Konark : A RFID based System for Enhancing In-store Shopping Experience

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ABSTRACT

In this paper, we introduce a Radio Frequency IDentification (RFID) based smart shopping system, KONARK, which helps users to check-out items faster and to track purchases in real-time. In parallel, our solution also provides the shopping mall owner with information about user interest on particular items. The central component of KONARK system is a customized shopping cart having a RFID reader which reads RFID tagged items. To provide check-out facility, our system detects *in-cart* items with almost 100% accuracy within $60s$ delay by exploiting the fact that the physical level information (RSSI, phase, doppler, read rate etc.) of *in-cart* RFID tags are different than outside tags. KONARK also detects user interest with 100% accuracy by exploiting the change in physical level parameters of RFID tag on the object user interacted with. In general, KONARK has been shown to perform with reasonably high accuracy in different mobility speeds in a mock-up of a shopping mall isle.

1. INTRODUCTION

The future of retail is one of seamless integration between the commercial and personal space. Imagine a scenario where customers can pick up any item in the retail environment, and simply walk out of the store. Payment and checkout will be completed without explicit intervention from the customer. This frictionless (and legal) transfer of property between retail and personal space is an important facet of future brick-and-mortar retail environments.

Seamless checkout is the key technology to realise this vision. A recent survey by Cisco [1] shows that of the 1514 customers studied, (a) 52% value the speed and convenience of self-checkout, (b) 42% prefer full automation in the retail environment, and (c) 58% value personalized in-store customer service. Hence, *a fully automated, personalized, and seamless checkout service is the key to ensuring the continued future growth of the retail industry*. In this paper, we present KONARK, a seamless shopping cart and checkout system that realises this vision.

Challenges in Retail Checkout. Retail checkout serves as both a gantry for the customer to complete his/her purchases, and a source of information for the retail owner to gain insight into customer interests. However, the current checkout structure has several limitations that hinder the ideal seamless shopping experience.

(a) Inefficient checkout process. Cashier-based checkout is the most widely used system today. However, it suffers from long delays [2] and variable customer service quality [3]. Self-checkout systems are the state-of-the-art solutions in retail automation, and aim to improve the checkout experience. However, inefficiencies in the self-checkout process, such as slow bar-code scanning technology [4, 5], non-intuitive user interface [6] can slow down the checkout process. Checkout wait-times is the main pain-point: research has shown that 77% of customers will prefer checkout optimization techniques to obtain estimated wait times [7]. However, it is important to optimize the entire checkout process to ensure that a pleasant checkout experience is maintained at no delay. This is an extremely difficult challenge: *Amazon Go* [8] (which is currently in beta mode) is one of the most recent attempts to improve the checkout process, by allowing users to come in the stores, pick up items, and head out (while being automatically billed). They claim to use deep learning powered vision based technology combined with sensor fusion to automate the checkout process [8]. This holds promise but may encounter privacy concerns and detection inaccuracy. Toshiba's Point-of-Sale (PoS) alternative *Touchless Commerce* [9] also uses vision based technique to checkout 10 or fewer items [10] but it is still perfecting identification technology for different types of items. In general, vision based techniques suffer from NLOS and occlusion while raising privacy concern and incurring huge computation cost. These technological challenges may have delayed the large-scale deployment [11] of *Amazon Go*.

(b) Limited personalization. Market research has also shown that 67% of customers demand targeted offers on products related to their personal interests [7]. The current checkout system is a monolithic step at the end of the shopping process, and cannot provide real-time, continuous personalization to the customer during the the shopping experience.

(c) Limited retailer insight. Fine-grained customer metrics are important to measure the effectiveness of the retail environment [12, 13]. Mining customer shopping behavior in online stores is easily achievable by analyzing the click streams and customer shopping carts [14]. However, retailers with physical stores still lack effective methods to identify comprehensive customer behaviors. The only information readily available to retailers is the sales history, which fails to reflect customer behaviors before they check out. So, it is essential to design an integrated checkout solution that can offer fine-grained insights into the customer behavior.

Our Contributions. To address these issues, we build a smart shopping system named KONARK which can help consumers and

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(a) Walmart (b) CVS (c) Sears (d) Target

Figure 1: Different shopping carts of major US departmental stores.

the owners simultaneously with minimal infrastructural change, cost, and privacy breach. More specifically, we aim to provide queue-less faster checkout and real-time user shopping interest detection while providing continuous feedback to the user. We make the following contributions and address several challenges:

(a) Off-the-shelf hardware. KONARK is built using Radio Frequency IDentification (RFID). RFID readers are integrated into any off-the-shelf shopping cart (such as those in Fig. 1), and integrates with the RFID tags that are deployed by the retailer. We envision that KONARK will be deployed in a setting where all of the items are tagged with unique RFID tags. The reason behind the selection of this technology for its affordability [15] and increasing adoption rate [16, 17].

(b) Seamless checkout. The RFID reader in KONARK continuously interrogates surrounding tags to determine the items have been placed inside the shopping cart. KONARK tracks these in-cart items, and will seamlessly purchase these items once the customer leaves the store. No manual checkout is required. In order for such a seamless checkout, KONARK must discriminate between tags that are inside, from those that are outside the cart. To this end, we exploit the fact that the RSSI and RF phase of the RFID signal of tags inside the cart has a smaller temporal variance than those outside the cart. In order to demonstrate the feasibility and accuracy of KONARK, we evaluate KONARK within a mock-up of a small retail aisle created in our laboratory. Our experiments reveal that KONARK detects *in-cart* items with almost 100% within $60s$ detection latency in this mock-up.

(c) Customer interest monitoring. KONARK also monitors the items that the customer interacts with (e.g., a bottle that is touched or picked up) even if it is not placed into the cart. We observe that the RFID tags on items picked up by the customer have a higher temporal variance in phase and RSSI change compared to those untouched items in the vicinity. This observation resides in the core of interest detection algorithm. Our system detects user interest with 100% by reading the information of RFID tag on the object.

In the rest of this paper, we begin with a background on RFIDs in §2, followed by a brief architectural overview and description of algorithms §3. Then, we describe the experimental setup and metrics used in §4. We then evaluate the KONARK in §5 and finally conclude in §7.

2. PASSIVE RFID PRIMER

Passive RFID system communicates using a backscatter radio link, as shown in Fig. 2. The reader supplies a Continuous Wave (CW) signal, a periodic signal that persists indefinitely. The passive tags purely harvest energy from this CW signal. The tag then modulates its data on the backscatter signals using ON-OFF keying through changing the impedance on its antenna. A typical passive RFID tag consists of an antenna and an integrated circuit (chip).

Passive RFID tag: A typical passive RFID tag consists of an antenna and an integrated circuit (chip). According to [18], passive RFID tag absorbs the most energy when the chip impedance and the antenna impedance are conjugately matched, *i.e.*, $Z_c = Z_a^*$ [19].860-960 MHz) passive tags come with proper matching [19].

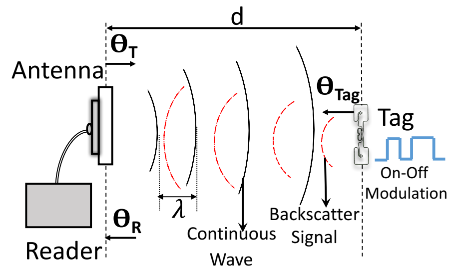

Figure 2: Operation of a RFID reader antenna and a tag

COTS RFID reader: COTS RFID reader [20] uses linear or circular polarized antennas for both transmitting and receiving. They generally provide facilities to access lower level information [21] like RSS and phase values etc. through SDK [22]. A COTS reader employs an open-loop estimation (*e.g.*, preamble correlation) or a closed-loop estimation technique for acquiring phase and RSS [23].

RF Phase: Suppose d is the distance between the reader antenna and the tag, the signal traverses a total distance of $2d$ (Fig. 2). Besides the phase change over distance, the transmitter, the tag, and the receiver circuits will all introduce some additional phase offsets, denoted as θ_T, θ_{TAG} and θ_R respectively. The total phase change [23] observed by the reader can be expressed as: $\theta = (\frac{2\pi}{\lambda} \times 2d + \theta_T + \theta_{TAG} + \theta_R) \; mod \; 2\pi$ where λ is the wavelength.

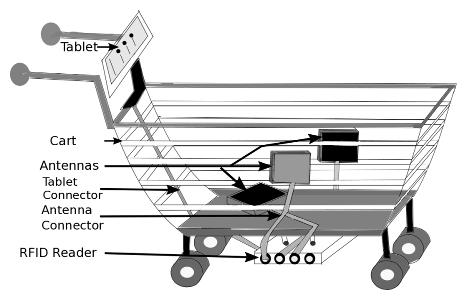

Figure 3: The customized shopping cart of KONARK

3. KONARK SYSTEM DESCRIPTION

This section describes the system architecture of KONARK and the algorithms used in the system. Different modules and their workings of KONARK is presented in Fig. 4.

3.1 Overview

In KONARK, a customer enters the shopping mall and picks up the customized shopping cart (Fig. 3). Customer then checks-in via an app in the tablet attached with the cart (Fig. 3) before starting his shopping. Then, customer starts shopping while navigating through different isles. At this instant, different modules of KONARK is invoked. As illustrated in Fig. 4, at the first step, *tag feature extraction* module runs in the tablet concurrently with the *cart mobility detection* module. *Tag feature extraction* module extracts features like RSSI, phase etc. from RFID tags from both in-cart and outside-cart items using the RFID reader and the antennas. *Cart mobility detection* module uses these features to infer the mobility of the cart (*i.e.*, static or mobile). These modules should run continuously to gather information from different nearby tags and feed into the next modules. In the next step, *In-cart item detection* module uses these sensed physical level parameters of nearby RFID tags combined with the mobility and reference tag information to detect exact *in-cart* items at any instant, as shown in Fig. 4. Furthermore, in parallel, these features combined with the inferred mobility state of the cart also help to detect the interest of users in particular items through *interest detection* module. This module identifies the items in which users have shown interest. The items of interest are those items which they have picked up but did not put into the cart. These four modules are the main components of the KONARK system.

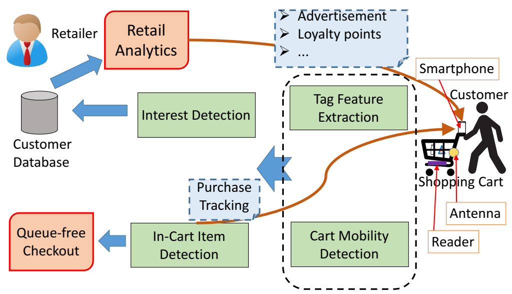

Figure 4: Architectural overview of KONARK

In the Fig. 4, we also show that how these four modules can help in achieving different goals in a retail setting. Firstly, the knowledge of *in-cart* items, at any instant, will help users to track their purchase and can help them to check-out any time through the app without standing in a queue. Secondly, this real-time user behavior combined with previous *customer database* can help *retailers* to generate *personalized advertisement* for customers, as shown in Fig. 4. These constant feedbacks during purchase powered by KONARK makes shopping experience more enriching.

3.2 Algorithms

In the following paragraphs, we describe the algorithms used behind KONARK.

3.2.1 In-cart item detection

The main intuition behind this algorithm is that the RSSI and RF phase of the RFID signal of tags inside the cart has a smaller temporal variance than those outside the cart. This is due to the fact that the tags inside the cart are stationary w.r.t. the RFID reader. As

Algorithm 1 Pseudo-code of *In-cart* item detection

```
while True do                                    ▷ Till the end of shopping.
    if Cart is mobile then
        Create temporal feature matrix from RFID tags.
        Create two seed matrices from reference tags.
        Employ K-means algorithm to get two clusters.
        Tags with cart reference tags are in-cart tags.
```

shown in the Algorithm 1, we first create a temporal feature matrix from features extracted from RFID tags. In this matrix, unique RFID tags represent the rows and the features computed in time segments represent the columns (Each column is of 1 second duration). Features we use are reading count, median RSSI value, median phase value, and median doppler shift value for RFID tags. This temporal feature matrix is created intermittently and then, fed into the clustering. We use *K-means* clustering on the temporal feature matrix to get two clusters, i.e., *in-cart tags* and *outside-cart tags*. This temporal feature matrix is created by extracting features from the data collected every 30 second duration. This *K-means* clustering process is provided with initial seeds from features derived from *inside-cart* and *outside-cart* reference tags, as shown in Algorithm 1. Fig. 5 illustrates that how both inside and outside reference tags help in clustering and the continuous change of outside tags helping in *in-cart* item detection. Fig. 5 illustrates that how the changing window of tags for a mobile user help in in-cart item detection; Because, the RSSI, doppler shift etc. of certain out-cart tags would be different than the in-cart tags. The step before the

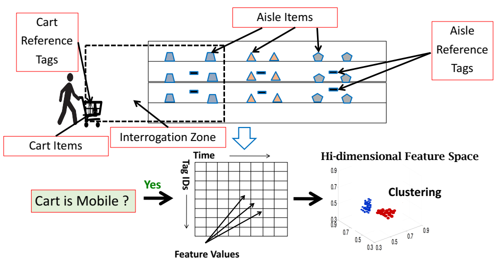

Figure 5: Algorithm sketch for in-cart item detection.

temporal feature matrix creation is to detect the mobility state (mobile or static) of the cart. Because, we start creating the temporal feature matrix after we detect the cart is mobile (Algorithm 1). If we move the cart, the out-cart reference tags (assuming we have already been precomputed the mapping of reference tags and aisle) and the population of tags will be changing. We track the change and find out that the change is over a certain threshold (2 radian in phase, 10dB in RSS, and 0.5 in Doppler) , we say the cart is mobile, otherwise static. We also track the variance of phase and RSSI of in-cart items which will be more in mobile setting compared to static situation. This also increases the confidence of cart mobility state detection. The intuition behind this algorithm is that the feature values inside the cart items change less compared to the items outside the cart.

3.2.2 Browsing Interest Direction

We infer the interest of the user on a particular item based on if user has picked the item or not. There are two main obstacles to detect if a user has picked the item : (i) Noise in captured features due to multi-path and blockage, and (ii) Very less number of reads or no read of tags of interest due to random back-off and collision (This can be caused by more reads of inside items or outside items in different section of a same aisle or residing on another aisle). If we ignore the impact of noise on different features by assuming the impact would be similar to outside tags, we have to handle the second issue. Algorithm 2 shows the pseudo-code of browsing interest detection.

As shown in the pseudo-code, we have employed a hierarchical approach to pin-down the tags of interest, which is described below : (i) We start our interest detection module, if we know the cart is static. (ii) We have increased the probability of reading chances of the tag of interest by filtering via the precomputed aisle level filter (which can reduce the interrogation zone of the reader only in the aisle) and by also filtering out the in-cart items (By creating item level filter of $32bits$ for each in-cart items). By doing this, we only concentrate our interrogation zone to aisle of interest without the in-cart items. (iii) Then, we record the values (RSSI/phase) of

Algorithm 2 Pseudo-code of *browsing* interest detection

```
while True do                                   ▷ Till the end of shopping.
    ic ← in-cart tag pattern.
    if Cart is static then
        Aisle-level filtering of RFID tags.
        Record parameters of in and outside tags.
        for all oc ∈ O do                       ▷ O is the set of outside tags.
            oc ← outside cart tag pattern.
            if Compare(rc, oc) > δ then
                User has shown interest in oc.
```

tags which are in the isle and outside the cart. We look for tags of which phase variation is more than a certain threshold (normalized value of 0.6) compared to other tags, as shown in Algorithm 2. We mark those tags as *tags of interest*. To achieve that, we compute KL-divergence of these tags compared to other tags.

4. SETUP AND METRICS

In this section, we describe the setup of our system KONARK which comprises of a smart shopping cart (equipped with a RFID reader and three antennas) and a set of reference tags attached with the cart and the isles. The reader is tuned to *Maxthroughput* mode and *Single* searching mode with 25 dBm power in circular polarized antennas with 70 degree beamwidth [1]. The Impinj R420 reader [20] continuously queries the tags in range (at 300 reads/second). We attach reference tags (SMARTRAC Dogbone Monza 4D tags [24]) 1m apart in an aisle and 6 reference tags in the cart. Reference tags are those tags which are put in both the cart and the aisle beforehand. The IDs of the tags with their corresponding cart and isle, are known to the system. The cart items are put randomly inside the cart and the items are of different sizes to emulate actual shopping scenario. We have created a mock aisle setup (Fig. 6) in our lab to test the algorithms. In this mock isle setup, two parallel wooden shelves are put (of length around 8m) and these are separated around 2m. For getting the ground-truth of the speed of the moving cart, we have built an arduino based speedometer containing an accelerometer and a gyroscope (Fig. 7).

Figure 6: Experimental Setup of KONARK system.

We use the following metrics to measure the efficacy of our system.

Detection Latency: The amount of time (in seconds) required to detect if the items are inside the cart or if the user has picked up the item. We create the temporal feature matrix for the item detection or the feature vector for user interest inference from the data collected in this duration. So, longer the latency or duration, one gets more data to predict. However, shorter latency makes the system more usable and provides real-time response.

[1]The frequency range is 902.75 - 927.25 MHz.

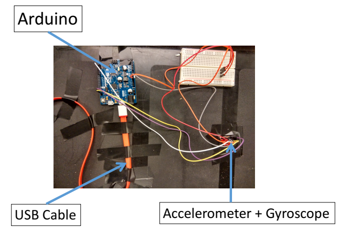

Figure 7: Speedometer for ground-truth measurement.

Accuracy: It illustrates the fraction of correctly predicted items either the inside items or the interested items. We calculate the accuracy by calculating correctly selected items inside or outside the cart.

False Positive Rate: It shows the fraction of detected items belonging to the wrong class.

5. EVALUATION

In this section, we discuss different types of evaluation in detail. First, we look at detection accuracy of items inside the cart in a shopping isle mock-up as shown before. Each of the experiment in this setup is done 20 times each with the speed range of 0.2 to 2m/s. We vary the number of items in a mobile shopping cart to observe the accuracy. Fig. 8 shows the accuracy of inside item detection accuracy in the cart, while changing the duration of mobility of the cart. As illustrated in Fig. 8, accuracy remains good even after putting items upto 82. If we assume the updating cycle of the duration of 60 seconds , i.e., if we check how many items are inside the cart after one minute of mobility, the detection accuracy reaches 100% over all trials. However, if we want to detect *in-cart* items too soon, the detection accuracy degrades but not by much. In the worst case, the *in-cart* detection accuracy is 95%, which is not desirable in real system but shows enough promise. Fig. 9

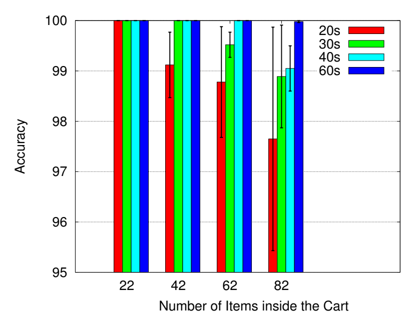

Figure 8: Number of items inside the cart and accuracy.

illustrates the detection latency compared with the false positive and false negative percentage for 82 items inside the cart. By false positive items we mean that the items which are counted as inside the cart are actually the outside or aisle items and by false negative we mean, the items which are counted outside are actually in-cart items. Both false-positive and and false-negative items are higher when the detection latency is low and which becomes more with higher detection latency.

Fig. 10 illustrates the phase patterns of items which have been picked and the items which have not been picked. So, our algorithm based on this variation to detect user interest gives 100% accuracy if we can read the tag of this particular items. So, to test the efficacy

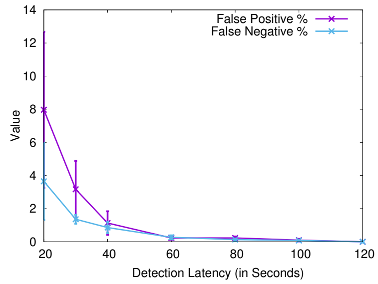

Figure 9: Dissecting the accuracy for predicting in-cart items.

of reading the phase information of the items in our aisle setup, we increase the number of items in the vicinity. Fig. 11 illustrates the interest detection accuracy, when we increase the number of items in the vicinity. If we wait for at least 40s we can detect the item which the user has shown interest in, even if there are 600 outside items in the vicinity as illustrated in Fig. 11. However, if the items in the vicinity are within 200, we can detect the items in which user have shown interest with 100% accuracy. There is a clear trade-

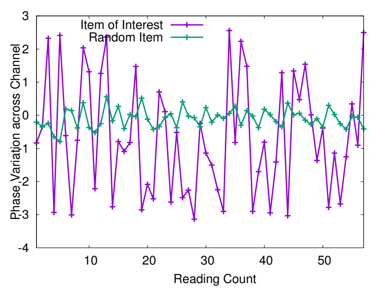

Figure 10: Phase variation of item of interest and other item.

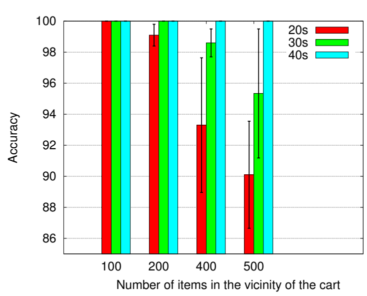

Figure 11: Accuracy of Interest detection result.

off between detection latency and accuracy. However, around 40 second window is enough for in-cart item and interest detection.

6. RELATED WORK

In the following paragraphs, we will describe related works of different aspects of our work.

Check-out Automation: Point-of-Sale kiosks have already been popular in different shopping stores which provide some sort of automation through self-checkout [1]. However, these kiosks are in general too slow and not intuitive to operate [4, 5]. There have also been an effort to automatic assignment of check-out queues for different customers based on their purchase amounts and the crowd size [25], which also failed to take off. Toshiba's Point-of-Sale (PoS) alternative *Touchless Commerce* [9]uses vision based technique to checkout 10 or fewer items [10]. However, its item identification technology, even for 10 items, is not perfect and they are yet to launch a commercial product. Most recently, *Amazon Go* [8] (which is currently in beta mode) allows users to come in the stores, and buy items seamlessly by picking up items. They claim to use deep learning powered vision based technology with sensor fusion (IMU sensors like accelerometer and gyroscope in smartphones) to automate the checkout process [8]. This holds promise but may encounter privacy concerns and detection inaccuracy due to NLOS and occlusion, which might be the reason of its delay in roll-out.

A few other studies equip shopping carts with sensors to expand their ability which might also help in easier check-out. In the study [26], a shopping cart actively tracks its lost customer via sensors and a localization algorithm. Another work [27] attaches a web-cam on a cart to guide a customer to the prescribed locations based on the shopping list. To avoid complex image processing, the supermarket is mapped with some colors, and each cart identifies the color to estimate its position. The work [28] puts sensors on shopping carts and product shelves in a shopping area, and uses 3D ray tracing to analyze sensor deployment to reduce interference and energy consumption. However, these works employ highly customized setup to accomplish limited goal through complex algorithms without addressing the check-out issue. These solutions also fail to provide real-time information on users' interest while shopping.

Interest Detection: Researchers have used RFIDs to observe the preference and the interest of customers on products. These studies [29, 30] associate products with passive RFID tags to detect their movement caused by customers. However, these systems lack interaction with customers and do not provide self-checkout facility to user. In another work [31], each customer uses a smart phone with an RFID reader to look for the location of desired product. However, it only guides the customer to the destination product shelf. People have used other technolgies to infer shopping behavior, like You et. al [32] discussed the usage of mobile phones to monitor shopping time at physical stores. Shangguan et. al. [33] exploits multiple RFID reader and antennas installed in a mall to understand buyers' interest and browsing behavior of RFID tagged objects. Furthermore, Rallapalli et. al [34] has focused to mine in-store physical browsing using google glass but does not provide an integrated retail solution. These systems suffer from issues like the need of high level of user involvement and huge infrastructure deployment.

7. CONCLUSION AND FUTURE WORKS

In-cart RFID reader provides benefit compared to traditional self-checkout system in terms of speed (on-the-go) and benefits (user interest detection). Furthermore, this in-cart solution is better than infrastructure RFID based solutions [29, 33] which work only with smaller number of tags. However, there is a need to thoroughly test KONARK with multiple carts at different mobility and different distances in real shopping mall scenarios. We also want to add more detailed retail analytics features to our current system apart from only user interest detection. Furthermore, we also plan to adopt sophisticated strategies like collaboration among shopping carts through a KONARK server or in an ad-hoc manner. There is also an option to build a customized energy-efficient RFID reader which is solely focused toward retail scenario to help in faster decoding of RFID tags utilizing a few recent advances [35, 36]. These and more are left to future work.

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