RFID-Based Deep Shopping Data Acquisition Scheme with Multiple Feature Extraction

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***Abstract*—In order to accurately collect the deep shopping data, such as which item a consumer picks in a shop, radio frequency identification (RFID) tags based deep shopping data acquisition scheme have drawn attention. The existing RFID-based deep shopping data acquisition scheme that uses received signal strength (RSS) is not accurate enough to use in practice. In this paper, we propose an RFID-based deep shopping data acquisition scheme with multiple feature extraction. To realize more accurate deep shopping data acquisition, we use not only RSS but also phase and RFID tag read count. Supervised machine learning technique together with such multiple features improve the accuracy. By introducing read count and the phase, it is possible to detect when the fluctuation amount of the RSS cannot be well observed. The proposed scheme was tested in the lab environment and it improves detection accuracy when the conventional scheme does not work well.**

***Index Terms*—RFID, Deep Shopping Data, Machine Learning, Read Count, Variance of Phase**

I. INTRODUCTION

For the future sales strategy, companies obtain purchase history from cash registers and extract meaningful knowledge [1], [2]. In recent years, the data that cannot be seen from the purchase history is drawing attention for acquiring potential interests of customers. Such data is referred to deep shopping data (DSD). If you were a customer in a physical store like a clothing store, and you would like to move the time back and forth to look closely, and then pick up the one of interest for detailed information. Actually, these behaviors reflect the customers intention, which contributes to composition of complex DSD. DSD can help retailers capturing customers' preferences and better/smarter marketing strategies. However, the conventional DSD collection scheme have some problems [3]. Primitive collecting DSD scheme to monitor items and customers continuously with camera deployed in a store, and in this way certainly collect the DSD [4], [5]. However, it is necessary to prepare the number of cameras as many as possible to capture any event in the store. Further more, it is not desired from the customers' privacy aspect. In addition, cost by shops becomes higher as the number of camera increases. Hence, a low cost, efficient and effective method to acquire DSD is in great demand in retail stores.

In this work, T. Liu *et al.* proposed TagBooth [9], which collects the DSD by taking advantage of the radio frequency identification (RFID) tags already attached to items. RFID is an object recognition technology using tags that can read and write via wireless communication. RFID is assumed to be widely spread in the future as an alternative technology of barcode. Although RFID is designed to enable product management, by utilizing the received signal strength (RSS) and the phase of the signal. It is possible to detect motion of the tags [6]–[8]. In addition, RFID tags are suitable for schemes of acquiring DSD because it is cheap as about 5 cent per piece per 10 cent. T. Liu *et al.* proposed an acquisition scheme of DSD using RFID tag [9]. This scheme leverages the fluctuating of the RSS from the RFID tags, and detects whether a customer picked out a commoditity or not. Phase fluctuation is used to judge whether a customer picks. However, since the RSS is linearly interpolated for interval adjustment of preprocessing, the fluctuation of the RSS decreases as the read count decreases. As a result, it fails to detect that an item is picked. Furthermore, it is not good to use just RSS for detecting whether an item is picked. Both RSS and phase are highly related to distance. According as Friis transmission formula [10], communication distance increaces as RSS decreaces. RSS has a low resolution with respect to the distance, and slight motions are hardly reflected in the fluctuation of the RSS. In addition, it is necessary to make threshold of the amount of fluctuated RSS for judging whether or not the items have moved. This threshold is obtained by conducting a preliminary experiment and measuring the fluctuation of the RSS when the items are actually lifted. However, since the appropriate threshold depends on the experimental environment, maintenance an optimal threshold is bloody hard for the shop side.

In this paper, we propose an RFID-based DSD acquisition scheme with multiple feature as an improvement of TagBooth. We suppose items as clothes commodity. If the RSS fluctuates before and after read count has changed extremely, in the interval time impossible to read the tag can be considered an item is picked. Due to that the RSS is inversely proportional to the square of the distance, if the distance from RFID reader to the commodity changes, the amount of RSS will change even with the same movement. Also, by using machine learning for judging whether the item moves or not from the tag reports, clerk can easily make threshold whether the commodities move or not.

In order to verify the effectiveness of the proposed scheme, we evaluate the proposed scheme when customer arbitrary picks an item and evaluate whether the item picked up was

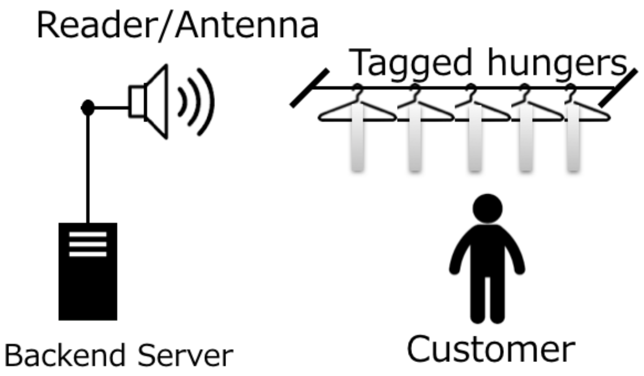

Fig. 1: System model

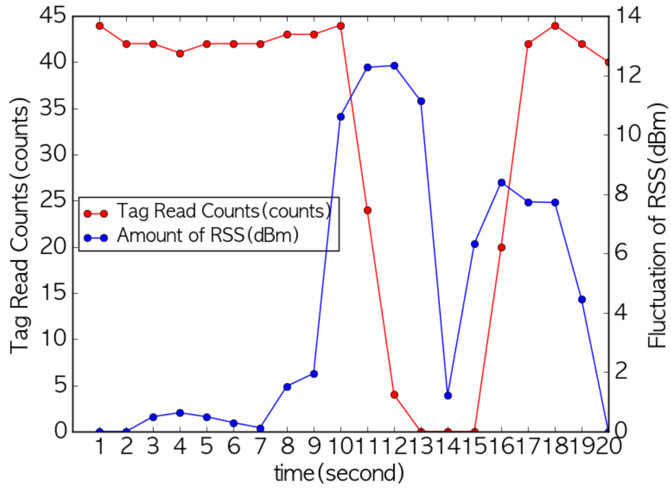

Fig. 2: A graph of the number of reads of the RFID tag and the fluctuation of RSS when the commodity is lifted from 10 to 15 seconds

correctly identified.

This paper is organized as follows. Section II deals with the system model and conventional scheme, In Secion III, the proposed scheme is described in detail. In Section IV, performance evaluation is shown. Finally, we conclude our paper in Section V.

II. System model and Conventional Scheme

In this section, firstly, the system model is introduced. Then, an overview and shortcomings of the conventional scheme is described.

A. System Model

Fig. 1 illustrates the model of RFID system for collecting DSD in physical stores. The system consists of commodities, a customer, an RFID reader, an antenna and back-end server. Passive RFID tag is attached on each hanger, with a unique EPC (Electronic Product Code). The customer picks up the hanger attached the passive RFID tag with the commodity. Only one antenna is needed and there are no requirements for deployment, except that the reading zone of reader antenna should cover all tags. As an edge device, the COTS (commercial off-the-shelf) reader repeatedly scans the reading zone and reports their readings to backend server where the system runs. The back-end server execute the algorithm for collecting DSD from the information received by the reader and saves the result.

B. Conventional Scheme

Tianci Liu *et*.al proposed TagBooth [9], which collects the DSD by taking advantage of the radio frequency identification (RFID) tags already attached to a clothes of a commodity. By continuously observing RSS and phase corresponding to a specific EPC, TagBooth enabled to collect DSD that the specific commodity is picked or toggled by a customer. Since phase more fluctuates than RSS for the same amount of movement, RSS is used for detecting a motion of a commodity (called as Motion Detection) and phase is used for classifying the detected motion into either the picking or toggling (called as Actions Recognition). If the phase fluctuation is larger than a predefined threshold value, the detected motion is regarded as the picking, otherwise it is regarded as the toggling. However, detecting garments movement using RSS is also varied due to a noise, such as multipath or interference by a human body and, sometime it can not be observed by the reader. Therefore, TagBooth leverages the linear interpolation so that the sampling interval of the observed RSS signals is 32 [Hz]. In addition, a low pass filter is used to remove the noise of multipath.

C. Shortcomings and Motivation

This scheme has three problems. Firstly, read count is decreased due to the interference by a body of a customer who touches a commodity and, thus the accuracy of Motion Detection is decreased. Since the total amount of variation of RSS within a certain period decreases as read count decreases, the amount can be below the threshold value regardless of an actual variation of RSS. Fig.2 shows the result of measuring the number of tag read count and the fluctuation of RSS with respect to the time when the commodity attached a passive RFID is lifted from 10 seconds to 15 seconds. From Fig. 2, it is proven that the read count is decreased while a commodity is picked up. It is also seen that the amount of RSS starts to decrease after the read count starts to decrease and vise versa. That is to say that as the read count decreases, the fluctuation amount of the RSS decreases. Secondly, RSS cannot accurately reflect the movement of a commodity. Since the RSS is inversely proportional to the square of the distance, as the distance from the antenna to the commodity decreases, the variation amount of RSS decreases for the same movement. For instance, the conventional scheme sometimes fails to capture motion of commodities. In other words, TagBooth cannot capture the slight motion of a commodity by RSS. Finally, a preliminary experiment is required for deciding the threshold. However, since the appropriate threshold varies

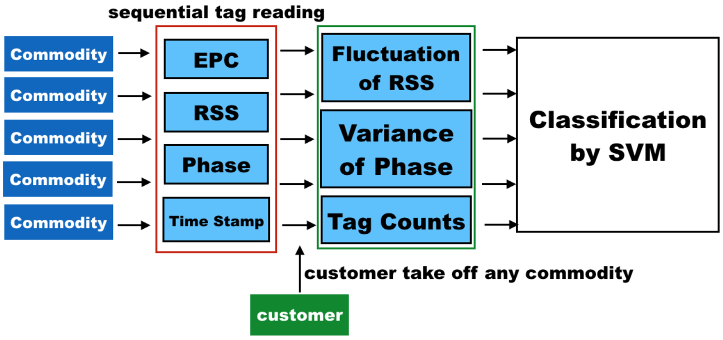

Fig. 3: Algorithm of proposed scheme

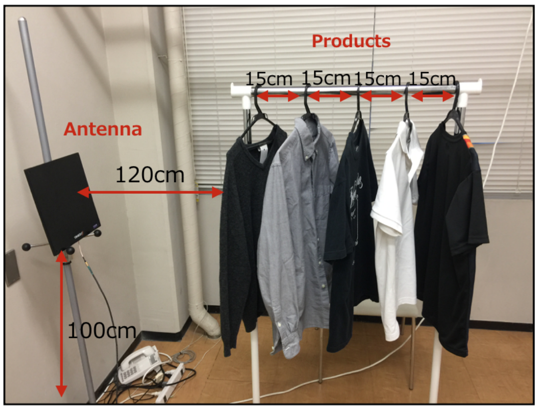

Fig. 4: Experimental environment

depending on the experimental environment, it is difficult to maintain an appropriate threshold on the shop side.

III. Proposed Scheme

Here, we propose an RFID-based deep shopping data acquisition scheme with multiple feature extraction. In order to address the shortcomings of Motion Detection mentioned above, we leverage a machine learning technique and two new features that are read count and phase. Firstly, in order to avoid the determination of the threshold, we leverage a machine learning technique. Secondly, in order to address the problem that the variation of RSS cannot accurately reflect the motion of a commodity due to the decrease of read count, we leverage read count as a feature for machine learning. We focus on the phenomenon that, the read count and the variation amount of RSS simultaneously change only when a commodity is picked up as described in Fig. 2 By learning a time series data consisting of sets of the read count and RSS, the classifier can capture this phenomenon and thus can correctly classify whether a commodity is moved or not even when the read count is dropped. We leverage phase to make the classifier possible to capture the slight motion of a commodity. Since phase is directly proportional to the distance, it changes by the same amount for the same motion regardless of the distance between the reader and a commodity. In order to reduce the noise, we use the variance of phase instead of using the raw value. System diagram of the proposed scheme is shown in Fig.3. The proposal consists of two stages: learning by preliminary experiment and collection of DSD.

A. Algorithm of the proposed scheme

1) Preliminary experiment for obtaining training data: The clerk repeatedly picks out each item attached passive RFID tag in his or her hand for a predetermined time and generates teacher data by labeling whether or not the data collected from the reader has been picked up. The reader continuously collects EPC, RSS, Phase and Time Stamp from each RFID tag.

2) Feature selection: Utilizing the time stamp and other data, we calculate the fluctuation amount of the RSS for each s second, the variance of the phase amount at every t second and the number of tag read count at every t second respectively. Together with these t second feature amounts, teacher data is as follows $<$RSS every s seconds, Tag Read Count every t seconds, The variance of phase amount, Label $>$. We feed a support vector machine with the data.

3) Collection of DSD: The reader get the EPC, the RSS, read count and the phase from all the RFID tags attached to the commodity within the reading range by utilizing the round robin, and transmits it to the back-end-server. The back-end-server calculates the variance of the RSS fluctuation amount, the variance of the phase and the read counts for each commodity using the EPC, and inputs it to the learned support vector machine. The support vector machine outputs classification results for each t seconds represented by time, classification result. By sorting the results obtained for each commodity, DSD can be obtained to show which commodity was picked up.

IV. Evaluation

A. Experimental Environment

In the reader Impinj Speedway R420 [12] used in this experiment, the RSS and the phase value of the received signal can be acquired. In this section, we show the details of the experiment environment in which the proposed scheme is introduced in the RFID system.

1) Hardware: In this experiment, we implement the proposed scheme using the RFID - Alien 9640 [13], Circularly Polarized Shelf Antenna A7030C [12] of Time7 company, Impinj speedway R420 [12] for Reader, and frequency band of reader signal set up 900(MHz).

2) Software: Utilizing the program Octane Sdk Examples [12] to activate the reader, to obtain tag information.

3) Experimental Scenario: Fig.4 shows the experimental environment. The customer was alone, the type of goods was clothing. The tags were installed hangers. The number of clothes was 5 and the distance between each good was 15(cm), and the distance between the antenna and the hanger rack's width was 120(cm). The distance of the antenna from the ground was 100 (cm) and the transmission power was 28.0 (dBm) and we tried 10 trials which mean twice for each clothes to take five items back in 5 seconds respectively.

TABLE I: Simulation Parameters

Parameters	Values
Computre language	Python
Classifier	linear support vector machine
Number of data sets (Commodity is in hands)	50
Number of data sets（Commodity is NOT in hands）	200
Number of data sets after downsampling（Commodity is NOT in hands)	50
Types of Evaluation	10-folds cross validation
Number of trials	100

TABLE II: Each TPR and FPR when changing the feature amount used for machine learning

Using feature	TPR(%)	FPR(%)
RSS（Conventional Scheme）	79.7	20.3
RSS + Read Count	81.2	20.1
RSS + Variance of Phase	78.7	18.4
RSS + Read Count + Variance of Phase（Proposed Scheme）	79.9	18.5

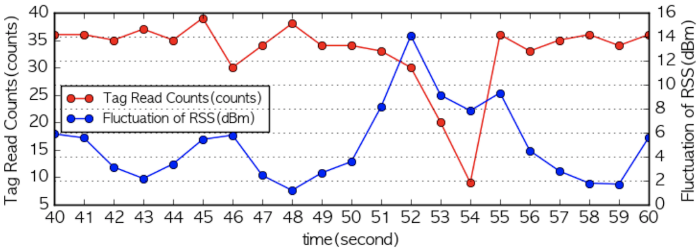

Fig. 5: RFID tag reading count and the fluctuation of the RSS when the commodity was lifted from 50 seconds to 55 seconds

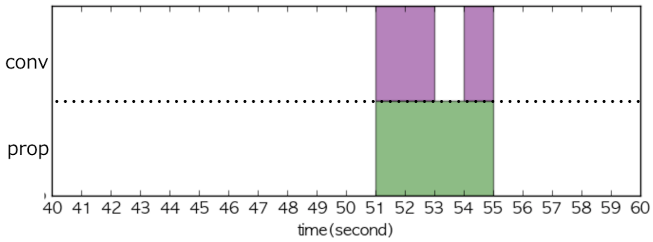

Fig. 6: The detection result of the conventional scheme (blocks colored by purple) and result of the proposed scheme (a block colored by green)

B. Simulation Method

In order to verify the effectiveness of the proposed scheme, experiments were conducted using COTS reader, an antenna and RFID tags, and data of EPC, RSS, phase and time stamp were collected. In this section, we calculate True Positive (TP) that clothes attached RFID tags was picked out and False Positive (FP) which is regarded as picked clothes hanging on hanger rack at that time, True Positive Rate (TPR) and False Positive Rate (FPR) are obtained. We also conducted downsampling of the data before doing machine learning and evaluated by utilizing cross validation. Equations how to caluculate TPR and FPR are shown in (2) and (3). In order to prevent the classification accuracy from decreasing by learning the imbalance data, to downsample the data of the commodity that the commodity has not been picked up according to the data picked up. In order to prevent variation in classification result due to different teacher data used for learning, cross validation is used to find the average of TPR and FPR obtained from multiple classifiers. We use linear support vector machine (SVM) in the machine learning method to perform classification. In order to investigate the contribution of each characteristic amount, the number of readings and the variance of phase, TPR and FPR when the feature quantity to be used were changed were also obtained. Table I shows the simulation parameters for evaluating.

$$TPR = \frac{TP}{TP + FP} \tag{1}$$

$$FPR = \frac{FP}{TP + FP} \tag{2}$$

We set window size of feature quantity $s = 4$, $t = 1$ and frequency threshold $f_0 = 2$ and set it as before. In addition, the threshold value of the fluctuation amount of the RSS was set to 8 (dBm) as same in the conventional scheme.

C. Result and Discussion

Table II shows each TPR and FPR when the feature amounts changed. Fig. 5 and Fig. 6 shows TPR and FPR of the conventional scheme, TPR and FPR of the proposed scheme. The TPR of the proposed scheme improved by 0.2% compared with the conventional TPR, and the FPR of the proposed scheme improved by 1.8% compared with the conventional FPR. In addition to the classification using only the fluctuation amount of the RSS and the amount of change in the RSS, TPR is improved by 1.5% in the classification used for. Fig. 5 shows the detection results based on tag read counts when the commodity is lifted from 50 seconds to 55 seconds, the amount of change in the RSS, and the classification result output from the proposed scheme and the conventional support vector machine. In the conventional scheme, it is judged that the commodity at the time of 53 seconds are not moving. The reason is that it is judged whether or not the commodity is moving or not using only fluctuation of the RSS with reference to a threshold value. Considering that the amount of fluctuation of the RSS decreases with the decrease in tag reading counts, the number of readings and the fluctuation amount of the RSS are used as the feature amount. We also conclude that significant results were not obtained for the classification results using the RSS as the feature quantity and the classification result using the variance of the phase variation amount in addition to the variation amount of the RSS.

V. Conclusion

In this paper, in addition to the RSS conventionally used as the feature quantity, the number of tag readings and the variance of the phase have been calculated for the acquisition scheme of accurate DSD using machine learning. By evaluation, we confirmed that the TPR of the proposed method improved by 0.2%, compared with the conventional TPR, and the FPR of the proposed method improved by 1.8% compared with FPR of the conventional one.

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