A Wireless Self-Service System for Library Using Commodity RFID Devices

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***Abstract*—Self-service libraries need self-service book collection and monitoring of book quality to improve user experience This article proposes a privacy-preserving alternative RFbook, a book classification and moisture sensing system formed from an array of passive commercial RFID tags. We have three key observations in designing RFbook for such benefits. The first observation is that when tags are in the vicinity, their interrogation currents can alter each other's circuit properties, based on which unique phase and amplitude signatures can be obtained from the backscattered signal. The second observation is that books with different thicknesses and sizes of material will have different signal features. Finally, we found that changes in book humidity are reflected in the reader's received signal strength (RSS). To turn the high-level idea into a practical system, we built a prototype of RFbook and conducted comprehensive experiments to evaluate the system's performance. The experimental results show that RFbook can distinguish different types of books with an average accuracy rate higher than 96% and monitor the humidity change of the book.**

***Index Terms*—Human-computer interaction (HCI), machine learning, RFID.**

I. Introduction

SELF-SERVICE library has become the trend of library development. Reducing costs and maintaining user satisfaction and timely book maintenance forces libraries to optimize technology to improve operations. One of the main problems with self-service pickup is the need to manually align the labels on the book with the scanner [1], another is the long waiting time for camera processing [2]. The systems currently required for these methods are relatively expensive. In addition, there are also loopholes in the quality management of books when self-service books are collected and returned. Presently, indoor hygrometers are usually used to monitor the humidity in the library, but this method cannot refine the humidity of each book. In this article, we propose RFbook an RFID-based self-service book pickup and quality monitoring system. Book classification and quality monitoring can be completed without using a large number of cameras for complex image processing algorithms. RFbook can greatly improve the user experience of self-service libraries.

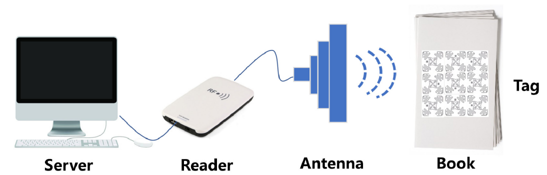

Fig. 1. Illustration of RFbook design. With a paper laying on the tag array, the backscattered signals convey paper-dependent and unique features so that the paper can be classified.

Radio frequency-based wireless sensing technology has excellent commercial prospects due to its low cost and ubiquitous nature. Especially in recent years, RFID has made essential breakthroughs in material identification. RFID sensing solution has been used for material identification [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], vital signs detection [13], [14], [15], [16], [17], [18], indoor localization [19], [20], [21], [22], [23], [24], human motion tracking [25], [26], [27], [28], [29], [30], [31] and humidity sensing [32], [33]. The RFID tag is an essential part of a radio frequency sensing system. Due to its low price and portability, it has been widely used daily. Although traditional image recognition methods have been developed very maturely, wireless perception systems have significant advantages in terms of privacy cost and computational complexity. For example, in the security check scene, the hidden weapons in the passenger's clothes can be known without infrared sensing. Artificial intelligence knows through material recognition that the object is an apple, not a pear, and can automatically adjust its grip. In addition, compared to the potentially colossal computing power consumption of

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image processing. The signal processing complexity of wireless sensing is relatively low, and it is more suitable for edge devices.

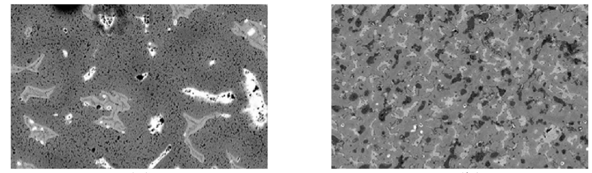
In this article, we make a attempt by designing a solution based on commercial off-the-shelf (COTS) RFID tag arrays [34], which can be easily applied to the application scenarios of book classification and book humidity sensing. Self-service libraries need self-service book collection and monitoring of book quality to improve user experience This article proposes a privacy-preserving alternative RFbook, a book classification and moisture sensing system formed from an array of passive commercial RFID tags. We have three key observations in designing RFbook for such benefits. The first observation is that when tags are in the vicinity, their interrogation currents can alter each other's circuit properties, based on which unique phase and amplitude signatures can be obtained from the backscattered signal. The second observation is that books with different thicknesses and sizes of material will have different signal features. Finally, we found that changes in book humidity are reflected in the reader's received signal strength (RSS).

However, translating this idea into a practical system entails multiple challenges.

1) Capturing the unseen features generated by RFID signals penetrating the book is challenging. We need to prove that RFID signals will produce different changes when penetrating different types of book.
2) Different types of books and the humidity of books will affect the values of RSS and phase at the same time. How to detect the humidity while accurately classifying books is a challenge.
3) The placement of books may be different each time. Our system needs to allow the existence of position diversity.

To address the first challenge, we used tag arrays to capture fine-grained features of the book. We conducted verification experiments to demonstrate that different types of books will reflect different RSS and phase changes to verify the feasibility of using the RFID system to classify the paper. For the second challenge, We design a neural network to classify books accurately and detect the humidity of books. To address challenge three, We design a multigroup sampling method to solve the book position uncertainty, which can significantly improve the system's robustness. In summary, the contribution of this work is as follows.

1) We propose a book classifier and humidity sensor using a passive RFID tag array. To the best of our knowledge, RFbook is the first RFID-based book classifier system.
2) We leverage solutions to the tag-antenna distance dependence problem and the random position of book to enable the RFbook design and address a set of technical challenges to obtain a reliable and robust book classifier.
3) We develop a RFbook system and conduct extensive experiments to evaluate its performance. The results demonstrate the effectiveness of our design: over 96% different types of book classification accuracy and can effectively monitor changes in book humidity over an extended period of time.



(a) (b)

Fig. 2. Different paper has different internal structure. (a) and (b) are the microstructure of different papers under the electron microscope.

The remainder of this article is organized as follows. Section II presents the feasibility analysis of applying RFID signals for book sensing. Section III present the whole system. Section IV presents the implementation of RFbook. Section V presents the system evaluation. Section VI introduces the related work. Section VII discussed the limitation of our work.

II. Feasibility Analysis

In this section, we introduce the unique properties of paper in terms of material and intrinsic structure, which can be manifested by changes in the received tag array signal of an RFID reader. Furthermore, we demonstrate that it is feasible to exploit these features to identify different types of books. Finally, we verified that RFbook can detect the change of signal characteristics of the same book under different humidity conditions.

A. Unique Structural Characteristics

Different types of paper has different production parameters and processes, as reflected in the selection and ratio of raw materials in the pulp. In addition, the dilution and stacking thickness of the pulp during paper making can lead to different densities and thicknesses of the finished paper, which determines paper products' application scenarios. As shown in Fig. 2(a) and (b), under the electron microscope, we observe that different papers are quite different in microstructure, demonstrating the essential difference among different papers. RFbook uses commercial RFID signals to detect different papers, and later we will verify the feasibility of using RFID to distinguish different papers.

B. Variation in the Phase of the RF Signal

The RFID reader captures the tag has reflected signal's RSS and phase changes. In this section, we first introduce the parameters that affect the phase value. We define that the phase value ϕ consists of the following three parts:

$$\phi = \phi_{\text{tag}} + \phi_{\text{pro}} + \phi_{\text{cir}}$$

where ϕ_{tag} is the phase shift caused by the tag, which is mainly related to the impedance Z_a of the tag's resistance. ϕ_{pro} is related to the flight distance d of the signal. ϕ_{cir} is the noise phase shift caused by the system's hardware. When we attach the paper to the tag. The impedance Z_a of the tag changes due to the influence of the paper, and this change causes the phase $\Delta\phi_{\text{M}}$ of the entire system to change as follows:

$$\Delta\phi_M = \phi_{\text{tag}\,B} - \phi_{\text{tag}\,A}$$

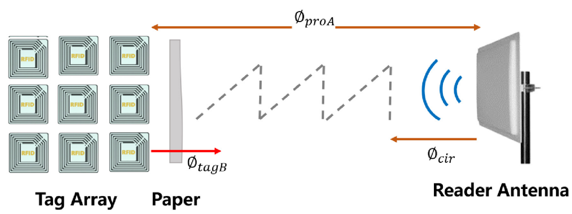


Fig. 3. Phase value of RFbook when paper is attached.

where $\phi_{\text{tag}\,A}$ represents the phase shift caused by the tag itself and $\phi_{\text{tag}\,B}$ represents the phase shift after the paper is attached. We define the paper-induced phase shift as $\Delta\phi_M$. As shown in Fig. 3, ϕ_A and ϕ_B, respectively, the readings before and after the paper is attached to the label are expressed as

$$\begin{cases} \phi_A = \phi_{\text{tag}\,A} + \phi_{\text{pro}A} + \phi_{\text{cir}} \\ \phi_B = \phi_{\text{tag}B} + \phi_{\text{pro}B} + \phi_{\text{cir}}. \end{cases}$$

$\phi_{\text{pro}\,A}$ and $\phi_{\text{pro}\,B}$ represent the phase change caused by signal propagation before and after the paper is attached to the tag, they do not need to be equal. By subtracting the two equations, we get

$$\phi_B - \phi_A = \left(\phi_{\text{tag}\,B} - \phi_{\text{tag}\,A}\right) + \phi_{\text{proB}} - \phi_{\text{proA}}.$$

Since $\Delta\phi_M = \phi_{\text{tag}\,B} - \phi_{\text{tag}\,A}$ we obtain

$$\phi_B = \Delta\phi_M + \phi_{\text{proB}} + \phi_A - \phi_{\text{proA}}$$

where ϕ_A is the phase value caused by the tag itself, which we call the reference phase. $\phi_A - \phi_{\text{proA}}$ is the phase change caused by the signal in the air and is related to the distance between the antenna and the tag. So we can treat ϕ_A and $\phi_A - \phi_{\text{proA}}$ as constants. Therefore, we know that ϕ_B is only related to the characteristics of the paper itself and the distance between the tag and the antenna.

C. Variation in the RSS of the RF Signal

RSS is an apparent characteristic value of the RFID system. RSS is mainly affected by the signal propagation distance and the impedance from the tag. Changes affecting RSS readings are mainly composed of the following:

$$\text{RSS} = 10\,\text{lg}\left(G_t^2 \Gamma_{\text{tar}} \frac{P_{Tx}}{1\ \text{m}W} T_r G_r^2 \left(\frac{c}{4\pi f d}\right)^4\right)$$

where G_t, Γ_{tar}, P_{Tx}, and T_r represent the antenna gain, radiation coefficient, antenna transmit power, and transmit loss, respectively, and are related to the system itself and can be regarded as constant. The RSS value in RFbook is mainly related to the antenna impedance and the distance d between the antenna and the tag.

D. Different Paper and Humidity

Different Paper: We placed an antenna on the table facing the paper and connected the antenna to the reader. We put the tag array on the table and placed the paper on the array. The distance between the antenna and the tag array is 15 cm. We aimed to measure the RSS and phase changes of different papers. To change the paper parameters. We use six

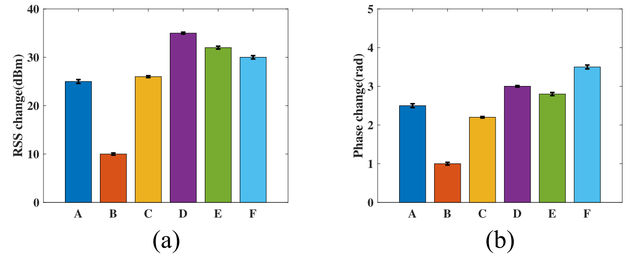


Fig. 4. RSS and phase change. (a) RSS change of different paper. (b) Phase change of different paper.

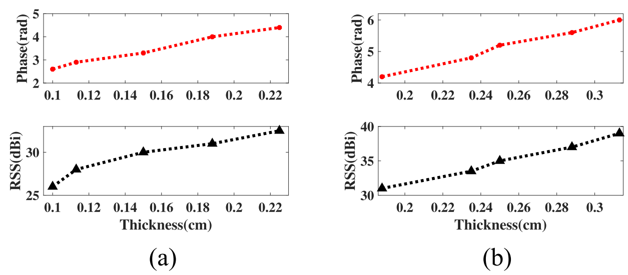


Fig. 5. Phase and RSS versus paper thickness. (a) Printer paper. (b) Insulating paper.

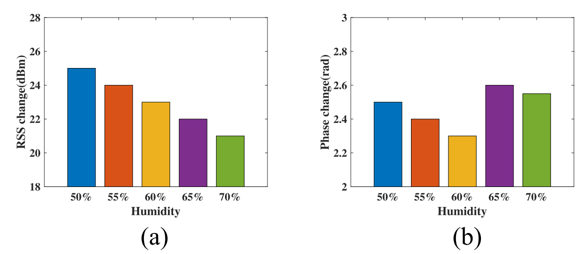
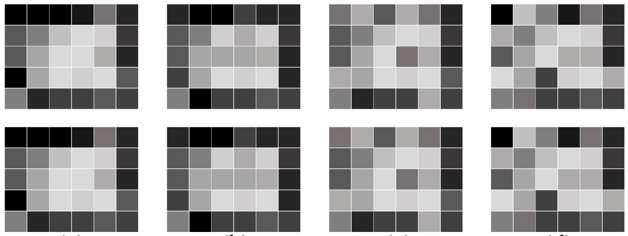


Fig. 6. Effect of humidity on RSS and phase. (a) RSS versus humidity. (b) Phase versus humidity.

kinds of paper with varying production processes: 1) printing paper; 2) wrapping paper; 3) drawing paper; 4) blotterpaper; 5) insulating paper; and 6) paperboard. We acquired changes in RSS and phase value taken by the reader before and after the paper attachment, as shown in Fig. 4(a) and (b). The phase and RSS changes were entirely different for the six different densities and thicknesses of paper. These results suggest that different papers cause different changes in phase and RSS value. In addition, we verified the following benchmark experiments, where we selected five thicknesses of printing paper and insulating paper and measured the relative changes in RSS and phase. Fig. 5(a) and (b) shows the variation of the RSS and phase change between printing paper and insulating paper with different thicknesses, and an apparent linear effect can be observed.

Different Humidity: We put the paper in the humidifier and recorded the different humidity levels labeled 50%, 55%, 60%, 65%, and 70%. The experimental results are shown in Fig. 6. Because the water inside the paper absorbs the signal received by the tag [33]. The greater the ambient humidity, the greater the signal attenuation on the tag antenna, and the RSS decreases as the ambient humidity increases in Fig. 6(a). However, the phase also changes with different



(a) (b) (c) (d)

Fig. 7. RSS distribution on the tag array corresponding to four different papers. (a) Paper 1. (b) Paper 2. (c) Paper 3. (d) Paper 4.

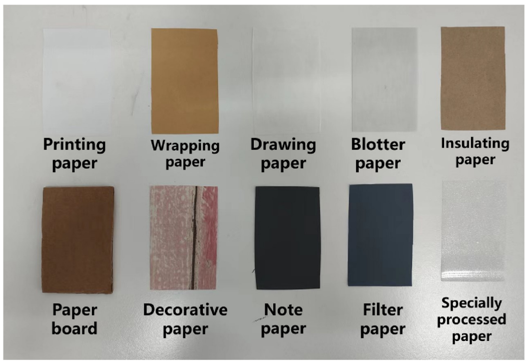


Fig. 8. Ten different types of paper.

ambient humidity in Fig. 6(b), and there is no clear pattern of change. It is worth noting that the impact of ambient humidity on RSS and phase is less than that caused by different types of paper.

E. Fine-Grained Classification Using Tag Arrays

Considering that a single tag cannot bring out the more exclusive features of the paper, we use the tag array for more fine-grained paper feature extraction. We used four sheets from different manufacturers and used a 6×5 tag array placed under the paper. The RSS distribution on the tag array we collected is shown in Fig. 7, and the signal color's depth represents the RSS reading's size. We further use a classifier to classify the difference between the RSS value taken and the phase value. We found that for the same paper, the distributions of RSS and phase are very close, while the distributions of RSS and phase are quite different for different paper types. Therefore, fine-grained paper differentiation is feasible using the reads from the tag array.

F. Paper Diversity

We selected ten different types of paper with different production processes, namely, printing paper, wrapping paper, drawing paper, blotterpaper, electrical insulating paper, paperboard, decorative paper, notepaper, filter paper, and specially processed paper as shown in Fig. 8. We also selected printing paper, drawing, bond paper, and insulating paper with different parameters (mass and density) for experiments to verify similar material paper.

We collected samples for each paper and fed these data into the neural network classifier. Fig. 9 shows that the

	A	B	C	D	E	F	G	H	I	J
A	1									
B		0.95		0.05						
C			0.98		0.02					
D		0.05		0.95						
E					1					
F						0.96	0.04			
G						0.02	0.98			
H								0.96	0.04	
I									1	
J								0.03		0.97

A: Printing paper B: Wrapping paper C: Drawing paper D: Blotter paper
E: Electrical insulating paper F: Paperboard G: Decorative paper
H: Note paper I: Filter paper J: Specially processed paper

Fig. 9. Identification accuracy for ten different types of paper.

identification accuracy for these ten paper types is over 95%. We also performed additional experiments to verify whether papers with slightly different thicknesses and densities could be distinguished. We selected printing, drawing, bonding, and insulating paper with different parameters. As a result shown in Fig. 10, the recognition accuracy of RFbook will decrease for papers with slightly different density and thickness materials. This is because for the same paper material, the RSS and phase difference change is tiny, but the accuracy of the RFbook is still higher than 90%.

III. System Design

In this section, we introduce the detail design of RFbook.

A. Overview

RFbook is an RFID-based book sensing system and the architecture diagram of the system is shown in Fig. 1. It consists of four main modules: 1) *data preprocessing*; 2) *value calibration*; 3) *feature extraction*; and 4) *classification module*.

1) *Data Preprocessing:* We receive data samples from the signal received by the directional antenna by attaching the book to the tag array. We send the data obtained from the reader to the server. We first need to perform data segmentation to determine the start time when RFbook starts classifying books. Then we need to solve a few problems to reduce the hardware error generated by the system.
2) *Value Calibration:* We use a phase calibration algorithm to replace outliers in the raw phase values with normal values. Finally, we use frequency hopping to reduce the extraction error of RSS readings.
3) *Feature Extraction:* To suppress the influence of environmental noise, we make the difference between the obtained RSS and phase readings and the readings when no book is attached and use this difference as the feature value. Then we construct two sets of feature vectors and input these two sets of feature vectors into our designed neural network.
4) *Classification:* RFbook uses a neural network to classify different books and humidity detection. The input to the network is an eigenvector containing phase and RSS values. The network's output is the probability that

(a)

	1	2	3	4
1	0.91	0.06	0.03	
2	0.04	0.93	0.03	
3		0.04	0.91	0.05
4			0.07	0.93

1: 70g/m^2 0.093mm 2: 100g/m^2 0.133mm 3: 140g/m^2 0.187mm 4: 180g/m^2 0.240mm

(b)

	1	2	3	4
1	0.92	0.05	0.03	
2	0.04	0.92	0.04	
3		0.04	0.91	0.05
4		0.02	0.06	0.92

1: 52g/m^2 0.065mm 2: 80g/m^2 0.100mm 3: 120g/m^2 0.150mm 4: 180g/m^2 0.225mm

(c)

	1	2	3	4
1	0.93	0.04	0.03	
2	0.03	0.93	0.04	
3		0.01	0.94	0.05
4			0.05	0.95

1: 50g/m^2 0.077mm 2: 70g/m^2 0.108mm 3: 120g/m^2 0.184mm 4: 150g/m^2 0.231mm

(d)

	1	2	3	4
1	0.94	0.04	0.02	
2	0.04	0.92	0.04	
3		0.02	0.93	0.05
4		0.01	0.04	0.95

1: 130g/m^2 0.17mm 2: 150g/m^2 0.20mm 3: 180g/m^2 0.25mm 4: 200g/m^2 0.28mm

Fig. 10. (a) Printing paper, (b) drawing, (c) bond paper, and (d) insulating paper with different parameters.

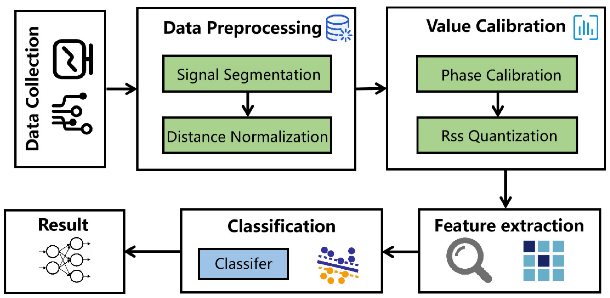


Fig. 11. System overview of RFbook.

this feature vector belongs to a particular book. Finally, to solve the problem of minor differences in the book placement each time, we propose a strategy to sample features in groups to optimize our neural network.

We designed extensive experiments to verify the robustness of RFbook, and the experimental results have proved that RFbook can classify different types of books and even distinguish books of the same material with different thicknesses and densities.

B. Signal Preprocessing

1) Segmentation: Before the work of book identification starts, we first need to determine whether RFbook starts to detect book. When the book is attached to the tag array, the part of the RSS reading on the array that is obscured by the book changes significantly, and we detect this change to determine the timestamp when the system starts working.

Specifically, we use the continuous RSS value changes of the central position tag in the tag array over a period of time to determine whether the detection starts. We use multiple sliding windows, once the RSS value of a sliding window far exceeds the previous sliding window and the RSS value after this sliding window is consistent with the current window. We set the start time of this sliding window to the time when the detection started. Then the system starts to collect data. We collect data from the initial timestamp for ten sliding windows, where each sliding window corresponds to a set of RSS and phase values. We will then calibrate the RSS and phase values in all windows and construct two sets of eigenvectors.

Although these two sets of feature vectors contain book features, there are still three challenges in identifying book using these two sets of feature vectors.

1) Random antenna starting position affects RSS and phase readings.

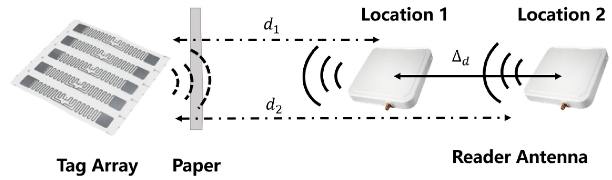


Fig. 12. Eliminate distance dependence between antenna and tag array.

2) Normal phase values are mixed with abnormal phase values.
3) Ambient and hardware noise is included in the book feature subblock.

To address these challenges, we design three modules: 1) distance-independent removal; 2) phase calibration; and 3) RSS quantization, to improve the robustness of RFbook.

2) Distance Independent: In book detection, the distance of the directional antenna from the tag array causes uncontrollable phase and RSS changes, making book feature extraction challenging. We can eliminate this detection error if the system can automatically obtain the exact distance (in millimeters) between the antenna and the tag array at each detection. However, this is not possible. We need a more appropriate way to solve this problem. Specifically, we tested by placing the antenna at two different positions to eliminate the problem of distance dependence on the tag reader as shown Fig. 12.

For RSS readings of RFID antennas at different locations, we have

$$\mathrm{RSS}_i = 10\lg\left(G_t^2\Gamma_{\mathrm{tar}}\frac{P_{Tx}}{1\ \mathrm{m}W}T_rG_r^2\left(\frac{c}{4\pi f d_i}\right)^4\right), i \in [1, 2]. \quad (1)$$

We extract the RSS readings for these two locations and get

$$40\lg\left(\frac{d_2}{d_1}\right) = \mathrm{RSS}_1 - \mathrm{RSS}_2. \quad (2)$$

We can know that the difference in RSS readings is only related to material and distance from (1) and (2) when the tested material itself is unchanged. Likewise, we can calculate the phase readings for these two different locations as follows:

$$\phi_{B_i} = \Delta\phi_M + 2\pi\left(\frac{2d_i}{\lambda} - k_i\right) + \phi_0, k_i = \left\lfloor\frac{2d_i}{\lambda}\right\rfloor, i \in [1, 2]. \quad (3)$$

By transforming (3), we can get

$$\frac{d_2}{d_1} = \frac{2\pi k_2 + \phi_{B_2} - \Delta\phi_M - \phi_0}{2\pi k_1 + \phi_{B_1} - \Delta\phi_M - \phi_0}. \quad (4)$$

Both (2) and (4) have the same term (d_2/d_1), we combine (2) and (4) to cancel the same item (d_2/d_1), get the following relation:

$$\Delta\phi_M = \frac{2\pi(\Upsilon k_1 - k_2) + \left(\Upsilon\phi_{B_1} - \phi_{B_2}\right)}{\Upsilon - 1} - \phi_0 \quad (5)$$

where

$$\Upsilon = 10^{\frac{\mathrm{RSS}_1 - \mathrm{RSS}_2}{40}}. \quad (6)$$

So far, we have successfully eliminated the dependence of material characteristics on distances d_1 and d_2.

C. Value Calibration

1) Phase Calibration: For wireless sensor systems, the phase will vary periodically between [0, 2π]. For RFbook, the phase error when collecting data mainly comes from two parts: 1) the interference of the hardware itself and 2) the slight change of the book position causes the other. The error caused by the hardware is caused by the unexpected position change of the antenna and the tag array, which will add an extra phase value to the standard phase value, resulting in an identification error. Second, during data collection, the relative position of the book to the tag array cannot be kept the same every time. It also causes phase measurement errors. Therefore, the collected phase values may cause serious identification errors.

Therefore, we design an algorithm to solve this problem. We are given a specific sliding window with ten consecutive phase values. Some of these ten phase values are greater than π and some are less than π. When there are more phase values greater than π than less than π, we use the average of the phase values more marvelous than π to replace the array of phase values less than π. This can effectively reduce the interference of outliers in minority groups.

2) RSS Quantization: We use frequency hopping, a commonly used method to find clean channels in rich multipath environments, to reduce multipath's effect on the system's detection results.

RFbook uses an Impinj 420 RFID reader with a frequency range of 902.75 to 927.25 MHz and 50 frequency channels. We use frequency hopping to pass more channels and get a unique frequency signature. Then, a 200-ms delay is required for the reader studio to perform frequency hopping, which means that the more frequency hopping is completed, the more serious the system delay will be. After many experiments (specifically in Section V), we found that after using more than 12 channels, the system's accuracy no longer improved significantly. So our system uses 12 channels to do frequency hopping.

The accuracy of system RSS readings can be affected by hardware noise. And we use the reader to get only 0.5dBm RSS reading resolution. Therefore, we need a way to reduce reading errors. To reduce RSS errors caused by multiple channel readings, our strategy is to make the RSS errors consistent across multiple channels. Since the RSS readings in different channels are different, we only measure the RSS on the first channel and use this RSS in place of the rest of the RSS values. In this way, we unify the possible RSS errors of all channels.

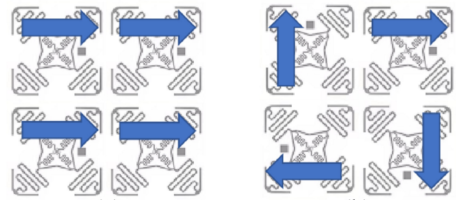


Fig. 13. Different tag array layout. (a) Universal layout. (b) Shuffled layout.

Although RSS errors can lead to incorrect book characteristics, all channel book obtained features will vary in the same trend. We use this method during data collection to effectively reduce measurement errors. For phase, we use the phase values of multiple channels to measure. Compared to RSS readings, the range of phase variation is smaller. We use the measured phase value of multiple channels and the measured RSS value of the first channel to reduce the interference of hardware factors to the system.

D. Layout of the Tag Array

Since there is electromagnetic interference between adjacent tags, the tags in the tag array may greatly interfere with the reading of adjacent tags as the layout as shown in Fig. 13(a), the generation of electromagnetic interference between adjacent tags under the dense layout of tags will seriously affect the signal quality. We use a well accept tag array Layout [35] to reduce the effect of this interference. Specifically, we disrupt the orientation of tags by placing adjacent tags perpendicular to each other, as shown in Fig. 13(b). This makes the electromagnetic interference perpendicular to each tag, which can minimize the interference of adjacent tags.

E. Feature Extraction

After RFbook receives the signal from the tag array, it uses RSS and phase readings to differentiate the book. Below we will introduce the feature extraction method adopted by RFbook.

During RFbook's signal acquisition process, random book placement and hardware noise can affect the readings of RSS and phase values read by the RFID reader. To improve the system's robustness, we reduce the effects of random book placement and hardware noise by calculating the difference between adjacent RSS and phase readings in the tag array. Specifically, the distance between adjacent tags is much smaller than between the tag and the environment, which means that even if adjacent tags receive environmental interference, the interference is similar. Therefore, calculating the difference between the RSS and phase readings of adjacent tags can effectively reduce environmental interference. We first calculate the phase difference between adjacent tags. After signal preprocessing, we record the tag phase difference calculated by RFbook as a feature, then the phase difference between adjacent tags can be calculated as

$$\Delta\theta_{rc} = \theta_{rc} - \theta_{rc+1} = \left(\frac{4\pi d_{rc}}{\lambda} + \Delta\theta_{\mathrm{tag}}^{rc}\right) \mod 2\pi \quad (7)$$

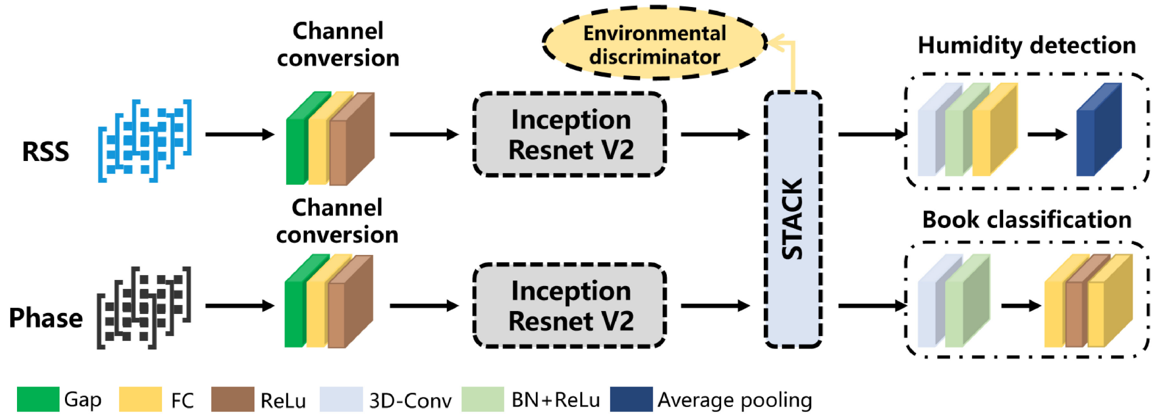


Fig. 14. Structure of neural network.

where d_{rc} is the difference between the tag in row r and column c and the tag in row r and column $c+1$ to the antenna distance. $\Delta\theta_{\text{tag}}^{rc}$ is the initial phase offset of the two tags. For the entire tag array, we can derive

$$\Delta P = \begin{Vmatrix} \Delta\theta_{11} & \Delta\theta_{12} & \dots & \Delta\theta_{1c} \\ \Delta\theta_{21} & \Delta\theta_{22} & \dots & \Delta\theta_{2c} \\ \vdots & \vdots & \dots & \vdots \\ \Delta\theta_{r1} & \Delta\theta_{r2} & \dots & \Delta\theta_{rc} \end{Vmatrix}. \quad (8)$$

ΔP is the eigenmatrix of the phase of the tag array, where $\Delta\theta_{rc}$ represents the phase value at row r and column c. By this method, we get the eigenvector of the phase difference value, and RFbook inputs this vector into the classification device.

Similarly, after getting the feature vector about the phase, we can get the feature vector of the RSS in the tag array as follows:

$$\Delta RSS = \begin{Vmatrix} \Delta R_{11} & \Delta R_{12} & \dots & \Delta R_{1c} \\ \Delta R_{21} & \Delta R_{22} & \dots & \Delta R_{2c} \\ \vdots & \vdots & \dots & \vdots \\ \Delta R_{r1} & \Delta R_{r2} & \dots & \Delta R_{rc} \end{Vmatrix}. \quad (9)$$

From (9) and (8) we get the feature vector of RSS ΔRSS and feature vector of phase ΔP of the book.

F. Classification Module

In this section, we will detail the structure of our neural network used in RFbook.

1) Structure of Neural Network: In this section, we focus on the neural network structure used by RFbook. To classify the materials and shapes of books, we carefully designed a two-branch neural network as shown in Fig. 14. The overall network structure mainly comprises channel conversion, environment discriminator, humidity, and book classification. We read the RSS and phase from the tag array as input. To make full use of the high-dimensional features in the RSS and phase matrix, we also process the extracted features in three modules: 1) channel conversion; 2) multiscale sensing; and 3) environment filter. Finally, we perform both classification and humidity detection on the books.

2) Channel Conversion: Due to the effects of multipath and object occlusion, the received RF signal may experience frequency selective fading. Therefore, we have the reader transmit on multiple frequency channels to enhance the robustness of our system. But in the case of multipath, different frequency channels may produce irregular changes that interfere with our reading. So, we need to select 'clean' channels for further classification.

We regard the choice of channels as the basis for accurate classification by a classifier. On this basis, in order to balance the weights of signals under different channels adaptively. We used the channel attention component. Specifically, it can adaptively learn the feature responses of channel directions by explicitly modeling the interdependencies between channels. Simply put, instead of discarding multipath interference, we use it to suppress less important signals while activating important ones for frequency calibration.

3) Multiscale Sensing: RFbook uses tag arrays for book classification, which can provide more spatial information than material classification systems that only use a single tag. This kind of spatial information is very important for classification, and we use neural network for spatial information extraction. We need to increase the depth of the network while reducing the computational burden of the network. Generally speaking, the method of increasing the competitiveness of the network is usually used to increase the depth of the network. But using this method will cause excessive skewing of the neural network. To solve this problem, we use ResNet V2 [36] architecture to optimize neural network. For ResNet V2, the identity mapping branch has no rectified linear unit (ReLU) activation function, and it can be unimpeded during forward propagation and backward propagation, and the identity mapping is truly realized. Such an architecture combines multiscale features extracted from tag arrays to enrich the sensing information greatly. At the same time, the remaining connections do not lose low-level key features, which can eventually speed up the training of the network.

4) Environment Discrimination: Due to some defects in the radio frequency system itself, it will inevitably be affected by environmental noise. At the same time, this influence also limits the use of the system in new environments, and the method of simply relying on Section III-B cannot completely eliminate this interference. Therefore, to improve the system's robustness, we also optimized the neural network to improve the system's anti-interference ability to noise. Inspired by domain adaptation techniques, we introduce an environment discrimination module. Eliminate the effect of environmental noise by exploring the reverse gradient loss.

Specifically, we take the stacked multiscale features as input, first into a 3-D average pooling layer and then into a fully connected layer to extract overall features. Then use this component to perform reverse training with the previous component, and use this method to eliminate the noise generated by the environment.

5) Humidity Detection: RFbook uses two networks for humidity detection and book classification. In the process of humidity detection, the collected feature vectors are first sent to the 3-D convolutional layer. Then the FC layer is activated using ReLU to form a new representation. In order to reduce the complexity of the model, we use the average pooling layer in the last layer to reduce the model's complexity and calculation, improve the model's generalization ability, and reduce the risk of overfitting. Average pooling fuses the information into a single feature vector to perform the final humidity detection.

6) Book Classification: In the book classification module, we first extract RSS and phase features from the book, which are then fed into the convolutional layer of the neural network. We incorporate ReLUs after each convolutional layer to enhance the network's nonlinearity and reduce interneuronal dependencies. Additionally, to ensure the network's robustness to changes in data distribution, we employ normalization functions following the convolutional layers. Considering the relative stability of RSS features compared to phase features, we assign weights of 0.6 and 0.4 to the outputs of the fully connected layer associated with the RSS value and phase, respectively. Doing so, we effectively prioritize the RSS information in the final decision-making process. Finally, the book with the highest probability, as determined by the input feature vector, is classified as the predicted book.

7) Dealing With Different Book Positions: During the operation of the RFbook system, the biggest challenge is the irregular placement of the book because, in the actual application scenario, the user cannot ensure that the book can be placed in the same position every time. The feature vectors collected in the training set may differ from those collected during the testing process, which may affect the performance of RFbook due to differences in book positions. We conducted a set of experiments to test this hypothesis. We collected feature vectors for the same book at two different positions. We used the same feature vectors to train and test the neural network, and the recognition accuracy was as high as 95%. However, when we used another set of training classifiers and then cross-validated them, the accuracy dropped to 80%. The results show that differences in book placement do indeed degrade RFbook performance.

To deal with random book potential positions, we use a method that randomly draws feature vectors from multiple training sets to deal with potential random book positions. Specifically, as shown in Fig. 15. We extract different feature vectors from different training sets to form a new feature vector, which contains the RSS and phase values of the book at different positions. In this way, the book classifier can obtain the feature vectors of the book in more positions, thereby increasing the robustness of the system. In order to verify whether this method is effective, we conduct classification experiments. We first fix the number of feature vectors in the training set to avoid the influence of the training set size. Through the cross-experiment, the classification accuracy of RFbook reaches 96%, which proves the feasibility of the method.

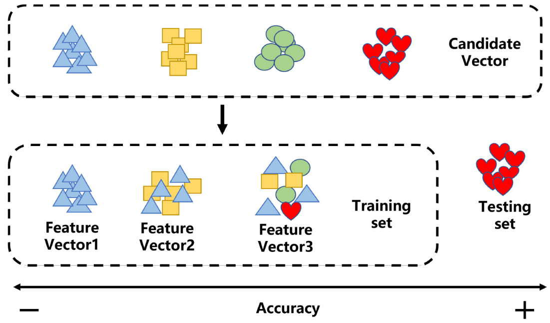


Fig. 15. Mixed feature vector.

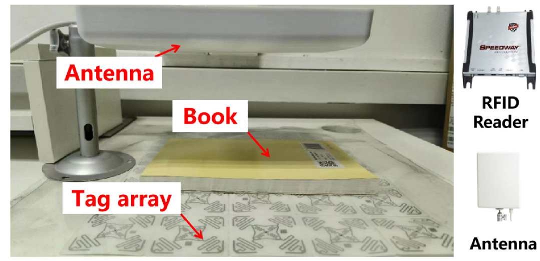


Fig. 16. Experiment setup of RFbook.

IV. System Implementation

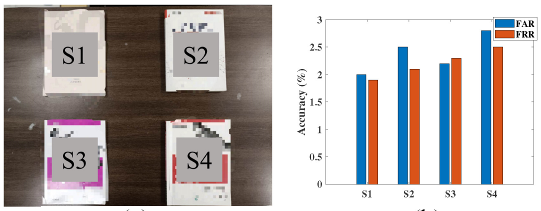
Hardware Prototype: The overall hardware prototype of RFbook is shown in Fig. 16. We use an Impinj R420 reader, which is currently a reader with high-comprehensive performance in the industry, providing a complete SDK development kit, demo software, and documentation support. We used a 2.4G directional 8dbi high-gain panel antenna to adapt to our experimental environment. We used the stand to align the antenna to the tag array on the table. Our experiments used cheap alien tags that cost only 0.3 cents per tag. A total of 30 tags are placed in a label array of 5×6.

Software: We use a desktop computer as a server with a 2.5-GHz i9-11900H CPU and 32-G RAM. All algorithms are implemented using JAVA and MATLAB. In the experiment, the data returned by the tag array is transmitted to the reader through the directional antenna. The reader transmits the data packet to the server through the Ethernet cable, and then the data analysis of RFbook is performed on the server.

Test Targets and Metrics: To verify the RFbook system, we selected 100 different types of books. These books contain different thicknesses and different paper materials. We collected the characteristics of each book. To characterize the

TABLE I
OVERALL PERFORMANCE OF RFBOOK

	Mean	Median	Standard Deviation
Precision(%)	96.6	96.5	3.3
F-score(%)	95.8	95.6	4.1
FNR(%)	2.7	2.6	2.5
FPR(%)	1.7	1.5	0.5



(a) (b)

Fig. 17. FAR and FRR performance of similar books. (a) Similar book. (b) FAR and FRR performance.

performance of RFbook, we mainly used three indicators: 1) the false positive rate (FPR); 2) false negative rate (FNR); and 3) accuracy.

V. EVALUATION

In this section, we evaluate the performance of RFbook in classifying different books. We first evaluated the system's overall performance and then tested the effect of various experimental parameters on the system. Note that To classify different books, we first register the books to be classified, and when detection is required, we match the features of the books to be detected with the features of all books in the database.

A. Overall Performance

We first evaluate the overall performance of RFbook in distinguishing different books. We use 100 books for our experiments. We labeled each book and collected and validated 100 sets of data for each book. Table I shows that the median values for precision and F-score are 96.5% and 95.6%, respectively. The average FAR of RFbook is less than 3%. It is worth noting that the FRR of most books is less than 2%, which means that RFbook can effectively distinguish different types of books.

Similar Book: We also made some challenging settings for RFbook, such as S1, S2, S3, and S4 as shown in Fig. 17(a), S1 and S2 have almost the same thickness but use different paper materials, S3 and S4 have slightly different thickness but use paper of the exact same material. We observed that their FRR and FAR still did not increase significantly as shown in Fig. 17(b), which shows that RFbook can well distinguish books with similar thickness or materials.

Humidity Detection: We evaluated the detection of the system in different humidity environments. We placed the books in the humidity box and selected two humidity sensors with different prices for comparison. As shown in Fig. 18, we tested under 10 different humidity environments, and the experimental results show that the accuracy of our system is much higher than that of low-cost sensors, and the performance of high-end sensors that sell for 200 dollars is comparable.

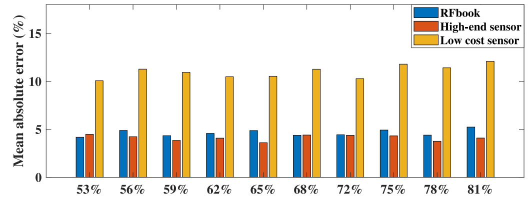


Fig. 18. Humidity detection estimation error at different levels.

B. Impact of Other Factors

Effect of Group Sampling: To address differences in paper placement, we use multiple sets of sampling features to reduce the effect of random paper placement. We use one, two, and three sets of feature vectors to train the neural network. The experimental results are shown in Fig. 19(a). Among them, We found that the classification and recognition accuracy of RFbook increases with the increase in the number of groups and feature vectors used, which proves that the grouping strategy is effective.

Effect of Distance: The distance between the antenna and the tag will affect the RSS and phase readings and thus affect the recognition results. We conduct experiments at different distances to test the effect on the robustness of RFbook. We placed the antennas at six different distances from the tag array, 10, 13, 16, 19, 22, and 25 cm. In Fig. 19(b). We found that the detection performance of RFbook is the best when the distance is 16 cm, and when the distance exceeds 22 cm, the detection performance will decrease. The main reason is that RSS readings exhibit logarithmic decay as the antenna gets farther from the tag array, making the target features less obvious than the ambient noise. Finally, the system has a more flexible space in the choice of distance.

Effect of the Number of Tags: We further explore the impact of the number of tags on RFbook. For each tag deployment, we use 30 books to collect data 50 times in the tag column. Then use the collected data to train again and use the trained model to evaluate the impact of the number of tags. The experimental results are shown in Fig. 19(c). It can be seen that more tags can provide the system with richer book feature information. But when the number of tags exceeds 30, the improvement is not obvious. Therefore, considering our experimental results, we finally use an array of 30 tags.

Effect of Environment: We selected four potential usage scenarios for RFbook: 1) library; 2) classroom; 3) restaurant; and 4) coffee shop. The multipath effects in libraries and classrooms are mainly caused by static objects, and the multipath effects in restaurants and cafes are mainly affected by human activities. In each environment we collected 20 samples and built a new data set. For these four different scenarios, RFbook maintains an accuracy rate of more than 96%, as shown in Fig. 20(a). The experimental results show that RFbook can still maintain robustness in various environments. This is due to the fact that the system focuses on paper and its features, while the antenna is always aimed at the tag array, reducing interference from surrounding objects.

Effect of Number of Frequency Channels: More frequency channels can generally achieve higher material identification

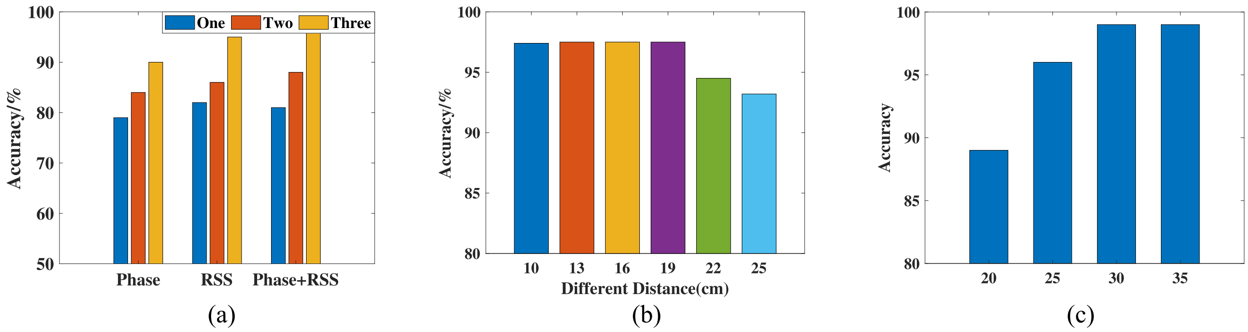


Fig. 19. Effects of different system settings. (a) Effect of group sampling. (b) Effect of distance. (c) Effect of the number of tags.

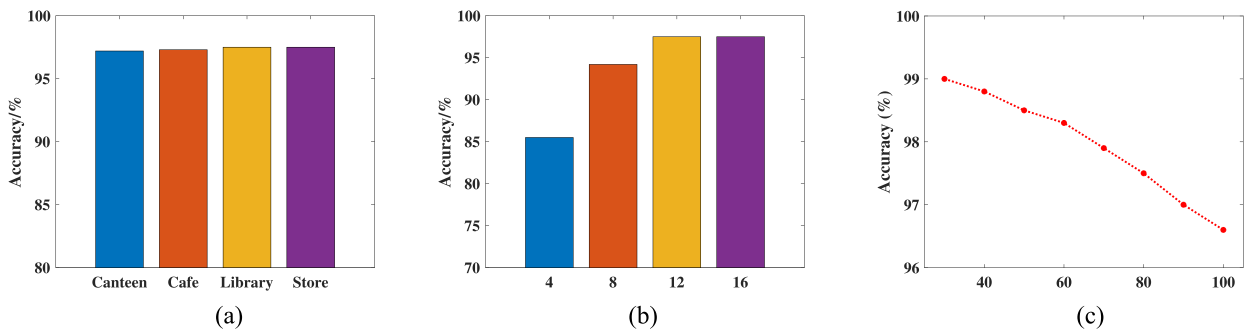


Fig. 20. Effects of different system settings. (a) Different Environment. (b) Different number of Frequency. (c) Different number of book.

accuracy but also bring higher latency, so we need to find a balance between accuracy and latency. As shown in Fig. 20(b), for our system, the recognition accuracy of four channels is 85.5%, the recognition accuracy of eight channels is 94.2%, the average identification accuracy of 12 channels is 96.5%, and the recognition accuracy of 16 channels is 96.5%. We find that as the number of channels increases, the frequency and eigenmodes of the system become more unique, increasing detection accuracy. But after going up to 12 channels, the increase in accuracy almost stops. Consider that the increase in channels will bring delays. We use 12 channels for paper recognition.

Effect of the Number of Books: We increased the number of tested books from 30 to 100 to detect the impact of increasing the detection range on the system. As shown in Fig. 20(c), as the number of book detections increases, the recognition accuracy of the system will decrease slightly. When there are only 30 objects, the detection accuracy exceeds 99%, and when there are 100 detected objects. The detection accuracy dropped to 96.6%. This result is understandable. As the number of books in the database increases, the average difference between books becomes smaller and smaller.

Effect of Tag Diversity: Since different RFID tags have antenna structure and chip type differences, leading to different working ranges, sizes and price differences between tags. For RFbook, since paper produces a small range of RSS and phase changes, we need to know which tags are most sensitive to RSS and phase changes. To evaluate the effect of different tags, we used six tags with different shapes as shown in Fig. 21(a), then used these six tags to form an array to detect the impact on RFbook performance. The experimental results

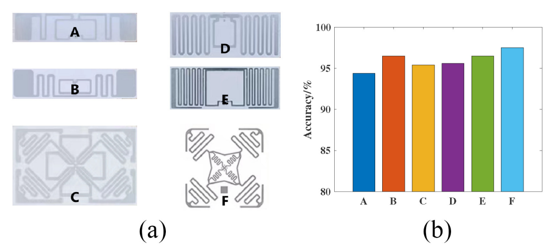


Fig. 21. Impact of different tags on RFbook. (a) Six different tags used in the experiment. (b) Accuracy of different tag.

are shown in Fig. 21(b). Among them, tag F performed the best. Because tag F is a relatively regular square, the formed array is also a fairly standard shape and can be well adapted to the array layout required by RFbook.

Effect of Model Adaption: To demonstrate the long-term performance of RFbook and to emphasize the necessity of model adaptation. The evaluation involved 100 books, each initially trained on the data set from the first session (called S1) and subsequently tested on all six sessions. Each book receives 100 tests per session. Fig. 21 illustrates the results obtained by averaging data collected from 50 books, with and without model adaptation.

When model adaptation is not employed, the FNR increases from 2.7% to 5.2% as shown in Fig. 22(a). In contrast, by implementing model adjustments, the average FPR remained at approximately 1.8% even after 20 days as shown in Fig. 22(b).

VI. Related Work

Sensing based on RFID signals has been widely used, including vital signs detection, material identification, indoor

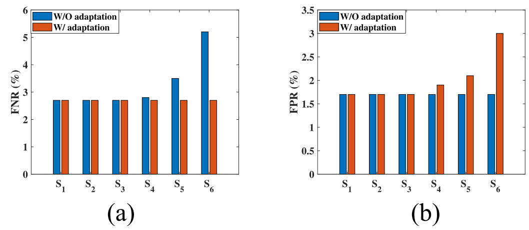


Fig. 22. Impact of model adaptation. (a) FNR of RFbook with/without model adaptation. (b) FPR of RFbook with/without model adaptation.

localization, etc. PaperID is inspired by these works and is closely related to the following works.

Vital Signs Detection: Human behavior detection has a long history, with early wireless signal-based detection using Doppler radar [37] to record random human motion. Advances in signal processing technology have driven the development of passive sensing systems. Lv et al. [38] used a set of matched filters to remove the interference of random body motions on vital sign detection. As sensor system developers became dissatisfied with the evolution of the sensor design world, researchers began designing their sensors. ViFi [39] can detect the breathing and heartbeat of drivers and passengers in moving cars. More-Fi [40] extract fine-grained vital signs information in the presence of human motion. MoVi-Fi [13] can perform contactless vital signs recovery on almost any commercial-grade radar. Zhao et al. [41] can use the reflected signals of the human heartbeat and breathing for emotion recognition. SitR [42] uses radio frequency signals for sitting posture recognition, which neither compromises privacy nor requires wearing various sensors on the human body.

Material Identification: Material identification using low-cost commercial RF equipment is now an exciting area of research. TagScan [43] identified the liquid with an inexpensive RFID device and was able to image the target simultaneously. Liang et al. [44] used mmWave radar to identify materials contactless. Xie et al. [45] found that changes in liquid concentration can cause changes in tag impedance. Based on this, they used the method of attaching the tag to the object for material identification. GreenTag [33] using a unique threshold judgment method to detect soil moisture using an RFID system. RF-Mehndi [46] uses an RFID-based method of preventing the card from being lost or stolen, which cannot be used illegally by an adversary. RF-ray [47] propose a generic wireless sensing system, that could recognize the shape and material of an object simultaneously, even for unseen shape-material pairs. Akte-Liquid [48] e present a low-cost solution for a liquid identification system that exploits acoustic signals generated by smartphones and reflected by liquids as a fingerprint of liquids.

Indoor Localization: Compared with traditional vision-based solutions, indoor positioning using wireless signals can better protect user privacy. Rf-Echo [49] used well-designed signal processing algorithms and machine learning techniques to significantly improve indoor positioning accuracy with limited bandwidth. Kotaru et al. [50] used the ubiquitous basic WiFi infrastructure for indoor positioning and improved the positioning resolution to sub-meter level. Vasisht et al. [51] proposed a novel algorithm to calculate the sub-nanosecond flight time of commercial WiFi signals to achieve centimeter-level positioning. TagSort [52] uses physical layer information, that is, the phase of RFID wireless signals to achieve relative positioning of different tags.

VII. Discussion

Status of Book: Books will depreciate and wear out over time, especially for old books displayed in some museums and libraries. These books may not be complete. How to solve this problem is also what we need to focus on in the next stage.

Latency: The delay of the RFbook system mainly comes from the two parts of signal acquisition and paper identification. In the current system, the signal collection is a time-consuming task and the time cost of feature collection per sheet is about 200 ms, and the time for the neural network to process one feature block is about 0.02 s. To improve accuracy, we may need to collect the signal multiple times. Therefore, RFbook needs 1–2 s to complete the paper classification detection. We believe that time costs can be significantly reduced by applying more efficient hardware device updates.

VIII. Conclusion

In this article, we present RFbook, a system for book maintenance and classification in unattended libraries. RFbook is designed to accurately identify and classify different books while monitoring the humidity levels of the books. To achieve this, we developed a neural network model for book classification and devised a set of algorithms to address challenges related to distance dependence and book location uncertainty in RFID systems. We conducted comprehensive experiments to evaluate the system's performance. We tested RFbook with 100 books, each with unique parameters. The experimental results demonstrate that RFbook can well perform book classification and humidity detection using a commercially available RFID system.

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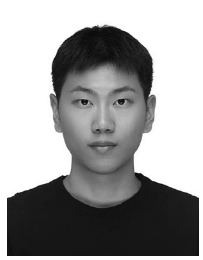

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