustrated in Fig. 1.

As depicted in Fig. 1, we place a slim tag 1 m in front of a reader antenna. The center of the antenna and tag is aligned to ensure that the distance between the antenna and tag does not vary. Then, the tag is rotated along each axis. Moreover, the tag is placed facing the antenna on the both front and side to investigate if the posture of tag influences the phase or not.

The result is shown in Fig. 2. In Fig. 2 (a), there is only one line, because, when the tag is rotated along the Z-axis, the posture of the tag does not matter. We can see that the phase does not change much while rotating along the Z-axis. However, it does shifts periodically when it is rotated along the X-axis and Y-axis as it is shown in Fig. 2 (b) and Fig. 2 (c). The phase changes linearly with rotation along

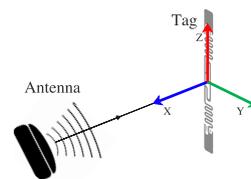


Fig. 1 Measuring the phase of a tag rotating along each axis.

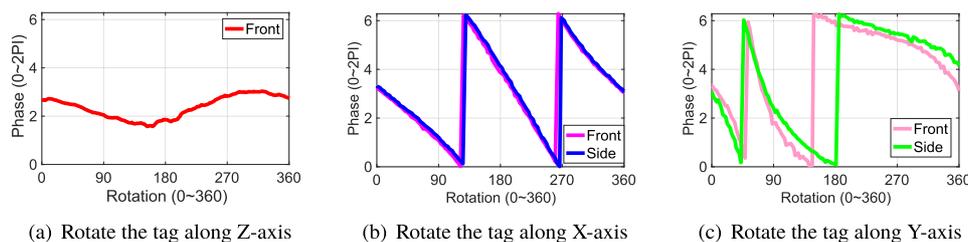


Fig. 2 Measured phase of a tag rotating along three axes.

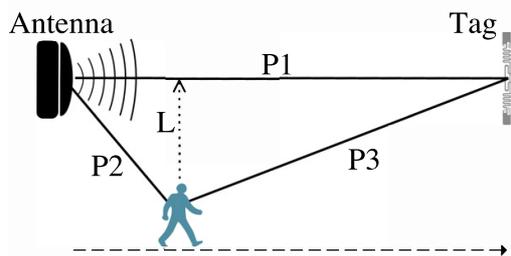


Fig. 3 Measuring the phase under multi-path effect.

the X-axis and nonlinearly with rotation along the Y-axis, and the phase jumps twice per period. Wei [11] explains this phenomenon with the polarity of RFID antennas. The tag's antenna is usually designed as a dipole, which is linear-polarized along the tag body. However, most RFID readers' antennas are circular-polarized. They comprise two perpendicular dipoles, fed with a signal of a  $90^\circ$  phase difference to ensure that they can read tags from a variety of angles. Thus, when the tag rotates, the phase of the signal received will change. Moreover, the signal traverses a round-trip, so the corresponding phase shift, measured by the reader, doubles. This means that the phase will change by  $\pi$  when rotating around both the X-axis and Y-axis by  $90^\circ$ . Furthermore, we find that whether the tag is facing the antenna on the front or side, the phase changes in the same pattern.

### 2.3 Multi-Path Effect

The RFID signal is a kind of radio wave with specific frequency. So, it undergoes the multi-path effect as other radio waves do [12]. The wireless signal is radiated to all directions rather than in a line. While some signals go directly to the destination, other signals are reflected by surroundings and then proceed to the destination. Thus, different paths are generated. The multi-path effect is caused by the difference in the distance of these paths. The multi-path effect influences the phase according to Eq. (1).

To better understand the multi-path effect, we monitor the phase under the multi-path effect in a real-world situation as described in Fig. 3. A tag is placed 2 m in front of the antenna.  $P1$  is the line-of-sight (LoS) path. A man walks along a straight line, parallel with  $P1$ , and the gap between  $P1$  and the man is  $L$ . Thus, the signal reflected by the man will generate a new path,  $P2$ - $P3$ . The man repeats walking along the line, changing  $L$  from 10 cm to 110 cm. The phase measured by the reader is shown in Fig. 4. From this figure, we can see that even when the distance between reader and book is 80cm, phase data can still reflect this motion. This range is large enough to cover the entire bookshelf from top to bottom.

From Fig. 4, we can see that the rangeability of the phase becomes decreasingly smaller with the growth of  $L$ . When  $L$  reaches 110 cm, it is hard to distinguish between the multi-path effect and random error. There are two reasons

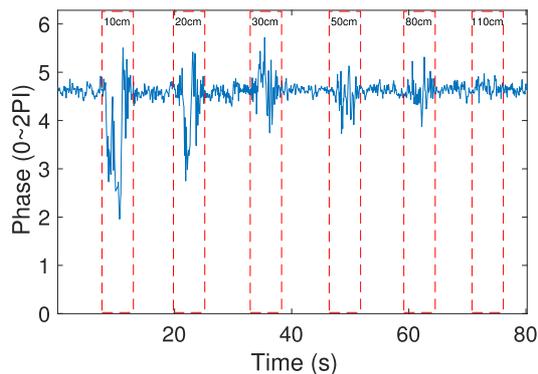


Fig. 4 The phase changes while  $L$  is set from 10 cm to 110 cm. The phase in the red frame is affected by the multi-path effect.

for this phenomenon. First, when  $L$  increases, the propagation fading  $F$  increases accordingly based on wireless communication principles [13].  $F$  is calculated as follows:

$$F = 10 \log \left( \frac{\lambda^2}{16\pi^2 d^2} \right) \quad (2)$$

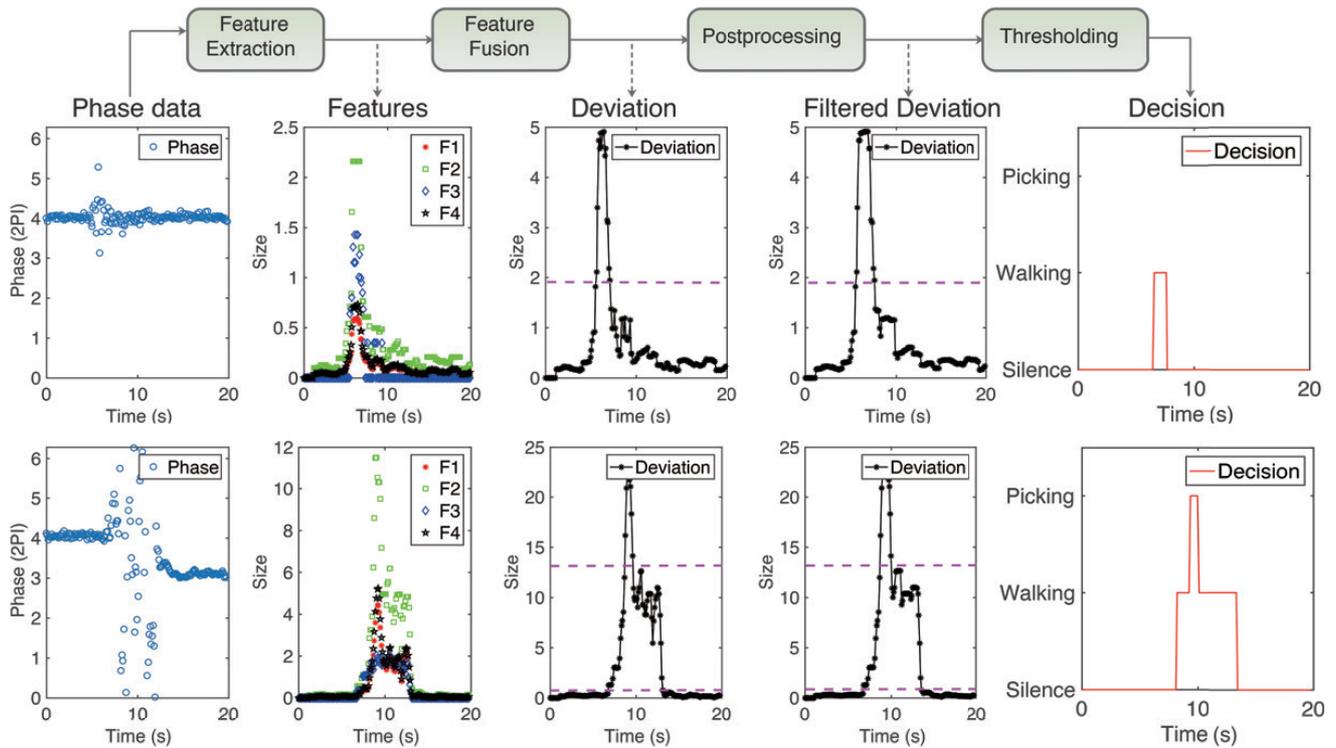
where  $d$  is the length of the path between the transmitter and receiver. The propagation fading may make the signal transmitted from the transmitter along  $P2$ - $P3$  invisible to the receiver sometimes. Thus, when  $L$  increases, there is no specific wave shape since  $L$  is larger than 30 cm.

Another reason is that the multi-path effect occurs when the path is within the Fresnel Zone [13]. A Fresnel zone is an ellipsoid whose foci are the transmitter and the receiver. Radius  $r$  of the circular cross section of the Fresnel Zone is given by:

$$r_n = \sqrt{\left(\frac{d}{2} + \frac{n\lambda}{4}\right)^2 - \left(\frac{d}{2}\right)^2} \quad (3)$$

where  $d$  is the distance between the transmitter and receiver and  $\lambda$  is the wavelength. Particularly,  $n$  is the Fresnel Zone number which is commonly smaller than 12. That is why when  $L$  is larger than  $r_{12}$ , the multi-path effect does not occur. It is clear that the length of the path within a Fresnel Zone becomes shorter as  $L$  increases. It is noteworthy that if the line along which a man walks is parallel to the LoS, the line will not stride across more than one Fresnel Zone. This means that the range of phase variation caused by the multi-path will never exceed  $2\pi$ .

**Inspiration:** Previously, we analyze three aspects that can bring about changes to the phase value. Specifically, activities in the library imply these aspects more or less. This inspires us to infer the activity by monitoring the transformation of the phase value. Although there are some applications based on RFID phase applied to areas, such as object use detection [14], [15], gesture recognition [7], and indoor localization [8], this study is the first to involve activity recognition in the library according to the intensity of the variation of phase. Details of our system are expounded in the next section.



**Fig. 5** The architecture of activity recognition approach. F1, F2, F3 and F4 in the second picture represent four features respectively. The upper line is an example of walking before a book and the under line is an example of picking up a book.

### 3. System Design

In this section, we present the details of our approach to detect the activity based on RFID in the library. Our approach utilizes the RFID reader antenna placed on the top of the bookshelf to monitor the phase value of tags attached to books. We first provide an analysis of the relation between activity and phase transformation. Then, a method based on the phase value distribution is proposed to infer the activity as shown in Fig. 5. We first collect phase data of every tag by an RFID reader and describe the dispersion of the phase data in a sliding window with four features. After feature fusion and postprocessing, we utilize thresholding to differentiate the states of each book and then recognize the corresponding activity of the reader.

#### 3.1 Activity Definition

In this study, we consider the reader in the library who wants to choose books at the bookshelf and then leaves to read as the target. Generally speaking, such a behavior in the library follows a common process. First, the reader walks to the area where there are books he has interest in. Next, the reader will pick up books one by one and read for a while to find out the ones that he prefers to read through. Then, he will take the books to the reading area. After reading, he replaces the books to where they were. This process actually contains four activities: walking before a book, picking

up books, taking books away and putting books back. Because the RFID antenna has a limited examination area, it is easy to detect whether one book is taken away or put back through the tag visibility. Thus, the challenge is how to distinguish the first two activities from each other. Of course, there is also the static status, which means that no one comes into the examination area.

According to the analysis in Sect. 2, it is clear that walking before a book only causes the multi-path effect. Meanwhile, picking up a book will change both the tag angle and the distance between the tag and antenna. When the reader walks before the bookshelf, the book on the bookshelf is labeled “Walking”, no matter if the reader is walking with books or without books. The book picked up by the reader is continuously labeled “Picking” until it is put back on the bookshelf. If no one is moving before the bookshelf, all the books are labeled “Silence”. Thus, the system is able to recognize the reader activity through the book state.

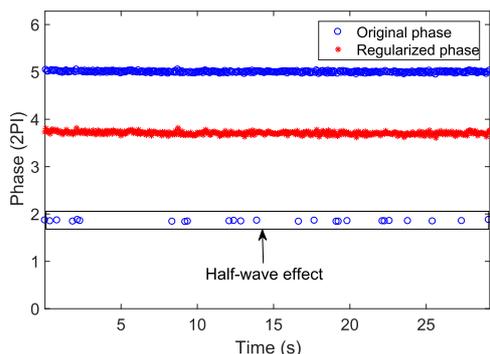
Furthermore, the reader sometimes returns the book to the wrong place. In this study, we propose a nearly zero-cost way to detect the misplacement of books.

#### 3.2 Data Collection

We carry out this approach in one bookshelf on which there are 50 books in total, as depicted in Fig. 6. The books are placed closely to each other in one row, to test the robustness of the system under the mutual interference of tags. We collect RFID data using an ImpinJ R420 reader with only one



**Fig. 6** The white antenna is placed at a  $45^\circ$  angle to the ground to ensure it can cover as much region as possible, because of its fan-shaped radiation regions.



**Fig. 7** Half-wave effect and the regularization. The blue circle is the original phase value and the red star is the phase after regularization.

antenna, setting the reader to max-through power and dual-target search mode [16]. The slim tags are attached to the back of each book. The reader keeps querying the state of each tag within the examination area. The RFID reader is set to only query the tags whose ID exist in the predefined list, so that the other books do not impact the specific bookshelf. In our situation, the mean sampling rate for each tag is about 12 times per second. In Fig. 5, blue circles represent the phase data of one tag, which fluctuate with different activities.

Actually, the attributes of the RFID signal include not only the phase but also the received signal strength (RSS) and Doppler shift. However, our pretest result shows that the Doppler shift is not accurate enough for our purposes, which was also mentioned by [17]. Moreover, it is difficult to combine RSS with different activities in theory. Thus, we just use the phase to achieve our goals.

Nevertheless, the pretest highlights a bug while measuring the phase. As shown in Fig. 7, the measured phase happens to generate a deviation of  $\pi$  randomly, which is called the “half-wave effect”. This will produce some fake phase values. Although some filters can overcome this, they are not portable to an online system. Thus, we constructed a regularized equation to solve this issue:

$$p_r = (p_o + \text{mod}(p_o + \pi, 2\pi)) - \pi \quad (4)$$

In the above equation,  $p_o$  is the original measured phase value, and  $p_r$  is the regularized phase value. Regularization first generates the mean value of the true phase value and the fake phase value. Then, it considers the values from  $0.5\pi \sim 1.5\pi$  to  $0 \sim 2\pi$ . Regularization does not need to distinguish if the phase is fake or not. Note, regularization does not affect the tendency of the phase, even though it changes all of the phase values. In this study, only the dispersion of phase value is important. Thus, regularization will double the dispersion, which is good for our approach.

### 3.3 Phase Dispersion of Activity

Other than the phase waveform-based activity recognition approach [7], we recognize the activity based on the phase dispersion within a sliding window. As depicted in Fig. 5, “Picking” causes much more violent dispersion than “Walking”. To quantify this phenomenon, we first extract the features to describe the phase dispersion. Then, we use the weighted summation method to fuse the features into a deviation index. After postprocessing, we can finally generate the recognition decision.

The traditional way to recognize the activity using RFID is based on the specific phase waveform caused by relative gesture. There are several reasons why the use of the waveform-method is not appropriate in the library. First, the distance between the reader and book has to be short enough that it can generate a stable waveform when the reader walks before a bookshelf. As shown in Fig. 4, the distance has to be less than 20 cm, which is impractical in a real scenario. Also, people may pick up a book in different ways, along with the fact that the stature of each reader is different. This makes it impossible to produce a congruent waveform when the reader picks up a book. Nevertheless, our approach will not suffer from the above problems.

There is the challenge of calculating the amplitude of the variation of phase. As introduced in Sect. 2, the phase value is a periodic function, called the wrapped phase, which causes the traditional functions not to calculate accurately. So, we have to unwrap the phase before computing the deviation. Here, we utilize a common way to solve this problem called the One-Dimensional Phase Unwrapping method [18]. This method is efficient and has a low computational complexity. It assumes that the difference between two adjacent sampling points over  $\pi$  is negligible. This is feasible since the phase is measured constantly, and the sampling rate is high enough.

The traditional indexes to weigh the dispersion include the standard deviation, range, entropy, and coefficient of variation. In this study, we mainly use the first three features to describe the phase dispersion. Furthermore, the arithmetical average deviation of phase values in a sliding window can also be used as a feature. For a phase dataset ( $X$ ) in a sliding window, the intensity of the phase variation can be described by the following indexes.

### 3.3.1 Phase Standard Deviation

In statistics, the standard deviation is used to quantify the amount of variation or dispersion of a set of data values. Generally, the standard deviation  $\sigma(X)$  is calculated by the following equations:

$$\mu = \frac{1}{N}(x_1 + \dots + x_N) \quad (5)$$

$$\sigma(X) = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (6)$$

### 3.3.2 Phase Range

The range is used to describe the scope of random variables. After phase unwrapping, the range of phase can be calculated directly by the difference between the maximum and the minimum.

$$R(X) = \max(X) - \min(X) \quad (7)$$

Range is easy to understand and calculate. However, it is sensitive to noise. Thus, other indexes are necessary.

### 3.3.3 Phase Entropy

Entropy can be used as an expression of the randomness of a system. In our approach, we use entropy  $H$  to describe the phase value distribution as below.

$$H(X) = - \sum_{i=1}^n p(x_i) \log p(x_i) \quad (8)$$

It is known that the phase value varies between 0 and  $2\pi$ . We divide the range into  $n$  equal portions, and  $p(x_i)$  are the quantities of the phase value that are within a specific portion. In this study, we set  $n$  equals to 10 and  $e$  as the base, serving as the default parameters. According to information theory, the larger the phase entropy is, the more evenly the phase values are distributed.

### 3.3.4 Phase Average Deviation

$$\delta(X) = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^n |x_i - x_j|}{\frac{n*(n-1)}{2}} \quad (9)$$

The phase average deviation  $\delta(X)$  is the mean value of the differences between any two phase values. This index can reflect the stability of the phase values in a sliding window.

### 3.3.5 Feature Fusion

Feature fusion merges all the features together to generate a robust index for recognition.

$$M(X) = \exp(c_1\sigma(X) + c_2R(X) + c_3H(X) + c_4\delta(X)) \quad (10)$$

Finally, the comprehensive deviation  $M$  can be calculated by Eq. (10), where  $c_j$  is the weight of features. In Fig. 5, we can see that four features describe the dispersion in different degrees. With feature fusion, the mixed set of indexes has the dramatic ability to discriminate the book state.

## 3.4 Thresholding

In this study, we first need to detect if there is an activity. Then, we further recognize if the activity is picking up a book or not. If a book is not picked up, the activity must be walking before a book. To ensure the system can achieve good instantaneity, we choose thresholding rather than a complex machine learning technique.

On the grounds of the analysis in Sect. 2, if the surroundings are steady, the phase value will not change. However, the phase measurement contains random errors in real-world situations, causing the phase to follow the Gauss distribution instead of an accurate value. So, we have to first obtain the phase dispersion in a static condition. We assume that the feature that describes the phase distribution also follows the Gauss distribution. Thus, we can use the upper limit of each tag phase feature distribution function to detect if there is an activity. If the value of the feature is greater than the upper limit, it is assumed that there is an activity.

Another threshold is needed to distinguish between walking before a book and picking up a book. This threshold is generated by a large number of experiments. As discussed in the previous section, picking up a book will change both the angle of tag and the distance between tag and antenna. Therefore, the phase dispersion of picking up a book is definitely larger than walking before a book. Therefore, we let several people who are different in stature walk before the bookshelf many times and collect the phase data at the same time. Then, we find the maximum phase dispersion with this phase data. Hence, the maximum value can be used as a threshold. However, we find that this does not work through experiment. The reason is that when the reader picks up a book, it will influence the neighboring books. Thus, the deviation index of these books will increase. So, we change the strategy. The volunteer is asked to pick up books successively from the first book to the last several times. Meanwhile, we record the phase values of all the books, and their deviation indexes are computed. Then, we count the maximum deviation index for all the books except the book picked up. Finally, we repeat a few times to generate the final maximum for every book and use this as the threshold.

In Fig. 5, the purple broken lines represent the threshold to distinguish the activities. Note that in the implementation, we set two parameters according to the pre-experiment for the two thresholds to generate a better result. The final experiment shows that the thresholds can be used universally.

### 3.5 Postprocessing

Using a threshold can distinguish different activities; however, it is quite essential to achieve a higher recognition post-processing rate. We find that the deviation index calculated by Eq. (10) is not a smooth function. Sudden drops and rises will cause incorrect recognition decisions. We process the deviation index with the following steps:

#### 3.5.1 Smoothing

We set two sliding windows  $w_1$  and  $w_2$ , for each deviation index point. When a deviation index is generated, we check the deviation indexes in  $w_1$ . We use the maximum in  $w_1$  instead of the current deviation index. This can filter out the sudden drops. Later, we compare the index with the thresholds to generate a pre-decision. Then, when a recognition pre-decision is generated, we check the pre-decisions in  $w_2$ . If they are equal, the pre-decision is true; otherwise, it is a sudden rising noise.

#### 3.5.2 Merging Adjacent Instances

If a book is picked up several times, while the reader is standing right in front of the bookshelf, we treat the activity as one time. This may happen when the reader is trying to compare two books with each other.

## 4. Experiment and Evaluation

To evaluate the proposed approach, we carry out some experiments. The performance is judged by recognition accuracy, as shown below:

$$P_a = \frac{\sum_{i=1}^N A_{ii}}{N * m} \quad (11)$$

$$P_b = \frac{A_{ii}}{m} \quad (12)$$

where  $N$  is the quantity of books which is 50 in this paper,  $A_{ii}$  is the amount of correct recognitions of book  $i$ , and  $m$  is the frequency of test activities. Equation (11) represents the overall accuracy and Eq. (12) represents the partial accuracy. Note that, if there is no one walking before the bookshelf, the system will stay silent. After 1 hour, there was no false positive. Thus, our approach works very well to detect the existence of the reader.

In the first part, we test the performance of detecting “Walking”. We ask five volunteers who differ from each other in both height and weight to walk past the bookshelf from left to right and in the opposite direction 25 times. Then, the accuracy is calculated with Eq. (11), as shown in Table 1. In this part, we only use Eq. (11), because all the books are in the same situation for the activity “Walking”.

From this table, we can see that our system performs well for detecting “Walking”. Moreover, this recognition is only achieved for an individual book, separately. If we

**Table 1** Performance of detecting walking past.

Volunteers	P1	P2	P3	P4	P5
Accuracy	97.28%	95.92%	96.76%	96.88%	95.84%

**Table 2** Performance of detecting picking up.

Result	Partial	Overall
Accuracy	96%	92.2%

merge the results for the adjacent books together, the accuracy may be even higher.

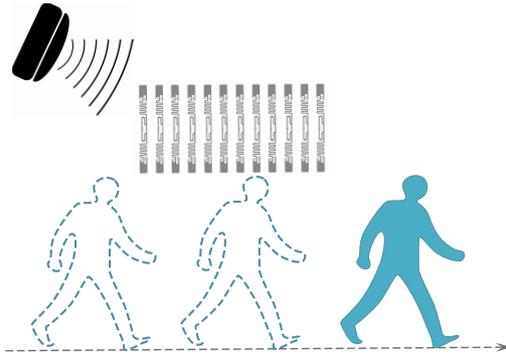
In the other part, we test the performance of detecting “Picking”. We ask a volunteer to walk to the bookshelf, randomly pick up a book, put it back, then walk away. This is repeated 50 times. The two results in Table 2 reflect the partial and the overall accuracy. For the former one, we only consider the books that have been picked up. The partial accuracy is calculated by Eq. (12), where  $m$  means the number of test activities which equals to 50.  $A_{ii}$  represents the successful recognition of book  $i$ . For the latter one, we consider all the books in the calculation with Eq. (11). For the chosen book, “Picking” is the right recognition. Meanwhile, for the other books, “Walking” is the right recognition. That is to say, this overall accuracy can be used to measure the global performance of the proposed system.

The overall accuracy is 92.2%, which is lower than the first part of the experiment. This is because when a book is picked up, it will affect the neighboring books. In future research, we will try to avoid this error.

## 5. Misplaced Book Detection

As mentioned above, the misplacement of books in the library causes difficulty in book management. How to detect misplaced books is a challenge for the future smart library. Note that books in the library are strictly ordered by their IDs to ensure that readers can find a specific book easily. The approach proposed by [5] utilizes the relative localization of RFID tags to locate the misplaced books. However, the approach needs to sweep all the books repeatedly, which results in a high workload in a large library. Our proposed work can greatly reduce the area that needs to be swept, because if none of the books in the area is picked up, there will be no misplacement. Furthermore, we present a zero-cost approach to detect the misplacement remotely, which can also work in real time.

We believe that when a reader walks before a bookshelf, it will cause phase variation successively to the books in one row. Through monitoring the phase deviation of each tag on the books, we can generate the order of the books. The basic idea is that once a reader walks before a bookshelf, our system can check the order of the books one time. If this order does not match the original order of the books, the misplaced book can be detected easily. In this way, the system can check the misplacement in real time, without any extra devices or extra work of the staff.



**Fig. 8** The sequence of time slot that caused by reader's movement reflects the order of books.

As shown in Fig. 8, our activity recognition model can obtain the time slot that the reader walks before a book. We use the timestamp corresponding to maximal deviation point within the time slot to mark the order of the book. After the reader walks before a row of books, there will be a sequence on the timeline. This sequence represents the order of books in a row. However, the result of the verification experiments shows that the sequence does not necessarily correspond to the order of books. The distance  $n$  between the misplaced book and its original position influences the performance of our proposed approach. Thus, a trade-off between accuracy and recall is performed by redefining the book misplacement. If  $n$  is less than limitation  $N$ , we do not treat it as a misplacement. In this study, we set  $N$  equal to 10, which is acceptable in the actual scene. To further reduce false detection, we label it a true misplacement only if the book is reported as a misplacement three times.

In this way, our approach can monitor the entire area in real time. The main advantage of this approach is that the reader is not hindered, which allows the library to be open continuously. On the contrary, the approach relies on the reader without any additional requirements. Theoretically, the more readers there are in the library, the more efficiently our approach works. Although it is a coarse-grained detection approach, it also can be used in cooperation with other robot-based methods to reduce the cost both in time and energy.

## 6. Conclusion and Future Work

In this study, we analyze the feasibility of detecting activity in the library using RFID phase, in theory. Then, we find that the variation of RFID phase can reflect the interaction between the reader and the books. Subsequently, we process the phase signal of tagged books and distinguish the different activities with thresholds. Finally, we implement our approach to evaluate the performance and overall accuracy, which reaches 92.2%. Also, we present a way to detect the book misplacement that works in passive mode.

Our proposed system can detect a reader's existence with very high accuracy and in real time. This makes reader location tracing possible, which is of great importance in a

smart library. Any indoor localization-based method may be introduced into the library, thanks to the high accuracy of localization with books. Furthermore, the system can navigate the reader to the desired book with the shortest path. Moreover, the library can adjust the book position based on the statistical result of reader trajectories.

In the future, we will focus on the personalized book recommendation system. This will bring benefit to both the library and reader. The library can acquire the demand of a specific book and put the popular one in a prominent position to attract more readers. The system can also help the reader to find what he might be interested in, not only based on the borrow record but also on the pick record from him and other readers. Similar personalized recommendation systems have been put forward in other areas. In this vein, the Han study on in-store shopping recommendations is worth learning. Han proposes CBID [15], which is a customer behavior identification system. With CBID, a store can discover a popular item and its relation to a customer's movement pattern. This is what we want to achieve in a future smart library.

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