GALGOTIAS UNIVERSITY

(Established under Galgotias University Uttar Pradesh Act No. 14 of 2011)

INTERACTION DATA DETECTION SYSTEM

A Report for the Evaluation 3 of Project 2

Submitted by

SHUBHAM GUPTA

(1613101717 / 16SCSE101823)

in partial fulfillment for the award of the degree

of

Bachelor of Technology

IN

Computer Science and Engineering

SCHOOL OF COMPUTING SCIENCE AND ENGINEERING

Under the Supervision of
Dr.Avneesh Kumar

Asst. Professor

MAY-2020

TABLE OF CONTENTS

1. ABSTRACT

The amazing growth of the online business has had a strong impact on brick and mortar stores due to the ease and efficiency of online transactions. Internet marketers can easily predict the sales trend of a product by analyzing the contact data collected when consumers scan web ads, save product items on e-carts, and make purchases. However, in the case of brick-and-mortar stores, an effective system to assist retailers in obtaining useful information for predicting product trends does not exist. This study introduces a radio-frequency identification (RFID)-based system to help offline retailers find and analyze contact data between customers and products during the sales process. In particular, the IDP can be expanded based on the contact details received. If sellers find that an item is popular with a high IDP value, they can keep it on top of it and advertise or recommend relevant information by displaying in their stores to improve sales volume; otherwise, they may arrange for the sale of the permit to reduce the chance of overcrowding.

.

2. INTRODUCTION

2.1. DESCRIPTION

Today, e-commerce is a primary driver of global retail sales growth, particularly in India. According to a report, online shoppers in India are expected to reach 220 million by 2025. This growth is fueled by mobile apps and better logistics networks, which have helped e-commerce companies reach new customers in smaller cities. Furthermore, e-commerce market retailers can easily predict product sales trends by collecting and analyzing big data when customers explore web advertisements, save products in e-carts, and perform purchase actions. Based on these big interaction data, retailers can efficiently optimize marketing by methods such as increasing stock and advertising for popular items, organizing clearance sales for outdated products, providing personalized service for customers. E-commerce and consumer internet companies in India received more than US$ 7 billion in private equity and venture capital in 2018,led by Flipkart,Amazon india and Paytm Mall. In the face of the online business boom, brick and mortar retail business in India shows a contrasting situation: thousands of brick and mortar retail shops closed during 2015, and the revenue in this segment has been declining continuously for several years, particularly for small shops. An increasing via e-commerce after reviewing and comparing them at brick and mortar shops. The brick and mortar shop is gradually transforming into a commodity exhibition place because the price of a commodity in online shops is typically less than in brick and mortar shops.

2.2. PURPOSE

Under such difficult market conditions, we aim to help brick and mortar shop retailers—who cannot easily access and analyze big interaction data—develop their sales strategies. Typically, these shops are small and located in smaller cities; therefore, the offline interaction data become a crucial resource that can help upgrade their marketing efforts. In this article, we propose an IDDS based on IDSense . The interaction data mentioned here represent the customer behavior information obtained when customers compare and select products during the sales process. Our proposed IDDS assists retailers in obtaining offline customer behavior information, including product browsing (PB), product checking (PC), tag touching (TT), and product trying-on (PT). Table 1 lists the offline interaction data and corresponding online shopping behaviors. Similar to online interaction data, offline interaction data can also be used to indicate the IDP and the product's sales trend; retailers can then develop their sales strategies in a targeted and timely manner according to the analytical results returned by the detected data.

Offline interaction data	**Online interaction data**	**Notation**
number of PBs,PCs,andTTs	Number of web advertisements views	Fa
Time duration of PB,PC,TT,andPT	Time duration of exploring advertisements webpages	T
Number of PTs	Number of product items in e-cart	Fb
Number of successful offline transactions	No. of successful online transactions	Nt
No. of customers	No. of web page visitors	Nc
Number of customers who purchased commodity	Number of webpage visitors who purchased commodity	Np
Offline purchase rate	Online purchase rate	R=Np/Nc

Table 1. Offline interaction data corresponding to online interaction data

2.3. SCOPE

To test our proposed IDDS, we will apply it at brick and mortar shops. The test results indicate that the product sales prediction and actual sales amount are proportional to the IDP, thus verifying the efficiency of our proposed IDDS. The proposed IDDS can correctly record customer's behavior information and accurately reflect their interest in the products. Furthermore, our proposed sales prediction model based on the IDP and previous records can effectively convey the actual sales amount of products to the shop retailers. Our IDDS and sales prediction model can not only help shop retailers save money by decreasing the probability of product overstocking, but also enhance their sales records by guiding them in creating suitable sales strategies. Customers also benefit from the IDDS, as it enhances their shopping experience; an interactive digital display placed near the product's location in the store can be used to learn more about the product of interest. Related products can also be advertised through these displays, to provide more choices for customers.

3. EXISTING SYSTEM

3.1. LITERATURE SURVEY

X. Su, R. Gu, G. Han and D. Choi,in IEEE Consumer Electronics Magazine, vol. 6, no. 4, pp. 57-63, Oct. 2017. doi: 10.1109/MCE.2017.2714422

we present our proposed IDP generation method with offline interaction data. First, we divided the interactions into two groups, i.e., strong interactions and normal interactions. The strong interactions include the customer behaviors PT and TT, which reflect strong customer interest in a product. The normal interactions include PB and PC, which indicate slight customer interest in a product. Next, for a product item i, we define IDP based on three parameters,i.e., I(i)=IS(i)+IF(i)+IT(i),where IS(i) is given by IS(i)={1, PT or TT is detected &{ 0, otherwise. IF(i) defines the normal interaction frequency for the detected times of PC and PB corresponding to the ith product item during time T, and IT(i) represents the normal interaction frequency for the detected PT and TT of the observed ith product item over time T. Note that product complexity weights should be used to adjust the last two parameters. This is because, for example, the complexity of a laptop with a complicated operation manual is higher than that of a T-shirt. In particular, the IDP value defined in this study was accumulated during time T, i.e., the IDP update cycle. . For example, a dress that is popular this year may be outdated next year; therefore, retailers should set time T according to the product classification. Thus, the product classification according to characteristics such as usage, suitable customers, and brand attributes should be meticulously considered in the development of sales strategies. During our research, we applied a genetic algorithm based on to classify product items, and we used an IDP update algorithm to calculate the IDP based on classification, adapting the sale seasons and fashion trends accordingly. After performing the aforementioned steps, we mapped the IDP values based on product classification via Cartesian coordinatesas illustrate in fig 1. The IDP values and previous sales records are used to predict future sales trends. For the ith product item in the (P+1)th sales stage, the sales trend is predicted by $F(I,P+1)=(1+d(I,P))T(I,P)$ to the power of $k.(I(I,p)/I(I,p-1))$,where $T(I,p)$ denotes the sales volume of the pth sales stage, $d(i,p)$ represents the ratio between the sales volume in the pth sales stage and the sales volume in previous records, and k is an adjustment weight assigned to adapt the season effect. The exponent part generates from the nonlinear relationship between sale volume and interest degree. A simple linear model cannot describe the reflection from interest degree to sale volume, and an exponential form can amplify the increase in the interest degree's influence on sale volume. A better function expression may exist to more accurately calculate (P+1)th stage sale volume. However, more experiments are required in various kinds of brick and mortar shops.For shop retailers, it is better to create sales strategies based on the sales prediction results because a product item with a higher IDP value is often associated with an optimistic sales expectation. Besides product stocking, clearance, and location rearrangement, the placement of a digital display near goods shelves can also be considered an efficient sales strategy. Customers can interact with the display to find out relevant information about the products, and a personal recommendation multimedia video can be played whenever customers start checking products.

3.2. PROBLEM STATEMENT

Traditional schemes that can be used to obtain offline interaction data include conventional RFIDs, quick response (QR) codes, bar codes, indoor positioning , and facial recognition . The first three schemes reflect only the status of the product as recorded on the retailer's server. The information conveys whether the products are being placed back on the shelves or if the products are scanned, purchased, and taken outside the shop. These schemes are comparatively cheaper to use; however, they cannot provide adequate information to help a shop retailer update sales strategies and predict sales trends. Indoor positioning schemes, such as Wi-Fi, ZigBee , and ultrawideband, are comparatively complicated and expensive to implement in brick and mortar shops, while ultrasonic and infrared ray positioning schemes do not obtain accurate interaction data owing to technical limitations. Facial recognition can accurately reflect customer interest in services and products. However, facial recognition is expensive to implement and requires the customer to face the camera sensor; the scheme does not work when the customer turns around or is outside the camera's field of view.

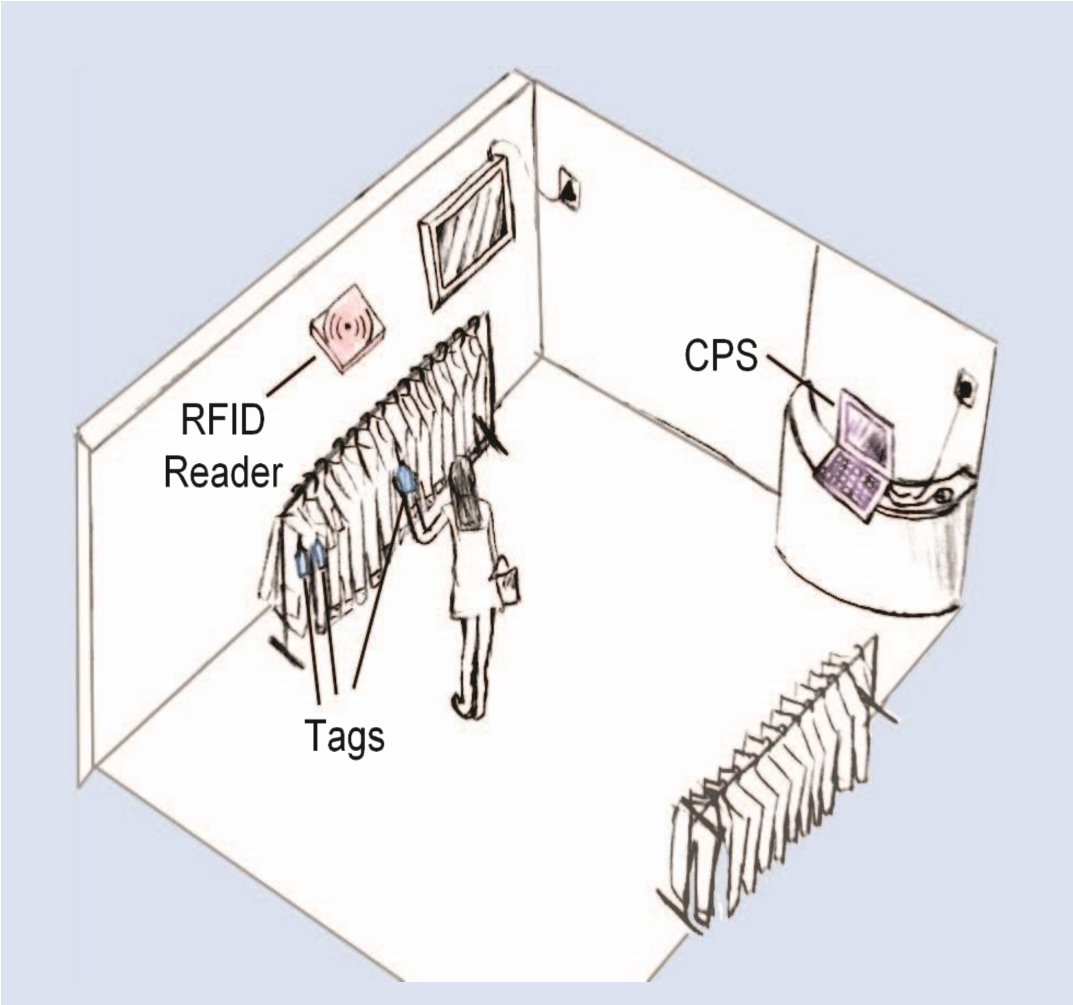
4. PROPOSED MODEL

The human object interaction detection system, i.e., IDSense, which is based on passive ultrahigh-frequency RFID, is proposed. This system classifies motion events and several types of touch events by measuring the changes in the physical layer of the communication channel between the RFID tag and reader; the measured parameters include the received signal strength indicator (RSSI), radio-frequency phase, and read rate. In this system, the researchers detected four events—still, motion, swipe, and cover—and focused on the conditions of the tags. Owing to the capability of events detection and the economic efficiency of RFID technology, our proposed IDDS is also based on RFID, and the measured RSSI value is used as a pivotal parameter to derive the IDP. Based on this IDP, which is similar to the IDP defined for online business, offline retailer can predict the sales trend of a product and develop corresponding sales strategies such as increasing the stock of a product, advertising a product, or organizing a clearance sale for a product. The product classifications must also be considered in the sales strategies that help retailers perform more meticulous marketing. To test our proposed IDDS, we applied it at two brick and mortar shops: a clothes shop and a shoe shop. The test results indicate that the product sales prediction and actual sales amount are proportional to the IDP, thus verifying the efficiency of our proposed IDDS. The proposed IDDS can correctly record customers' behavior information and accurately reflect their interest in the products. Furthermore, our proposed sales prediction model based on the IDP and previous records can effectively convey the actual sales amount of products to the shop retailers. Our IDDS and sales prediction model can not only help shop retailers save money by decreasing the probability of product overstocking, but also enhance their sales records by guiding them in creating suitable sales strategies. Customers also benefit from the IDDS, as it enhances their shopping experience; an interactive digital display placed near the product's location in the store can be used to learn more about the product of interest. Related products can also be advertised through these displays, to provide more choices for customers.

4.1 Application Scenario And Related Work

Figure 1 depicts an application scenario for our IDDS at a clothes shop. As illustrated in Figure 1, every item of clothing has an RFID tag, and the customer's behavior information, reflected in terms of the RSSI, is detected by the RFID reader located on the ceiling of the room. A cloud platform server (CPS) analyzes and verifies the detected actions of customers as they compare and select clothes. Generally, during this process, we observe four common behaviors: PB, PC, TT, and PT. PB represents the action of a customer briefly reading the label of an item of clothing and then placing it back at its initial location immediately. When compared with PB, PC represents a stronger action, indicating that an item of clothing's RSSI was picked up or flipped. This action implies that a customer wants to understand the details of an item of clothing; if they obtain the desired information, such as the size, price, and date of manufacture, but are not satisfied with it, they place it back at the initial location. The time interval of TT lies between that of PB and PC; TT denotes that a customer may be interested in the size and appearance of the clothing item and would like to obtain further details by examining the RFID tags, beside which the brand and price information is typically indicated. In general, PT often has the longest time duration and may occur at a different location, e.g., a fitting room, where an RFID reader should also be placed. In addition, a digital display is placed near the clothing shelf, advertising the details of clothes with higher IDP values as well as other relevant products, e.g., a certain type of shoe that goes well with the items being promoted.

Figure 1. An application scenario for our IDDS being implemented at a clothes shop.



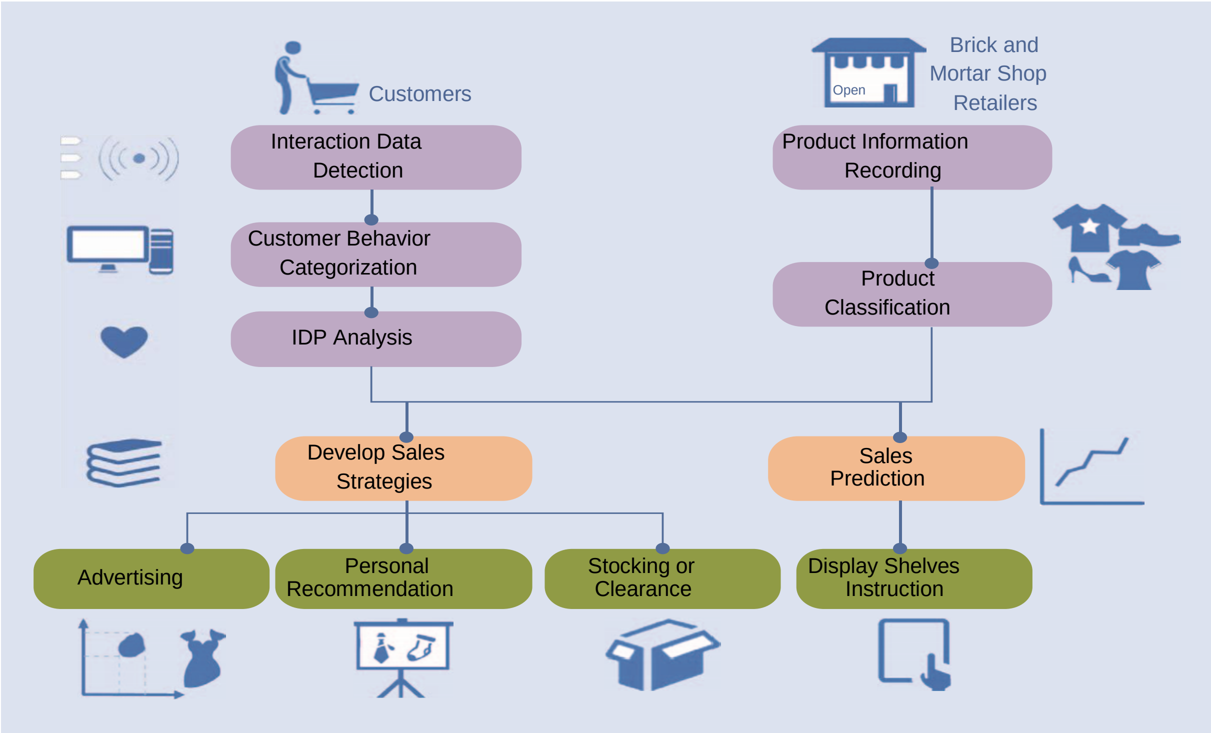
A conventional RFID-based system only notifies managers about whether the products are being placed back on shelves, being checked, being paid for, and being taken outside the shop. It is a comparatively cheap system for the reporting of product status; however, it cannot offer retailers substantial information to help them update sales strategies and predict sales trends. Based on the idea presented in our study, we used RFID technology to detect the interaction data between customers and products instead of only reporting product status; The details of our proposed IDDS are explained in the following section.

4.2. Interaction Data Detection System

4.2.1. Upgraded Marketing Scheme

Figure 2 shows a representation of our suggested marketing scheme for brick and mortar shops. The offline interaction data obtained when customers compare and select products are initially detected and reported to the CPS. From the detected data, the CPS categorizes customer behavior based on the action (PB, PC, TT, or PT) performed by a customer while comparing and selecting products. By using the online IDP calculation and the correspondence between online and offline interaction data as listed in Table 1, the offline IDP of a product can be represented mathematically based on customer behavior reports. Shop retailers can record product information in the CPS and classify products according to their characteristics. Product classification enables retailers to accurately observe product features and establish a correct model description for each product item. To maintain the correct classification, shop retailers can classify products strictly according to their characteristics, including usage, suitable customers, and brand attributes. After determining the IDP value of a product based on its classification, shop retailers can predict the sales pattern of the product and develop appropriate sales strategies, including advertising, personal recommendations, increasing stock or putting the item on clearance, and changing its location on the goods shelf.

Figure 2. Our suggested marketing scheme for brick and mortar shops



4.2.2. Received Signal Strength Indicator

Based on our experiments, we obtained the RSSI for the four examined interactions, (PB, PC, TT, and PT). The analysis of the measured RSSI, as shown in Figure 3, requires a static reference RSSI value (SRRV) as a comparison baseline. The reason for this requirement is that variations between the measured RSSI and SRRV can clearly represent the different types of interactions. Thus, we measured SRRV initially when no interaction occurred; we observed that the value remains at a median of –32 dBm and generally fluctuates within a range of 5 dBm. For convenience, we defined the RSSI difference (RD) between the measured RSSI and SRRV as an index to describe the strength of the observed interactions.

The experiments indicate that the detected RD value in the average PB actions is approximately 10 dBm, whereas the RD values in the average PC, TT, and PT actions are approximately 23, 16, and 32 dBm, respectively, thus differentiating the interactions. Further, the detected duration of customer actions for PB, PC, TT, and PT were 0.02–0.5 s, 3.0–12.0 s, 0.2–1.0 s, and 25.0 s, respectively. To ensure the accuracy of interaction classifications, we determined interactions at first based on the detected duration of customer actions because the duration often varied significantly. If the differences in the action duration were not clear enough to classify the interactions, then we examined the RD to guarantee accurate classifications. Based on the results of hundreds of tests, the ratio of correct PC and PT determinations reached 99%, as a PC often took 10 s and a PT usually took longer than 20 s. By setting the RD threshold at 13 dBm, the ratio of correct PB and TT determinations reached 90%, even though the duration of these actions often differ by just 1 s. Particularly in the case of PT, the commodity is not often placed back at its initial location. In addition, the detected interaction data recorded in the Hadoop database at the CPS may be affected by interference; therefore, undesired interference must be eliminated to ensure data stability and correctness. To achieve this objective, we periodically calculated the variations of the RSSI over a time interval; if the variations exceeded a predefined threshold, an.

interference cancellation procedure based on was performed.

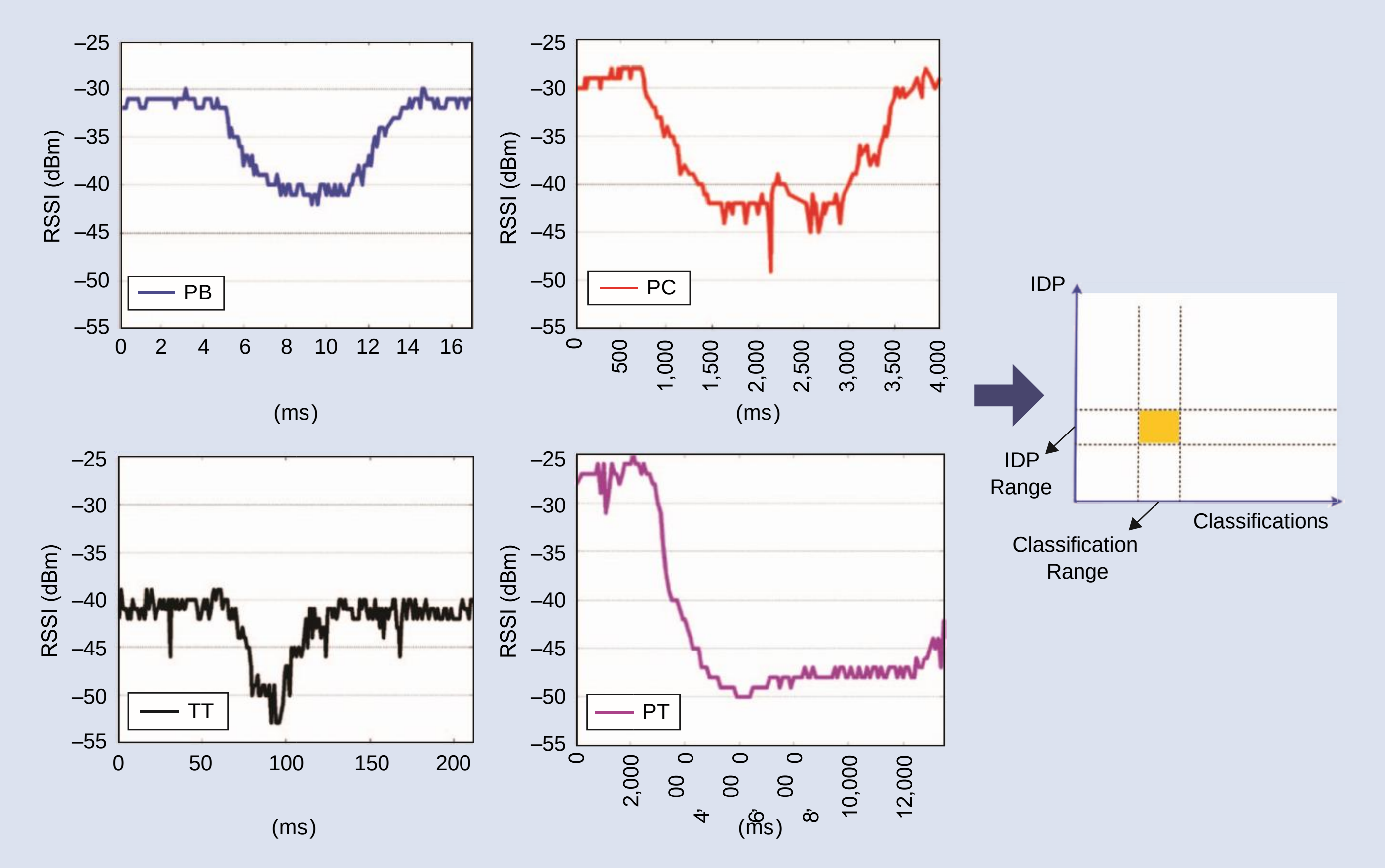


Figure 3. An experimental RSSI used to generate the IDP.

5. Implementation

To test our proposed IDDS, we implemented it at brick and mortar shops: one for clothing and another for shoes. The CPS is built based on Apache Hadoop, which is an opensource software framework for distributed storage and distributed processing of very large data. Based on the observation, with the IDP update cycle being set to 60 days, we obtained Figure 4, which demonstrates the relationship among the IDP, sales predictions, and actual sales amounts. In our actual tests, we tracked ten product items at each shop; Figure 4 plots the test results of only the products with the lowest and highest IDP values. A digital display was placed beside the product with the highest IDP, and a multivideo advertisement was automatically played when a customer approached the product after being detected by a sensing camera. The first sales stage lacked previous IDP information and the actual sales amount for sales trend prediction; therefore, Figure 4 does not show the sales prediction at the first sales stage. From Figure 4, we can observe that the product sales prediction and actual sales amount were proportional to the IDP.

Our proposed IDDS has therefore correctly recorded customer behavior information and accurately reflected their interest in products, thus verifying the efficiency of our proposed IDDS. Figure 4 also illustrates that the sales prediction derived from the IDP and previous records can effectively in- form shop retailers about actual sales amounts. The estimation validity obtained by comparing the actual sales amount with sales predictions is illustrated additionally in Figure 4, which shows the proposed IDDS can reach over 95% estimation correctness generally. This step not only reduces the cost for shop retailers by decreasing the probability of product overstocking, but also boosts sales records by guiding them in the creation of suitable and timely sales strategies.

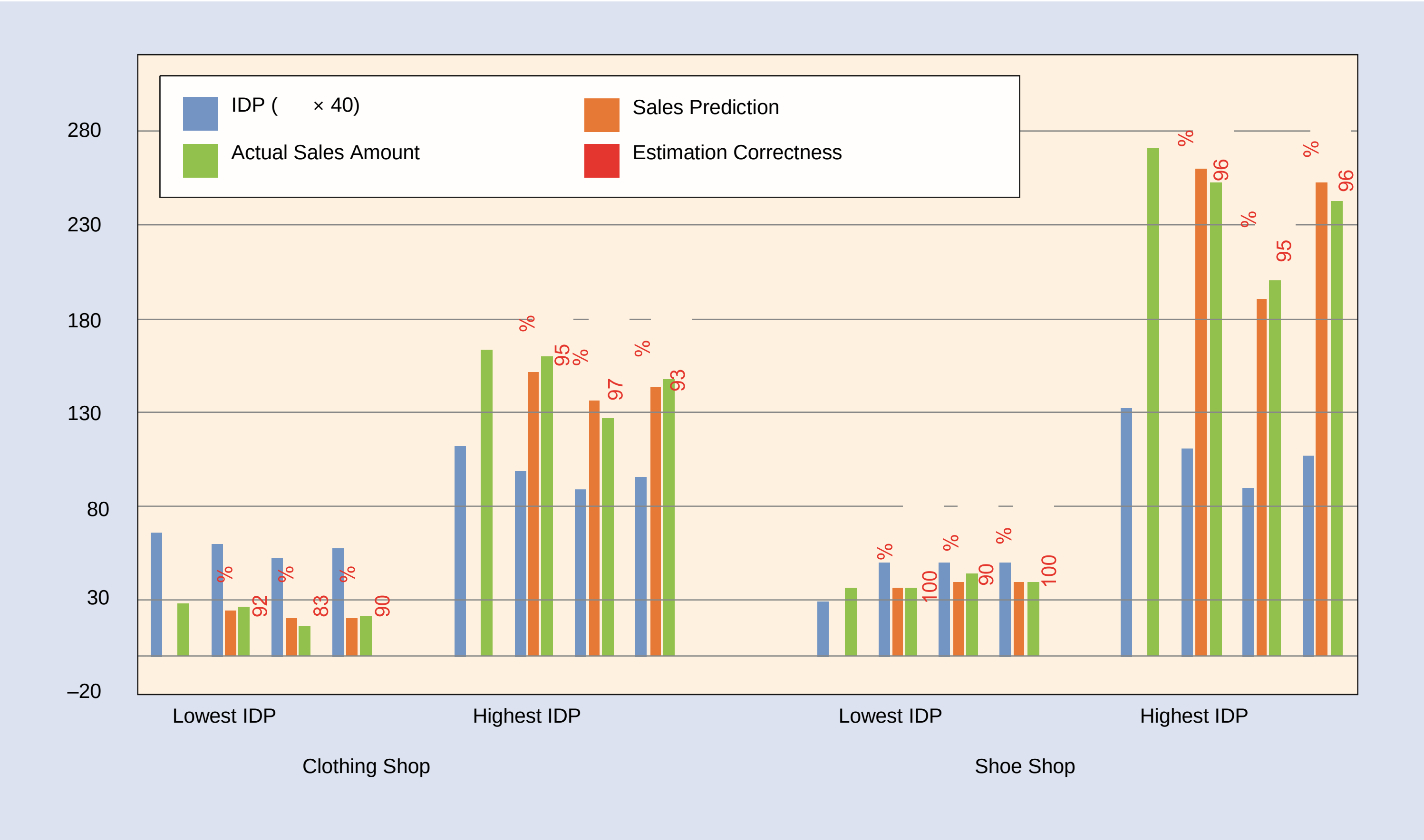


Figure 4. The IDP, sales prediction, and actual sales amounts over two months of observation.

6. OUTPUT:

The results in the “IDDS Implementation at Brick and Mortar Shops” section confirmed the validity of our proposed IDDS. Unfortunately, so far, we have been unable to provide a performance comparison between the IDDS and conventional systems because the systems described did not provide the IDP calculation and sales prediction models, and conventional RFID, QR, and bar code schemes lack the capability to obtain accurate interaction data. Therefore, in this study, we provide a comparison table that lists only the pros and cons of these systems. From Table 2, the system can be implemented in small shops that support ambulatory personal tracking with high accuracy. However, it is comparatively expensive to implement indoor positioning, and customers are required to wear transmitters that inevitably impair the shopping experience. The system can accurately reflect customer interest; however, it is expensive because it requires camera sensors. In addition, this system requires the customer to face the camera sensor and does not work when the customer turns around or is outside the field of view of the camera; for instance, it is inappropriate to place a camera in a fitting room. Conventional RFID, QR codes, and bar codes are inexpensive and easy to use; however, similar to the system, the detected interaction information in these systems is not adequate to reflect IDP accurately. Inspired by IDSense , our proposed IDDS shows a validated system that is inexpensive and easy to use without a big data and cloud computing environment. We aim to support any type of brick and mortar shop and prove that the detected interaction information is substantial enough to reflect IDP accurately. With the booming impact of online business, our proposed IDDS has demonstrated its efficiency in helping brick and mortar shop retailers predict sales trends to obtain profits. For the customer, the IDDS can improve shopping experiences; a digital display placed near products with higher IDP values that advertises those products as well as related and companion products provides more choices for the customer.

Table 2. A comparison between IDDS and conventional data tracking systems

	Interaction Data Acquisition	Advantages	Disadvantages
System 1	Customer trajectory and stay period detection	For a small retail store, supports ambulatory personal tracking with high accuracy	Comparatively expensive; requires the use of a wearable transmitter that impairs customer experience. Interaction information is not adequate to reflect accurate IDP.
System 2	Customer facial recognition	Reflects customer interest accurately.	Expensive to implement; requires the customer to face a sensing camera. Inappropriate to place a camera in a fitting room.
Conventional RFID, QR, and bar code	Product status	Inexpensive & easy to use.	Interaction information is not adequate to reflect accurate IDP.
Idds	RSSI analysis	For any type of brick and mortar shop, it is cheap and easy to use. Interaction information is adequate to reflect accurate IDP and sales trends.	Shop retailers must classify products, and signal interference cancelation is required

7. CONCLUSION

In this project, we highlighted the challenges in the market for brick and mortar shops owing to the impact of e-commerce and proposed a system that helps shop retailers develop sales strategies in a correct and timely manner by using interaction data. We have provided a detailed design of the key components of the proposed prototype IDDS. Similar to online interaction data, offline interaction data, which are available when customers select and compare products, can be accurately detected by IDDS. Customer action reports can be analyzed to quantify the interest in a product. The product sales prediction is then modeled based on sales records and interest in the product; suitable sales strategies can therefore be created, cutting costs and boosting sales. The shopping experiences of customers can be boosted by the IDDS, as well, because it can promote more product choices in a timely manner using a digital display. The IDDS implementation, combined with the observation at brick and mortar shops, has proved the validity of our proposed IDDS. In addition, Table 2 provides a brief comparison between the proposed IDDS and conventional systems. We are investigating future work that will consider advanced RFID readers that are adapted to larger brick and mortar shops. The detection of offline interaction data when customers examine products such as books and electronic devices is complicated. This scenario requires an updated mathematical model to derive the IDP and predict sales.

8.REFERENCES

[1] H. Li, C. Ye, and A. P. Sample, “IDSense: a UHF RFID-based human-based discovery system,” Proc. ACM Conf. in Human Factors in Computer Systems (CHI), April 2014, p. 34-50.

[2] Q. Yang, J. L. Pan, and W. C. Zheng, "Estimating location using Wi-Fi," IEEE Intell. Syst., Iv. 23, no.1, p. 8–13, Jan./Feb. 2008.

[3] J. H. Chai, "Zigbee-based hospital patient care program," Proc. Intelligent Computing and Bio-medical Instrumentation (ICBMI), Dec. 2011, p. 159-16-162.

[4]C. Abou-Rjeily, "Modular space time modulation module for unipolar MIMO IR-UWB Communication," IEEE Trans. Wireless Commun., Iv. 14, no. 10, p. 5602-5515, Oct. 2015.

[5] M. M. Saad, C. J. Bleakley, T. Ballal, and S. Dobson, “Highly error-free estimation of an idle local register,” IEEE Trans. Instrum. Meas., Vol. 61, no. 6, p. 1561-1570, June 2012.

[6] Y. Ohtaki, D. Hu, K. Hashimoto, and H. Inooka, "A personalized approach to tracking household customers using inaccessible sensors," Int. J. Appl. Electrom., Iv. 36, no. 1-2, pp. 75-83, Jan. 2011.

[7] L. T. Dang, E W. Cooper, and K Kamei, "Development of visual recognition training Training representations for video customer users," in Proc. IEEE Int. Conf. in Fuzzy Systems (IEEE-FUZZ),July 2014, p. 1297-11303.

[8] J. T. Li, Y. Guo, and Z. J. Tang, “User interest rate based on consumer behavior,” Computer Eng. Des., Vol. 33, no. 3, p. 968-972, Mar. 2012.

[9] K. Xing, B. F. Zhang, B. Zhou, and Y. C. Liu, "Beagax based on consumer behavioural complaints," in Proc. IEEE Int. Conf. in Internet of Things and cyber, Physical, and Computer Science (Things /CPSCom), Oct. 2011, p. 448-452.

[10] L. Zheng, S. Cui, D. Yue, and X. Y. Zhao, "An interesting user model based on behavioral modeling," in Proc. Int. Conf. in Advanced Computer Theory and Engineering (ICACTE), Aug. 2010, p. 455-458.

[11] D. Guang, D. B. H. Tay, and S. Marusic, "Signal denoising algorithm based on surface wavelet presentations and Gaussian models," Signal procedure, iv. 87, no. 5, p. 866-876, May 2007.

[12] X. J. Shi and H. Lei, "A gene-based approach for the detection of a dividing line," in Proc. Int. Conf. Information Management, Resource Management, and Industrial Engineering (ICIII), December 2008, p. 175-178.

[13] J. C. Cohen and S. Acharya, "Integrating Apache Hadoop hardware trust," in Proc. IEEE Globalbecom Workshops, December 2012, pages 769-774.

[14] G. J. Han, W. H. Que, G. Y. Jia, and L. Shu, "A practical scheme for integrating a multimedia cloud computing machine," Sensors, vol. 16, no. 2, Section 246, February 2016.

[15] (2017, Mar. 29). 2017 China online shopping B2C market for comprehensive analysis. International critics. Thursday. [Online]. Available: http://www.useit.com.cn/thread-14928-1-1.html