ShopMiner: COTS RFID 디바이스를 통한 의류 매장에서의 고객 행동 마이닝

SHOPMINER :

MINING CUSTOMER SHOPPING BEHAVIOR IN PHYSICAL CLOTHING STORES WITH COTS RFID DEVICES

February 3rd | 2024

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CONTENTS

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ABSTRACT & INTRO

Shopping Behaviour Data

- Data such as the stream of clicks a customer makes while shopping and the shopping cart history
  ➡ Become a very important factor in understanding the effectiveness of marketing and product sales + many methodologies have been proposed to identify customer behavior based on such data

- Compared to the current state of the online market, there is a lack of comprehensive shopping behavior identification methods that can be effectively used by offline clothing store operators

➡ **Propose a framework called ShopMiner to detect customer shopping behaviour**

- The proposed framework utilizes the backscatter signal from passive RFID tags to detect and record the garments that customers have noticed

- Implemented a prototype of ShopMiner using a COTS RFID reader and 4 antennas, tested its effectiveness in a typical indoor environment, and achieved high accuracy & efficiency in identifying customer shopping behavior

ABSTRACT & INTRO

- Until now, the only information that was immediately available was the sales history

➡ Limitation that it does not reflect customer behavior

Video Cameras	Saliency Calculation
required complex computer vision implementations & vulnerable to the NLOS environment	limited by the difficulty in providing high-quality information related to specific shopping behaviors such as product search and try-on

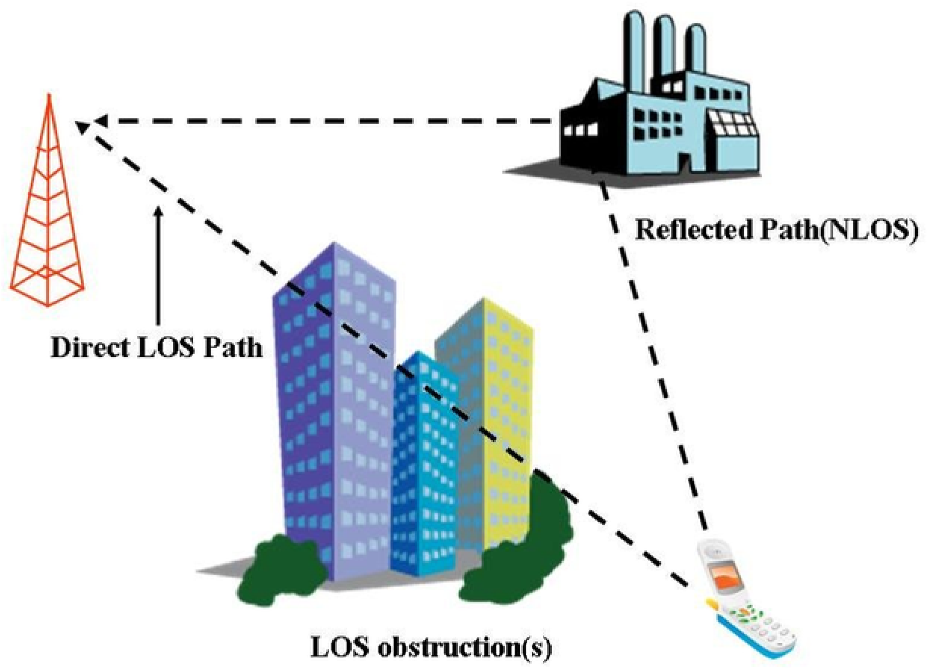

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Figure 1.
NLOS(Non Line of Sight)

ABSTRACT & INTRO

Commercial Off The Shelf	Radio Frequency Identification
stands for "Commercial Off-The-Shelf", which means that products, SW, etc. can be sold or purchased commercially	Form of wireless communication that utilizes electromagnetic or electrostatic coupling in the radio frequency portion of the electromagnetic spectrum to uniquely identify objects

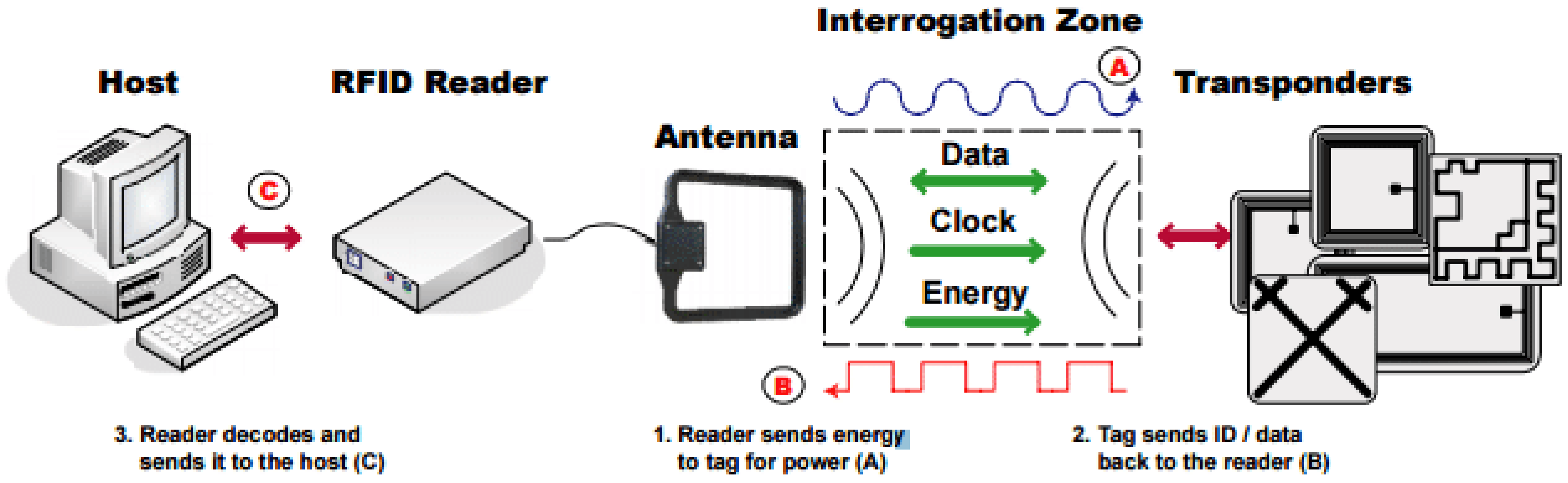

Figure 2.
How RFID works

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ABSTRACT & INTRO

1) Popular Categories

- A factor that indicates the apparel that customers have viewed most often
- Can provide important information for a retailer's trading strategy by indicating customer preferences

2) Hot Items

- Indicates whether a customer is more interested in the same item the first time they see it and the second time they see it, and includes clothing that is picked up again or constantly turned inside out

3) Correlated Items

- Refers to clothing that is frequently paired with a particular product
- Can help retailers deduce a customer's shopping habits and introduce bundled sales strategies to boost revenue

➡ **By jointly analyzing these three kinds of shopping data along with sales records, merchants can gain much deeper business value, the paper shows.**

FRAMEWORK SCOPE

ShopMiner & Shopping Process

(a) Browse the merchandise and stand still in front of an attractive item

(b), (c) Pick up or flip through the merchandise and look at items of interest

(d) Take the desired item and try it on in the fitting room

➡ Hlighted that these steps contain comprehensive data, which can help sellers optimize their strategies, such as adopting linked promotions by identifying implicit correlations between garments

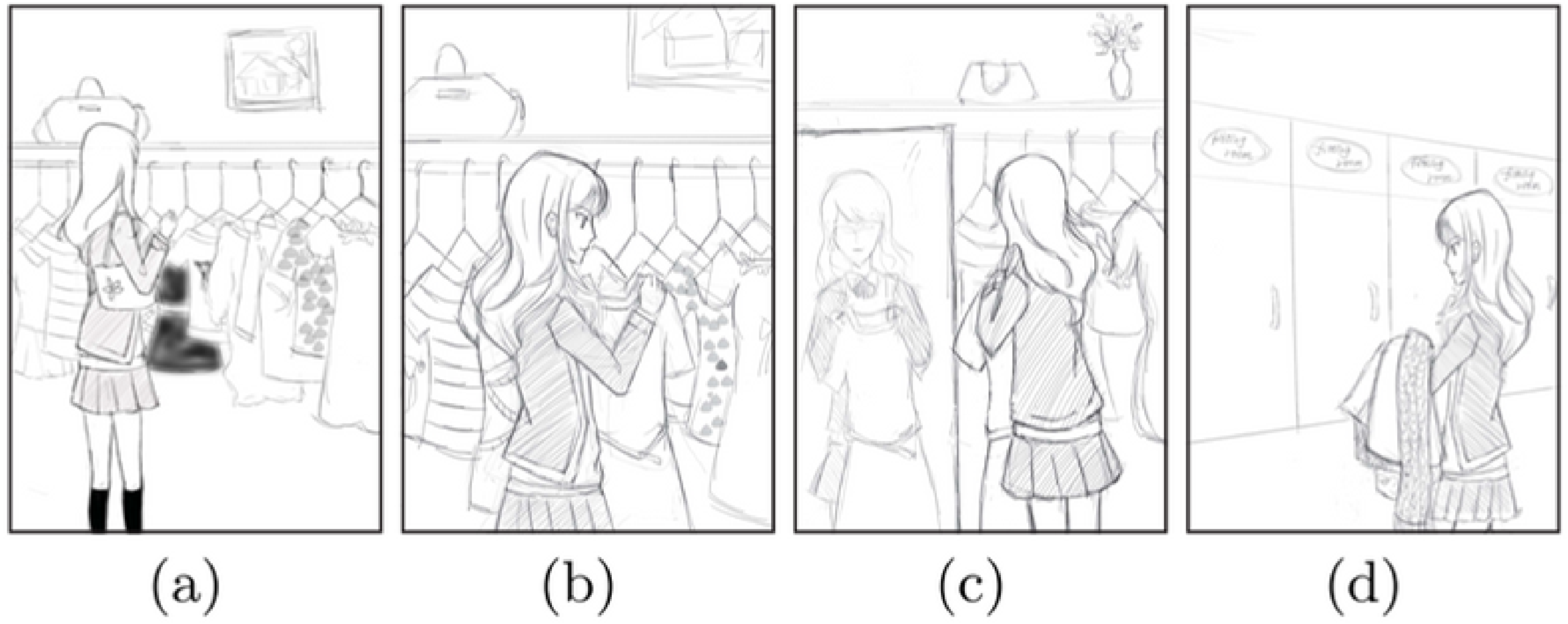


Figure 3.
typical shopping process in store before checkout

FRAMEWORK DESIGN

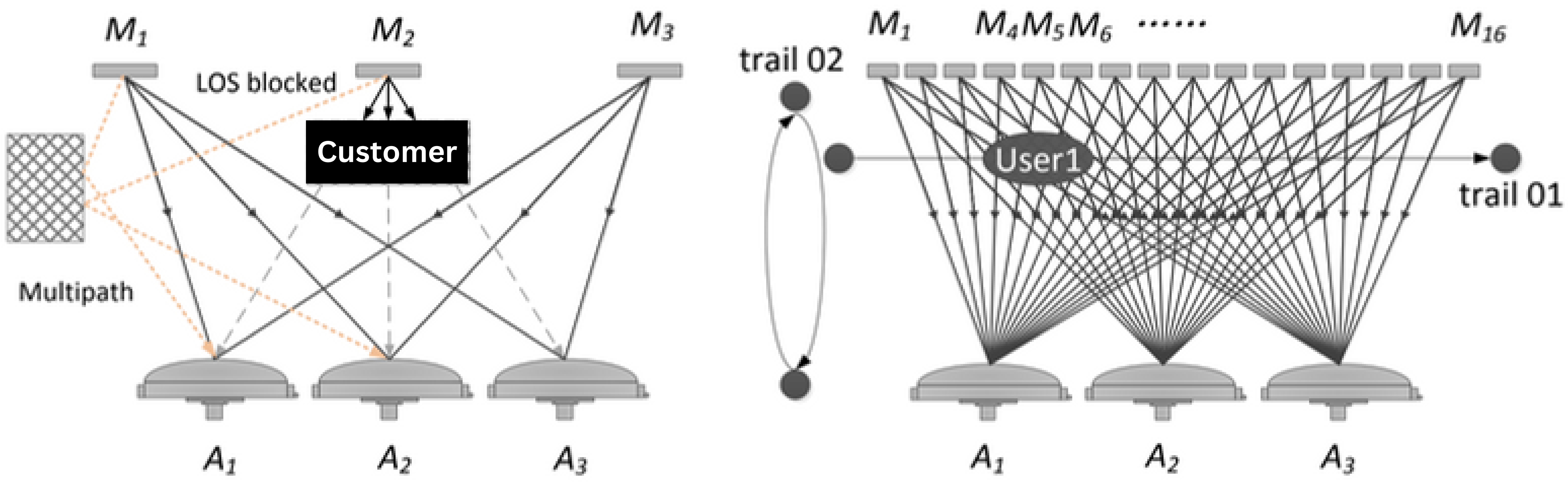
1) Popular Categories	• **1-A)** Shadowing effect of human body • **1-B)** Multipath Effect • **1-C)** Detection scheme
2) Hot Items	• **2-A)** Exploiting the similarity of pick-up and turn-over for action detection • **2-B)** Exploiting the dissimilarity of pick up and turn over for action identification • **2-C)** Identification scheme
3) Correlated Items	• **3-A)** Spatial-temporal correlation of signal features • **3-B)** Clustering correlated items

FRAMEWORK DESIGN

1-A) Shadowing Effect of Human Body

- **Human Body Shadowing Effect :** body naturally blocks the LOS link between the reader antennas and the focused product
- A product with a high shadowing rate ➡ customers have spent a long time in front of it

Figure 4.
Illustration of popular zone discovering



(a): LOS path blocked/multipath (b): moving trail of a user

FRAMEWORK DESIGN

1-A) Shadowing Effect of Human Body

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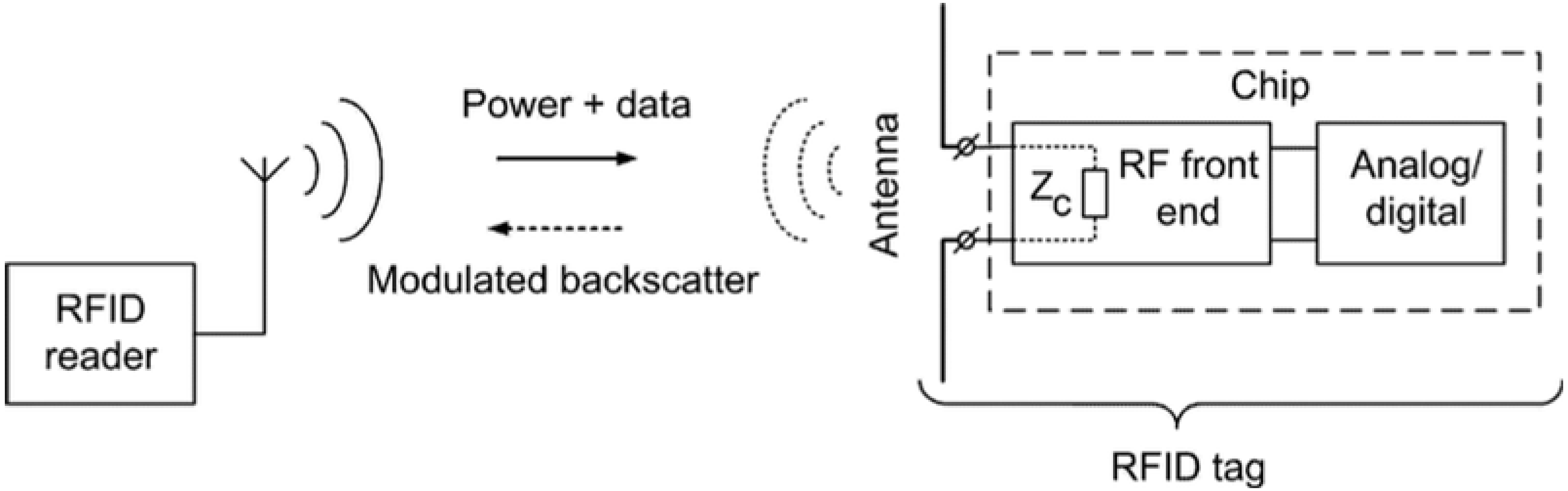


Figure 5.
Backscatter Operation

1. An RFID reader sends a radio signal of a specific frequency to an RFID tag
2. The RFID tag receives this signal and uses the energy it receives to reflect a new signal containing data]
3. The RFID reader receives the reflected signal, interprets the information in the tag, and extracts the data

FRAMEWORK DESIGN

1-A) Shadowing Effect of Human Body

1. Person walks along trail 1
2. When the person encounters item 4, i.e., M4, while walking, they stop for about 8 seconds
3. After 8 seconds, the person moves along the original path again

Figure 4.
Illustration of popular zone discovering

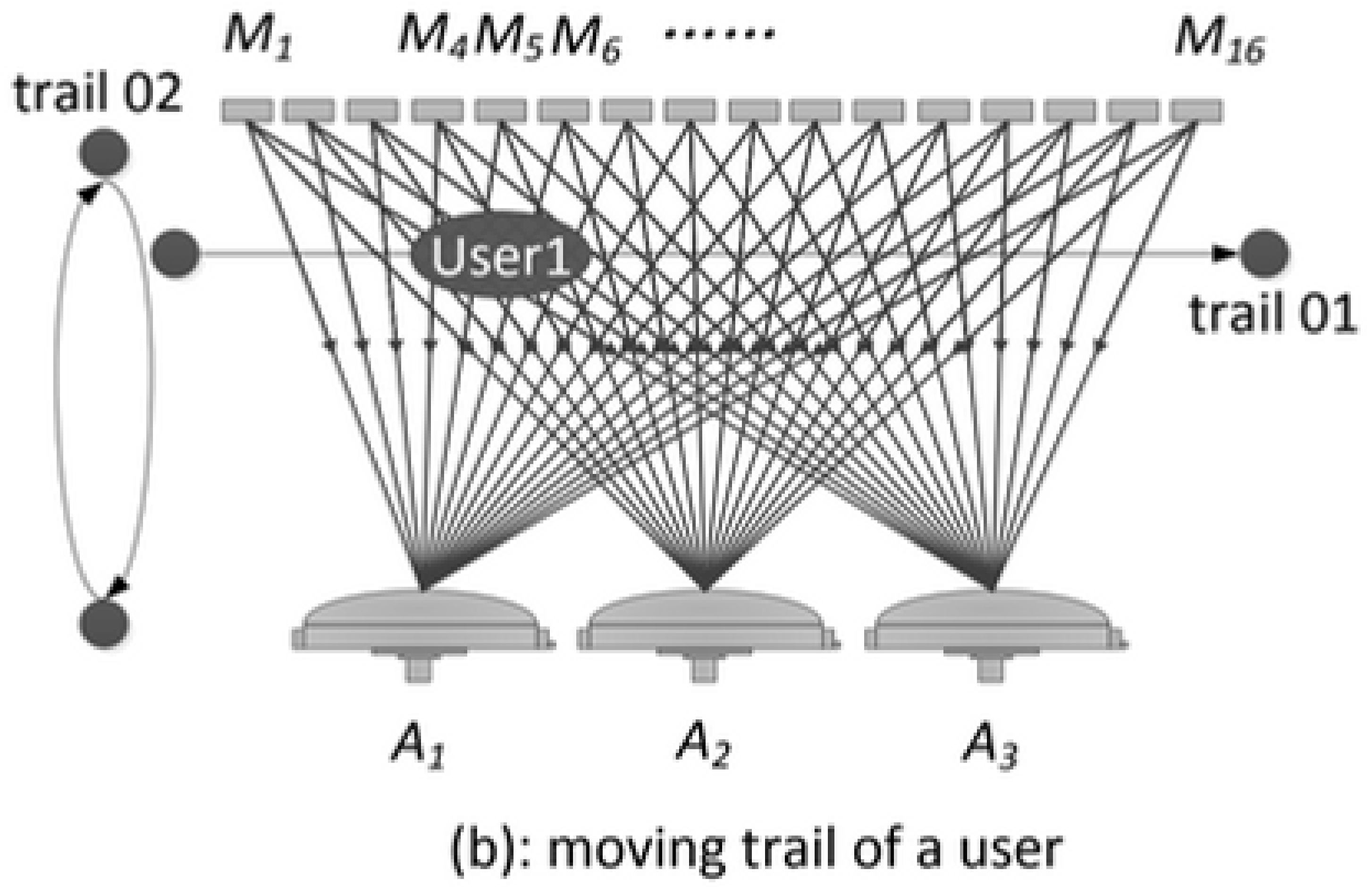
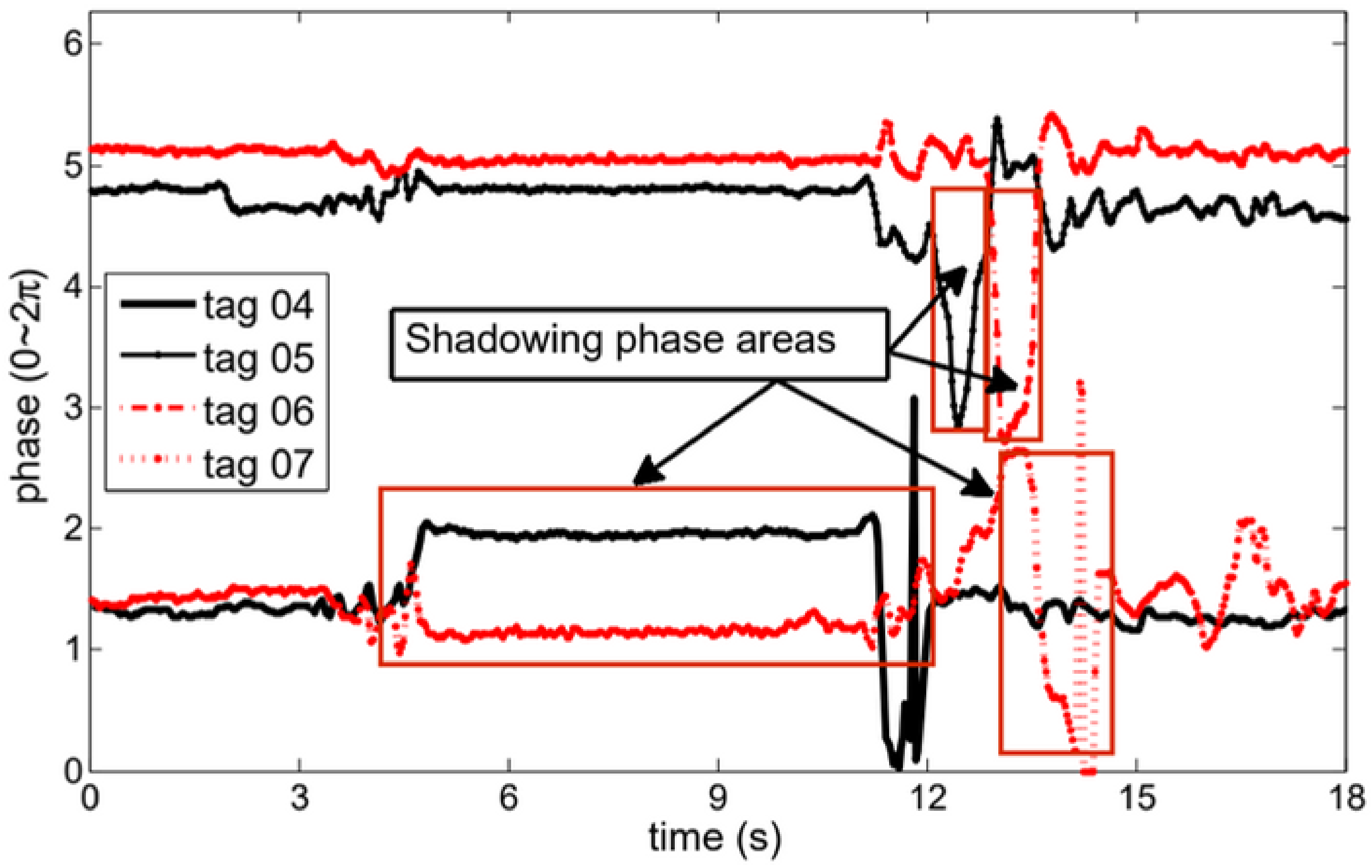


Figure 6.
Illustration of phase trends of four tags



FRAMEWORK DESIGN

1-B) Multipath Effect

- In general, signals propagate through multiple paths instead of just one
- **The multipath effect :** phenomenon in wireless communications where a signal is sent and received via multiple paths
- The change due to the multipath effect is significantly less compared to the change that occurs when the LOS is directly blocked

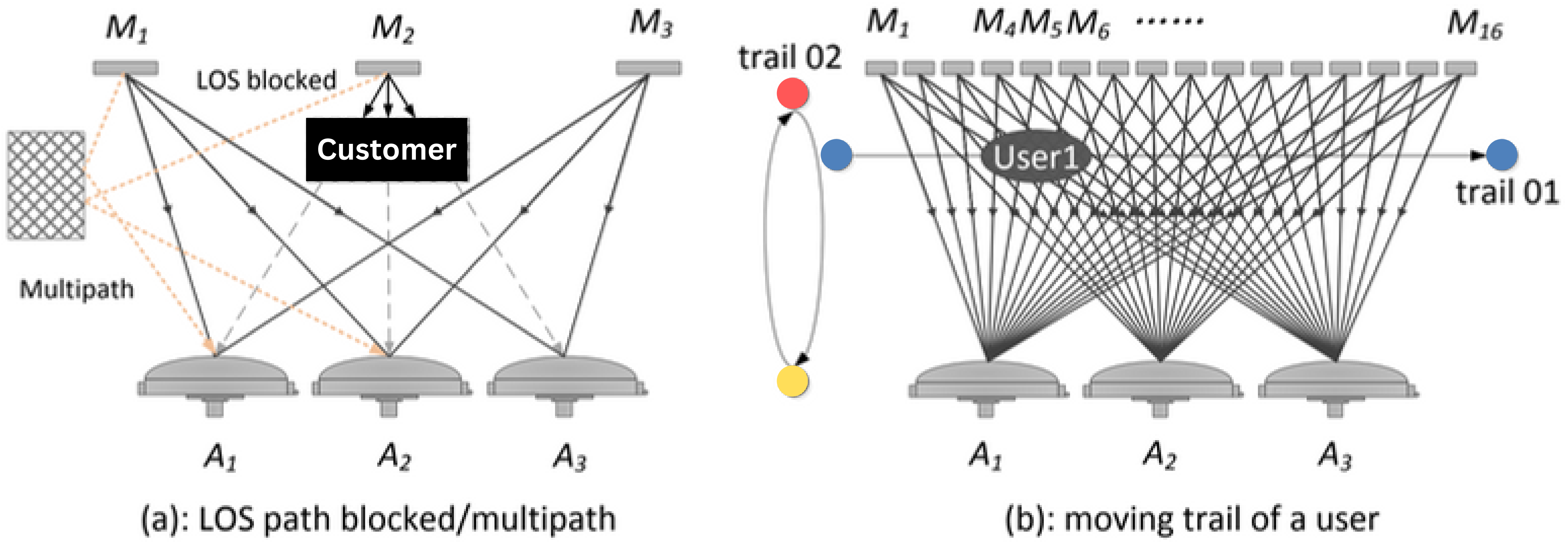


Figure 4.
Illustration of popular zone discovering

1-B) Multipath Effect

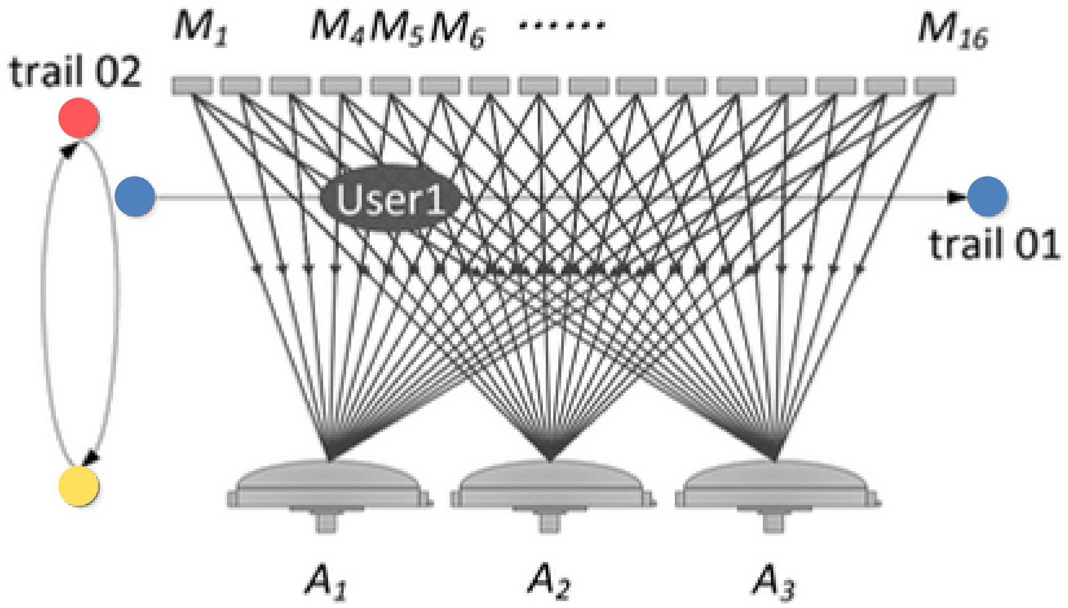
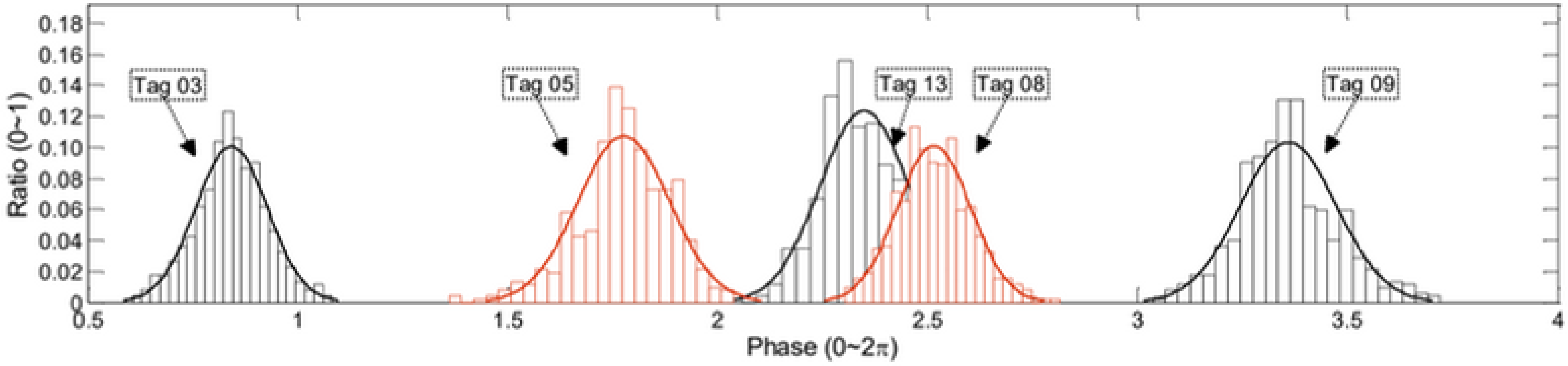
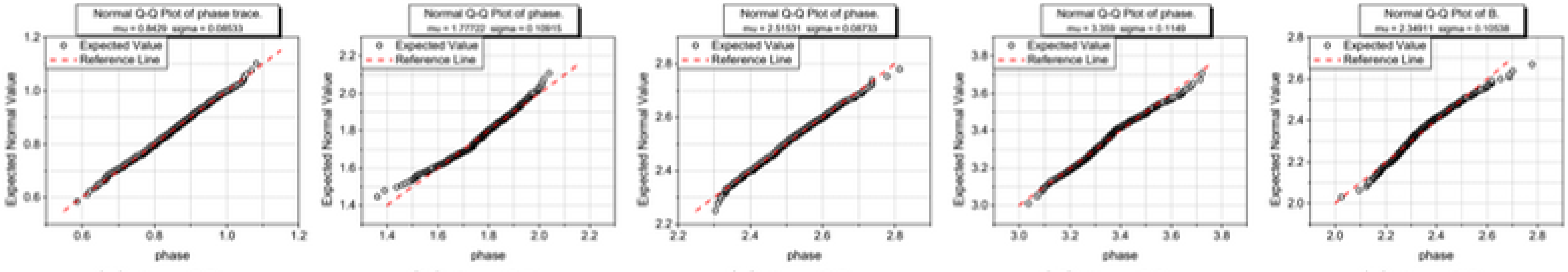


Figure 4.
Illustration of popular zone discovering

Figure 7.
Phase value distribution of 5 tags





(a) tag 03 (b) tag 05 (c) tag 08 (d) tag 09 (e) tag 13

Figure 8.
QQ Plot of sample data VS standard normal

FRAMEWORK DESIGN

1-C) Detection Scheme

- Split time into consecutive windows and focus on foreground pixels with significant phase changes between consecutive image frames over time
- Pixel values that differed from the background distribution were considered background, and those that did not were considered foreground
- Generated **m** Gaussian models and assigned each one to a tag
  ➡ Compared each pixel to the corresponding distribution, and finally established the above hypothesis test
- If **more than 80%** of the pixels in the i-th row are detected as foreground in a single frame
  ➡ All links between the tag and the reader antenna are blocked by the human body

Expression 0.
Foreground & Background Hypothesis Test

$$\begin{cases} H_0 : r_{i,j} \notin (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \\ H_1 : r_{i,j} \in (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \end{cases}$$

Expression 1.
Popular & Unpopular Category Hypothesis Test

$$\begin{cases} H_0 : s_i \geq \theta \\ H_1 : s_i < \theta \end{cases}$$

FRAMEWORK DESIGN

1-C) Detection Scheme

- **H0 :**

  The observed pixel value does not belong to the background
  ➡ A person is standing in front of it, obscured by an object ➡ Popular category

- **H1 :**

  The observed pixel value belongs to the background
  ➡ People are not interested in it and it is not covered by objects ➡ Unpopular category

Expression 0.
Foreground & Background Hypothesis Test

$$\begin{cases} H_0 : r_{i,j} \notin \left(\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}\right) \\ H_1 : r_{i,j} \in \left(\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}\right) \end{cases}$$

Expression 1.
Popular & Unpopular Category Hypothesis Test

$$\begin{cases} H_0 : s_i \geq \theta \\ H_1 : s_i < \theta \end{cases}$$

FRAMEWORK DESIGN

2-A) Exploiting the Similarity of Pick-Up & Turn-Over for Action Detection

- Proposed an identification method that utilizes phase changes caused by two customer behaviors: **Flipping and Grabbing**
- Both flipping and grabbing actions change the state of an item from stationary to kinetic ➡ Kinetic items experience a violent phase change, which naturally distinguishes them from stationary items
- Demonstrated in this paper that it is possible to detect pickup and turnover behavior by observing the phase evolution of the tag

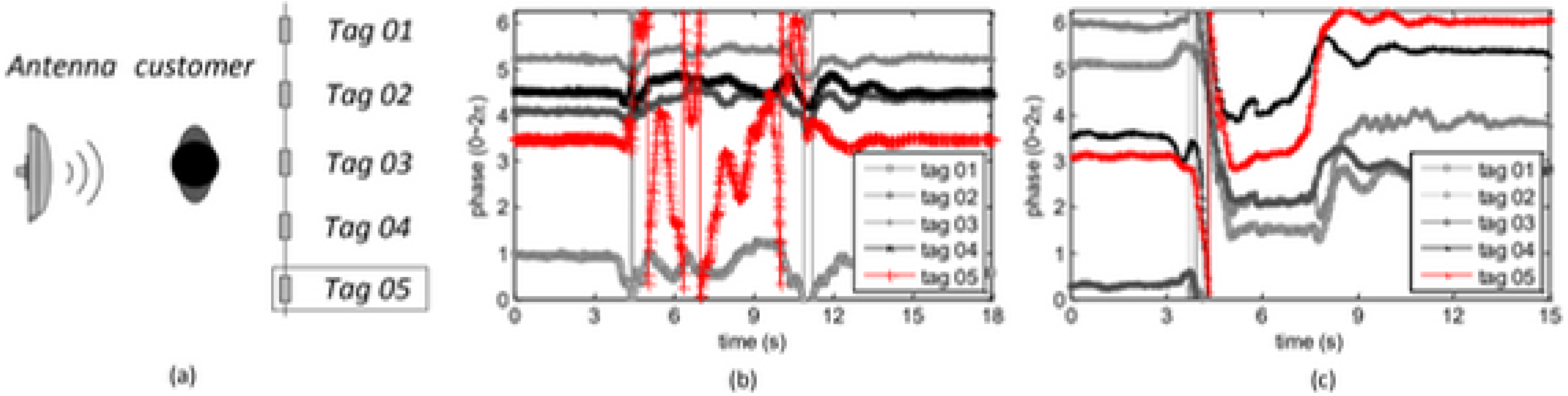


Figure 9.
(a): the sketch of experiment field
(b): pick-up case
(c): turn-over case

FRAMEWORK DESIGN

2-B) Exploiting the Dissimilarity of Pick Up & Turn Over for Action Identification

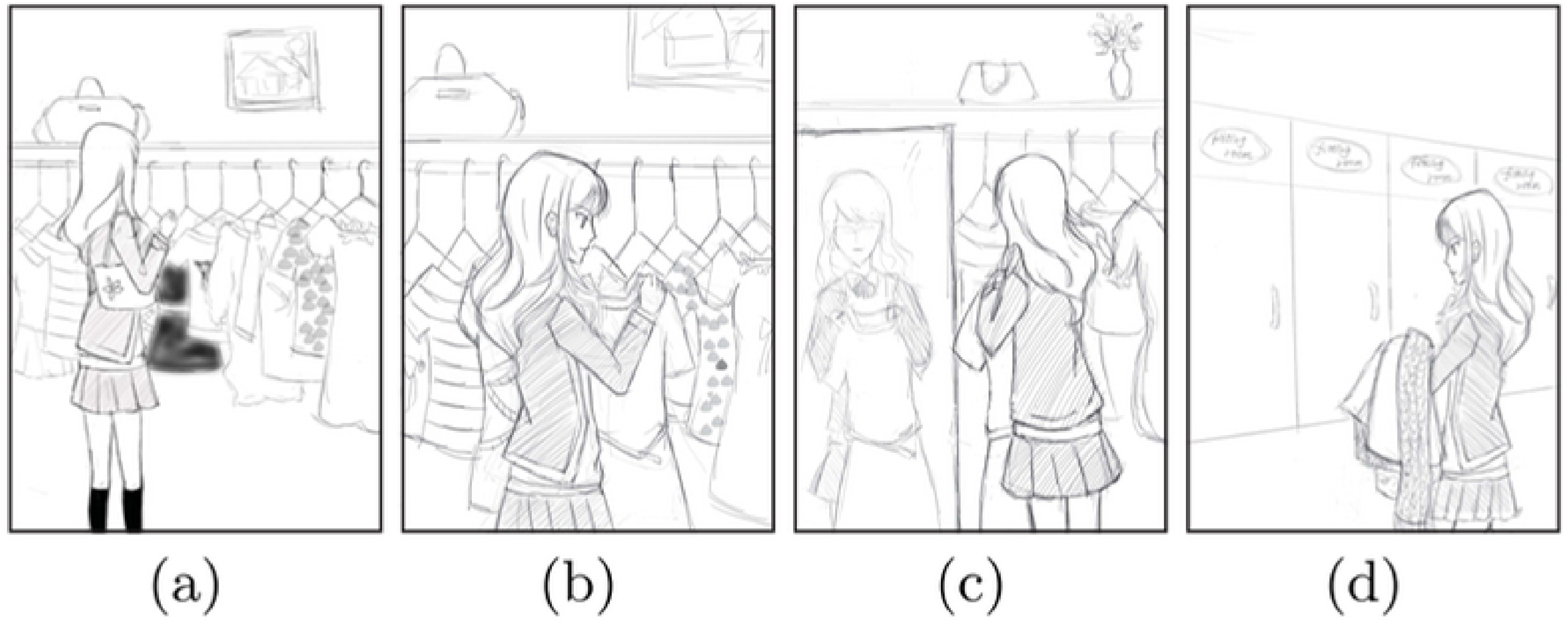
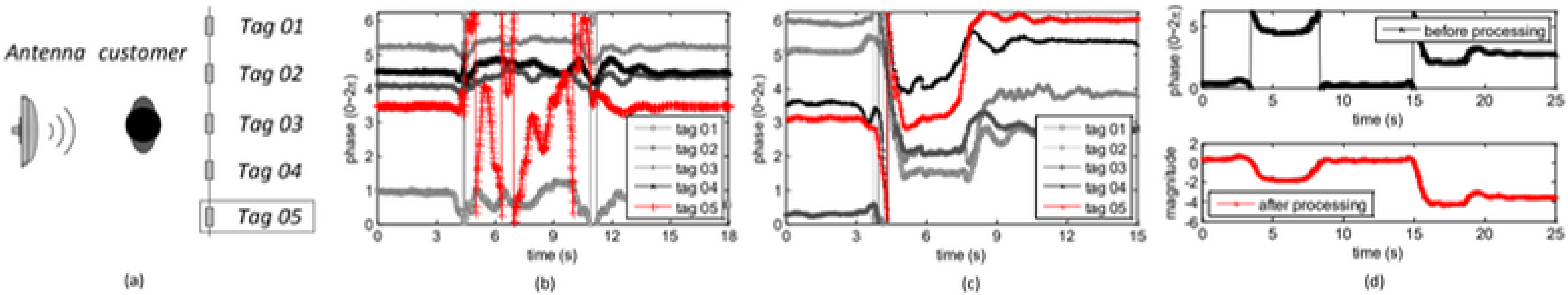


Figure 3.
typical shopping process in store before checkout

Figure 9.
(a): the sketch of experiment field
(b): pick-up case
(c): turn-over case
(d): the phase trend before/after de-periodicity



FRAMEWORK DESIGN

2-C) Identification Scheme

- ShopMiner performs segmentation on the phase trend to detect whether a pinching or flipping behavior occurs

- Within each window, categorized the phase values into multiple bins and obtained a discrete probability distribution function(PDF) for the phase values within each window ➡ Given 2 consecutive windows wi & wj, letting P and Q be their PDFs, we can calculate the KL-divergence of the two PDFs

- Use **DKL(P||Q)** to check whether the current window is within a quiet period ➡ Exploring all windows that fall within the quiet period ➡ Extracted action intervals accordingly

- Tags containing action intervals suggest that a grab or flip action occurred

Expression 2.
Denoted Phase trend

$$S = (s_i) \in R^{1 \times N}$$

Expression 3.
KL-divergence defined given 2 probability distributions

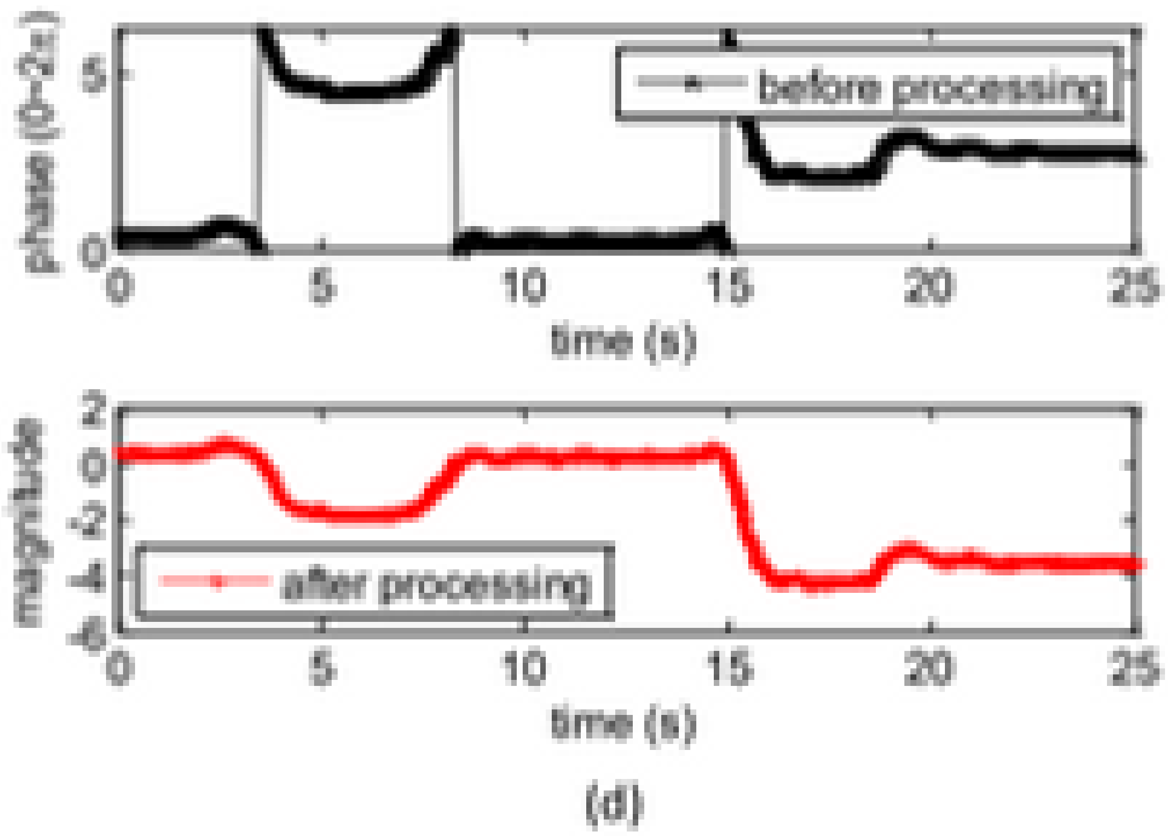
$$D_{KL}(P||Q) = \sum_i P(i) \cdot ln \frac{P(i)}{Q(i)}$$

2-C) Identification Scheme

- **The Problem :** Motions cause turbulence in the phases of neighboring items, and those changes can also be detected by segmentation-based methods
- **De-Periodicity :** Introduced a method that adds or subtracts 2π to the phase value when phase hopping occurs
- **Variance Comparison :** Calculate variance of each tag, the tag with the highest variance ➡ selected product

Figure 9.

(d): the phase trend before/after de-periodicity



Expression 4.

Sampling phases within a motion period for each tag i

$$S_i = (s_j) \in R^{1 \times N_i}$$

Expression 5.

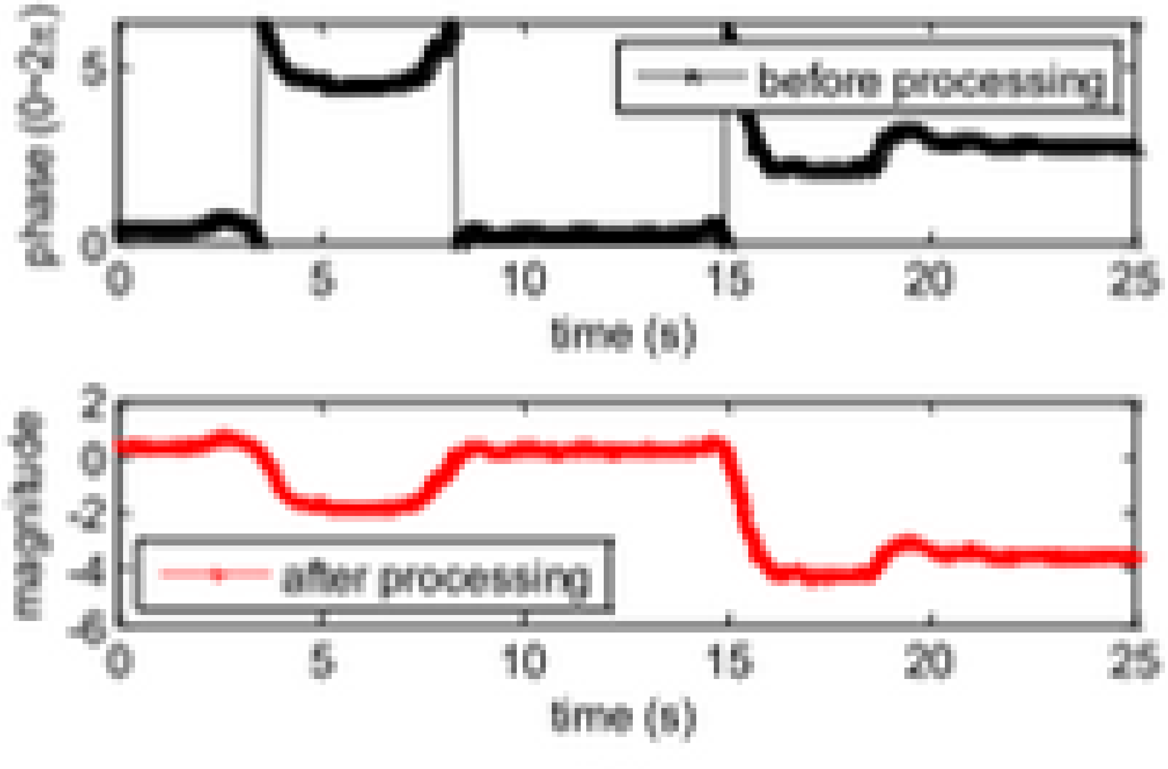
Computed variance of Si

$$Var(S_i) = \frac{1}{N}\sum_{j=1}^{N}(s_j' - \mu)^2$$

2-C) Identification Scheme

- The phase changes of neighboring goods show similar fluctuations in the case of flipping, but differently in the case of pinching
- Normalize the phase change to a constant ➡ Check the autocorrelation coefficient to see if the behavioral period is recognizable

Figure 9.
(d): the phase trend before/after de-periodicity



Expression 6.
Phase Trend Partition Notation

$$S = (s_i) \in R^{1 \times N}$$

Expression 7.
Autocorrelation performed on S

$$\chi(m,\tau) = \frac{\sum_{k=0}^{k=\tau-1}[s_{m+k} - \mu(m,\tau)][s_{m+k+\tau} - \mu(m+\tau,\tau)]}{\tau \cdot \sigma(m,\tau) \cdot \sigma(m+\tau,\tau)}$$

3-A) Spatial-Temporal Correlation of Signal Features

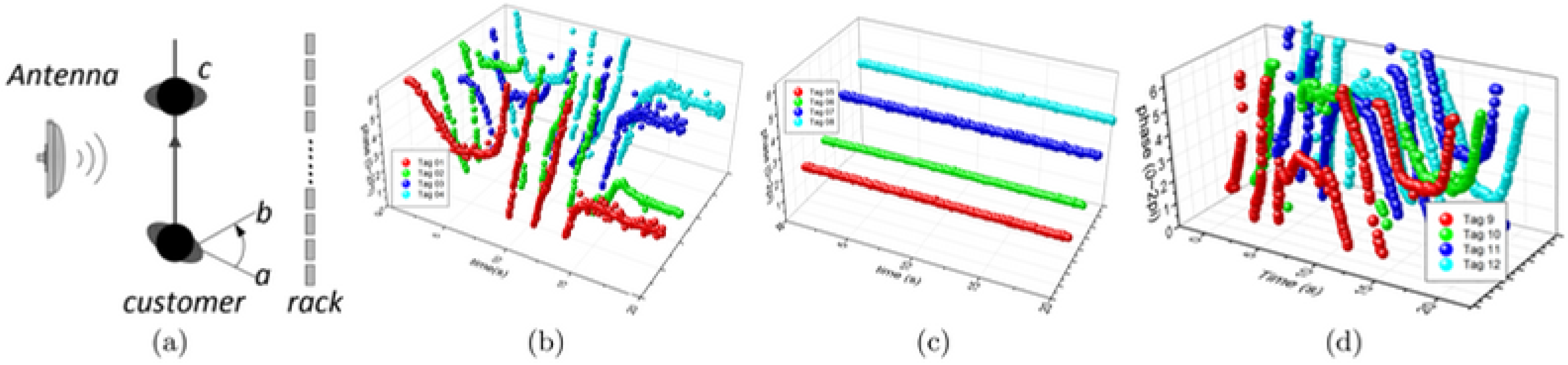
- A traditional method of detection is RSS-based location detection
- However, RSS-based localization has a limitation: it is based on the assumption that correlated items owned by the same person will be close together
- Noted that other items in the vicinity of the item in hand can also affect the RSS value, and in environments such as clothing stores, the signal propagation path dynamically changes as customers move around, resulting in unstable RSS values
- To overcome the limitations of these existing methods, a method that focuses on the spatio-temporal correlation of phase flow was proposed
- **The Core Idea :** products held by customers have the same movement pattern and experience consistent temporal signal changes

FRAMEWORK DESIGN

3-A) Spatial-Temporal Correlation of Signal Features

- Experiments show that all four products have similar phase changes, as shown in b in Figure 10
- Tags in different categories have different temporal phase profiles and naturally separate

Figure 10.
(a): the customer moving trail
(b): the phase trends of correlated items
(c): the phase trends of stationary tags nearby
(d): the phase trends of another group of correlated items



FRAMEWORK DESIGN

3-B) Clustering Correlated Items

- Want to divide a given set of phase change collections x1 through xn into a total of m clusters, and the goal of the process is to minimize the sum of squares within the clusters
- Minimizing the sum of squares within a cluster means that the cluster is cohesively formed, which indicates that correlated items are located close to each other.
- For this optimization, this paper designed a heuristic algorithm as shown in Figure 11

Expression 8.
Formula for minimizing the sum of squares within cluster

$$\underset{\mathbf{S}}{\operatorname{argmin}} \sum_{k=1}^{m} \sum_{i,j \in S_k} \mathcal{T}(x_i, x_j)$$

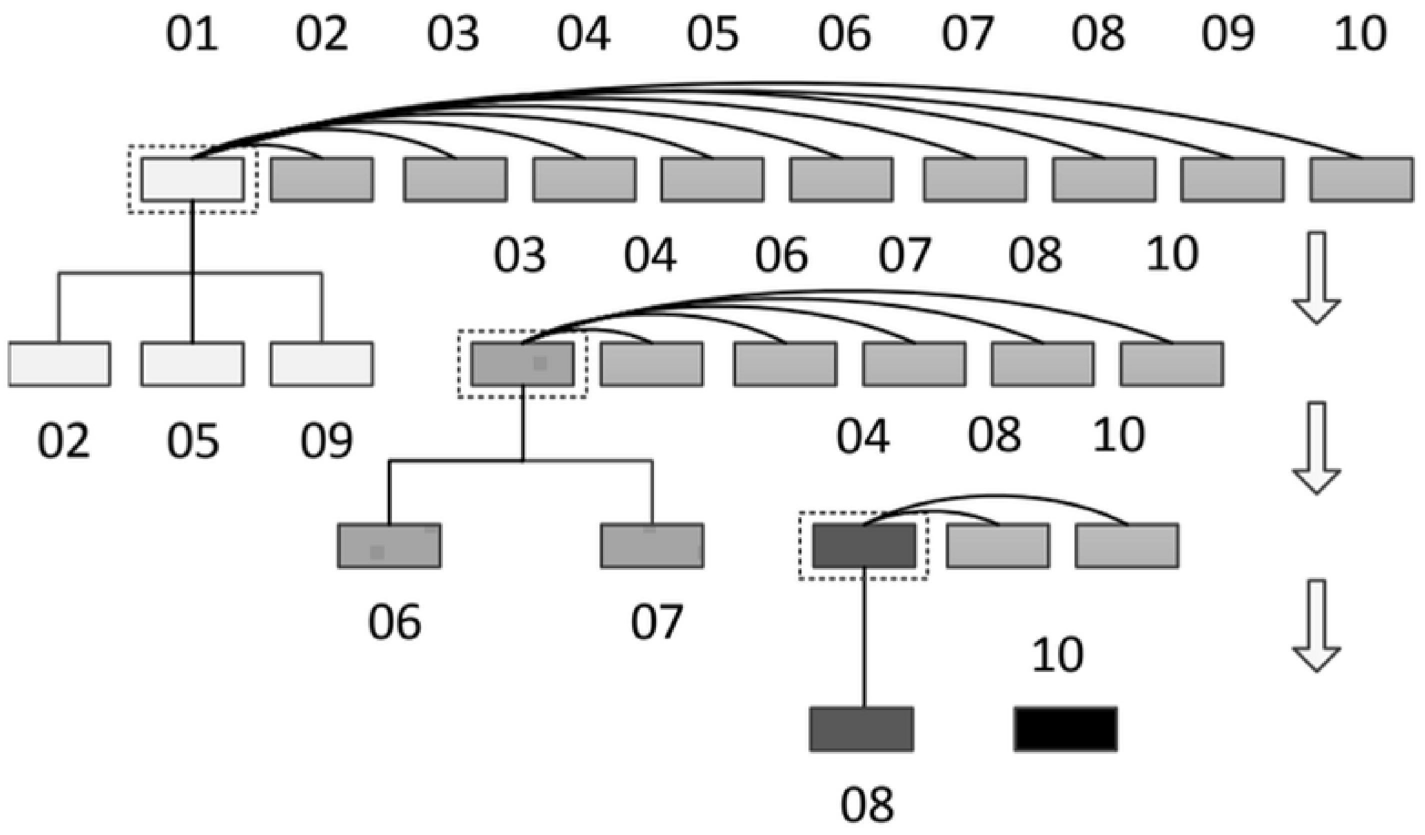


Figure 11.
Sketch of clustering procedure

IMPLEMENTATION & EVALUATION

A) Hardware Methodology

- A prototype was built using commercial radio frequency identification devices
- ImpinJ reader R420 & Yeon antenna model YAP-100CP act as receivers to activate the passive tag and collect information

B) Software Methodology

- Lowest level is data acquisition module integrated with the Octane SDK, which continuously queried neighboring tags to capture phase reads
- The query rate is about 340 per sec, ➡ tag reads are grouped by tag ID and stored in a local DB
- he initial data processing module takes the phase data and feeds it to the popular category discovery module
- After discovering, Detects behavior on tag

➡ Clusters the hot items to find related items

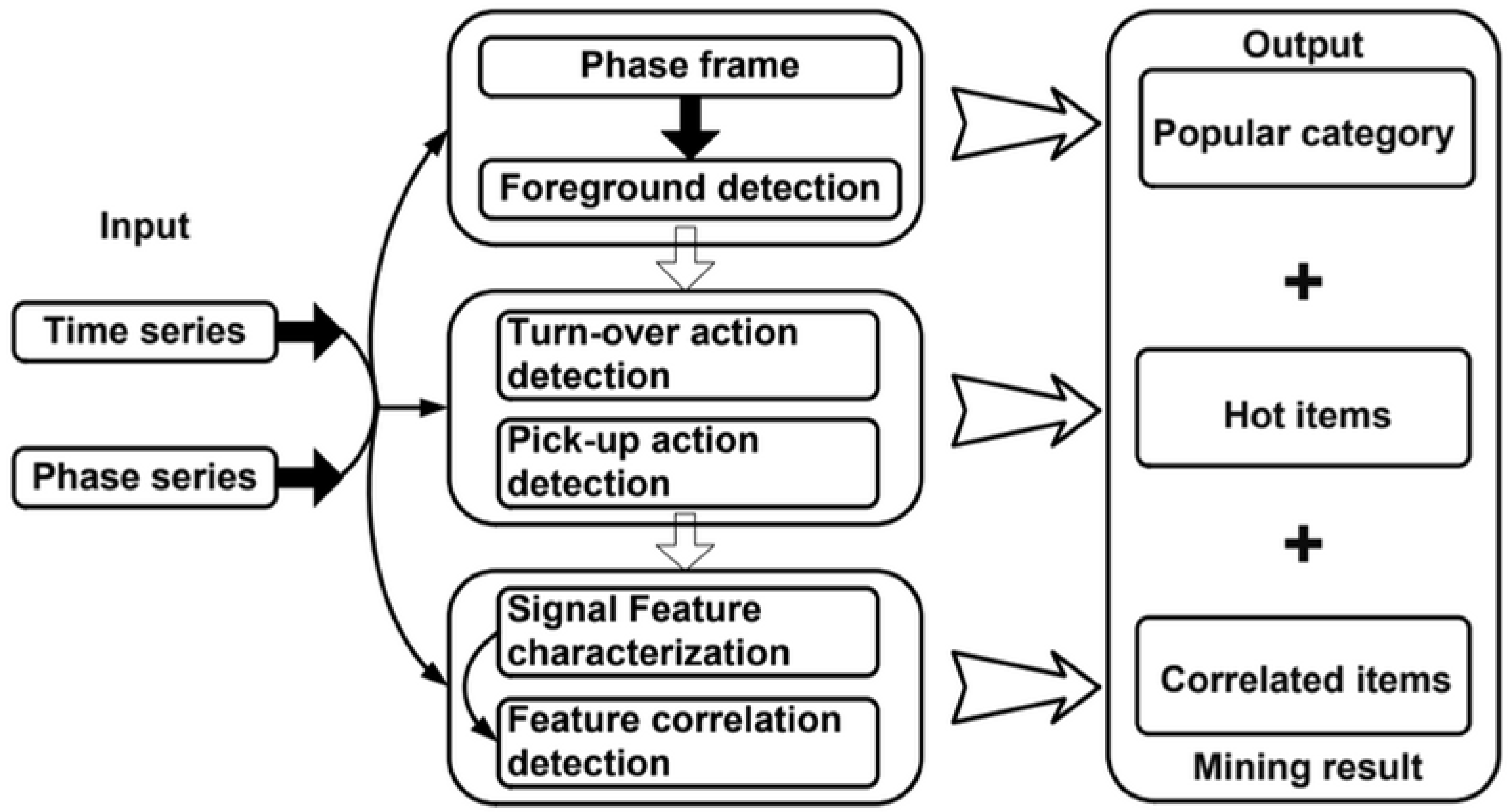
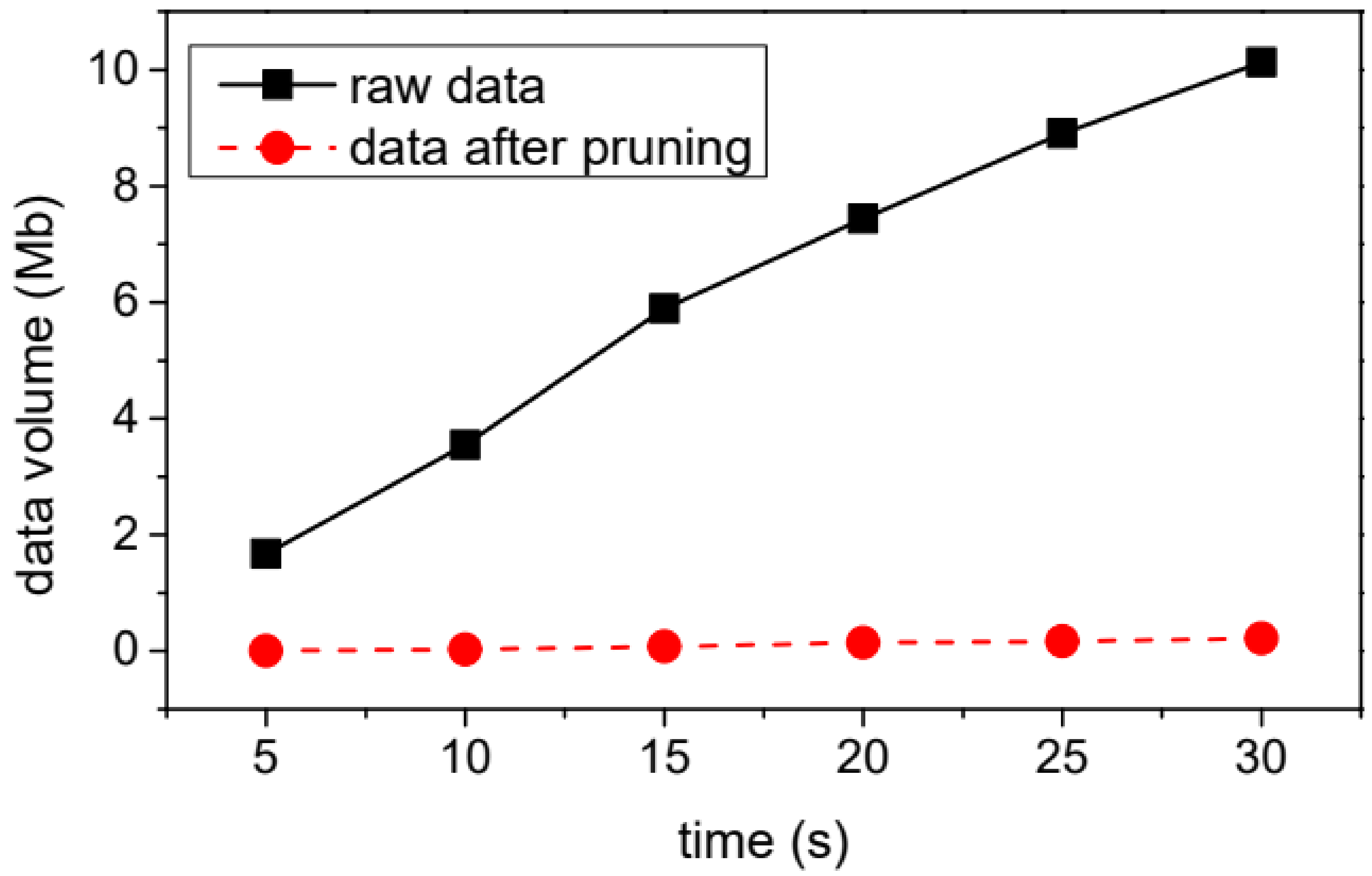


Figure 12.
Workflow of ShopMiner

Deployment Issue & Data Storage

- ShopMiner acquires data by having the RFID reader periodically query the tags
- Observe that the amount of data grows linearly with time, rapidly increasing to more than 10 Mb after 30 seconds
- To reduce this data storage burden ➡ Early Data Pruning Process



- Popular category exploration & hot item identification module are executed in real-time ➡ Only important items are considered, & Stored in the DB

- Sorage overhead is lower after applying the pruning process

Figure 13.
Snapshot of data storage in ShopMiner

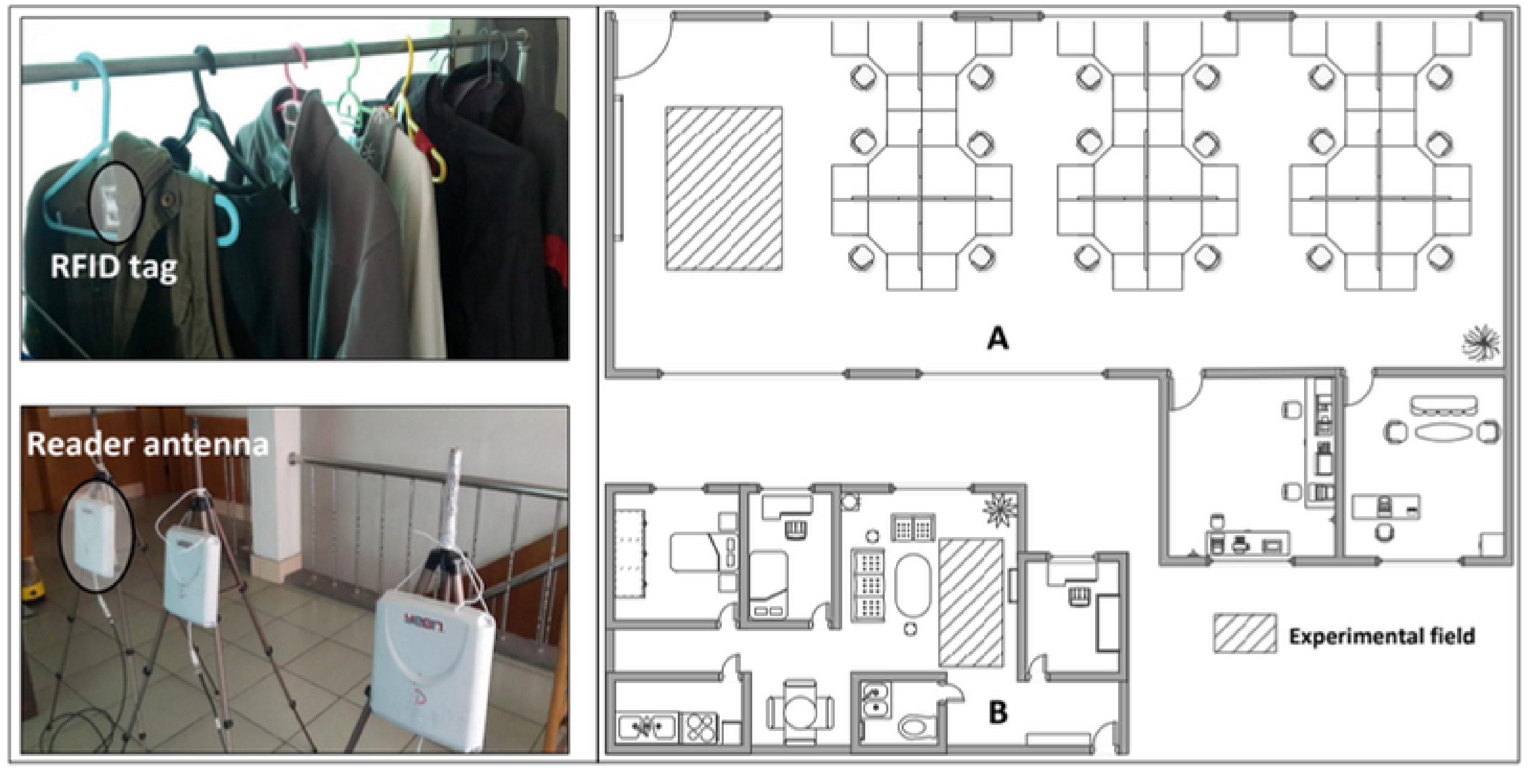
IMPLEMENTATION & EVALUATION

Evaluating ShopMiner's Performance

$$\begin{cases} H_0 : r_{i,j} \notin (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \\ H_1 : r_{i,j} \in (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \end{cases}$$

Expression 0.
Foreground & Background Hypothesis Test

Figure 15.
Illustration of testing scenarios



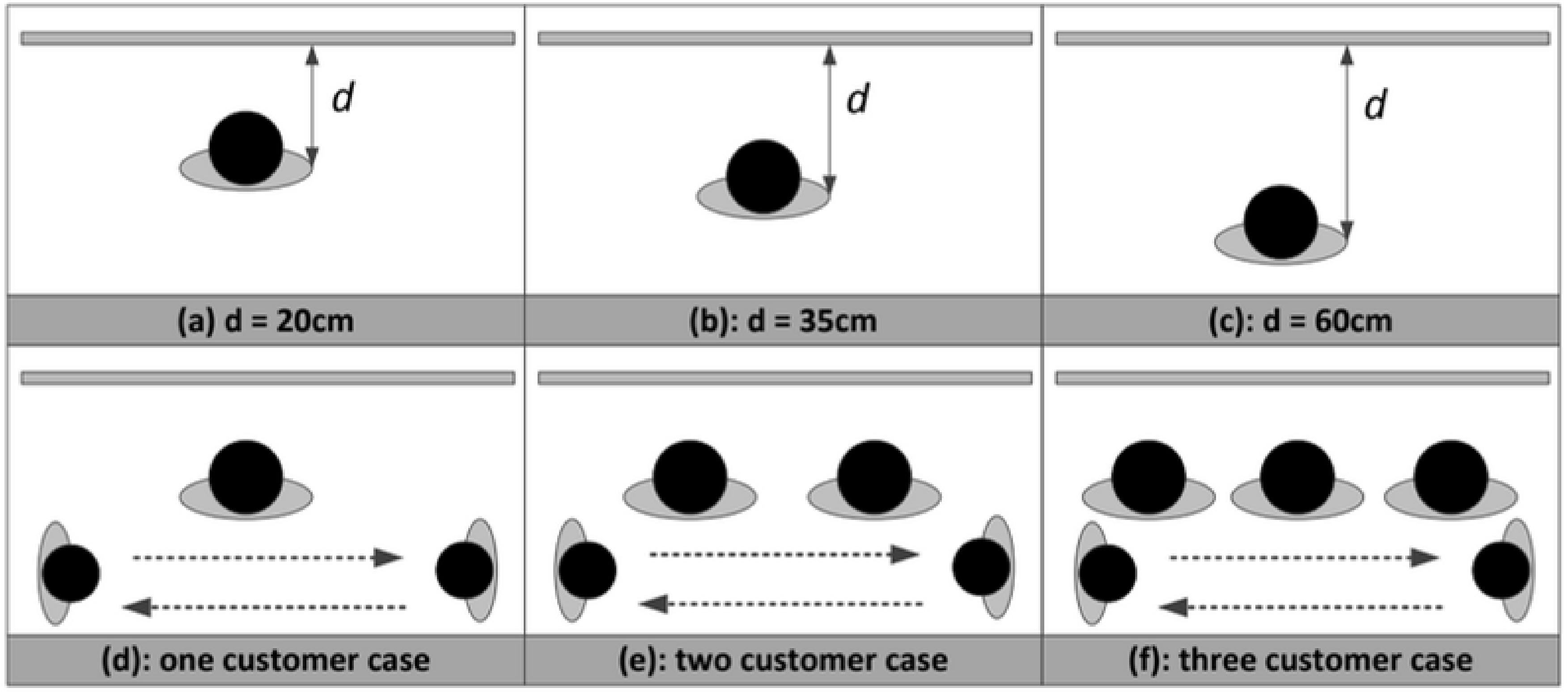


Figure 14.
Deployment of the prototype in the office/home environment

IMPLEMENTATION & EVALUATION

Evaluating ShopMiner's Performance

Figure 16.
Impact of confidence level

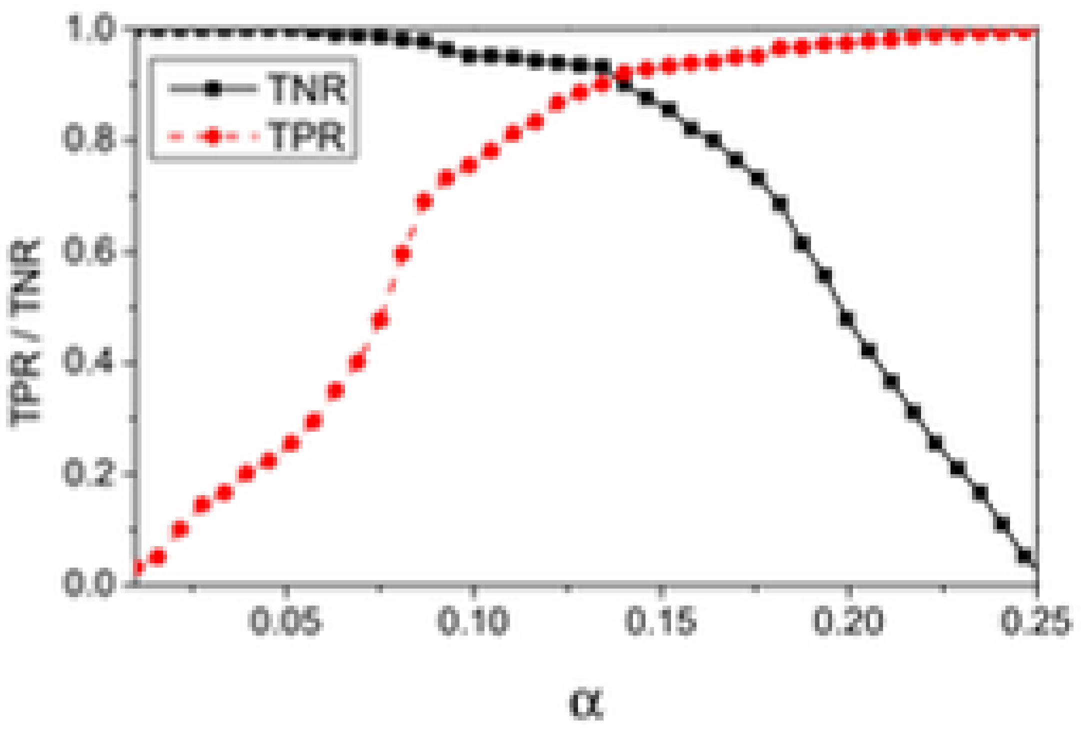


Figure 17.
Impact of threshold

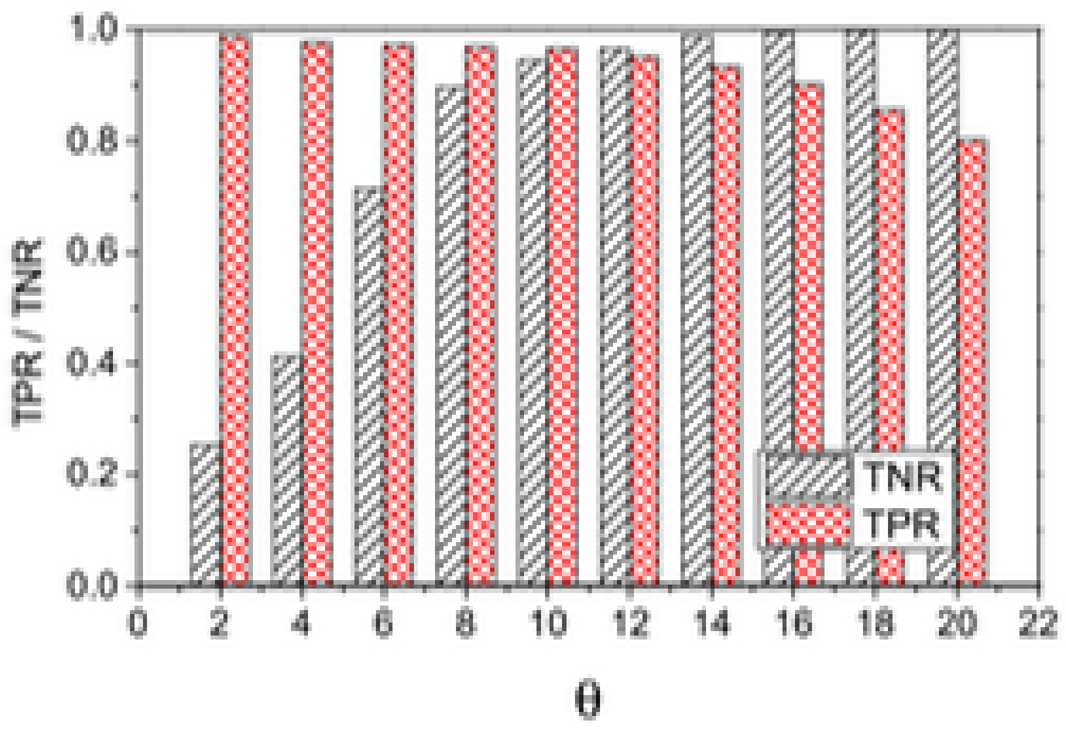
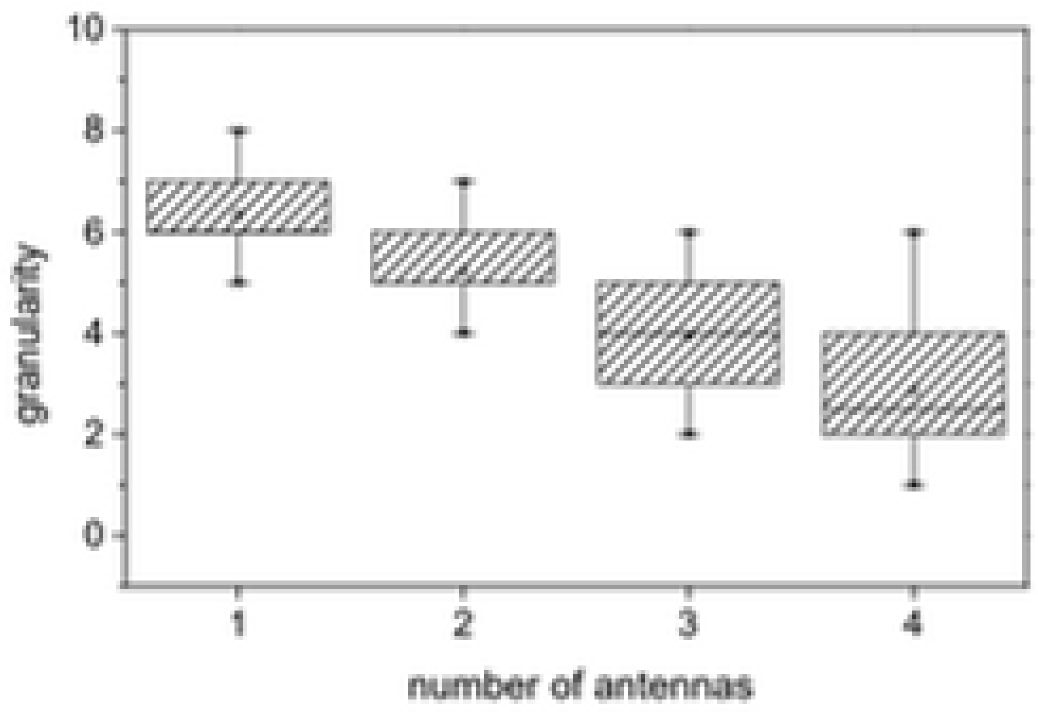


Figure 18.
Impact of different number of antennas



Expression 0.
Foreground & Background Hypothesis Test

$$\begin{cases} H_0 : r_{i,j} \notin (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \\ H_1 : r_{i,j} \in (\mu_i \pm \frac{\sigma_i}{\sqrt{k_i}} \cdot z_{\alpha/2}) \end{cases}$$

Expression 1.
Popular & Unpopular Category Hypothesis Test

$$\begin{cases} H_0 : s_i \geq \theta \\ H_1 : s_i < \theta \end{cases}$$

IMPLEMENTATION & EVALUATION

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Figure 19.
Impact of item to customer distance

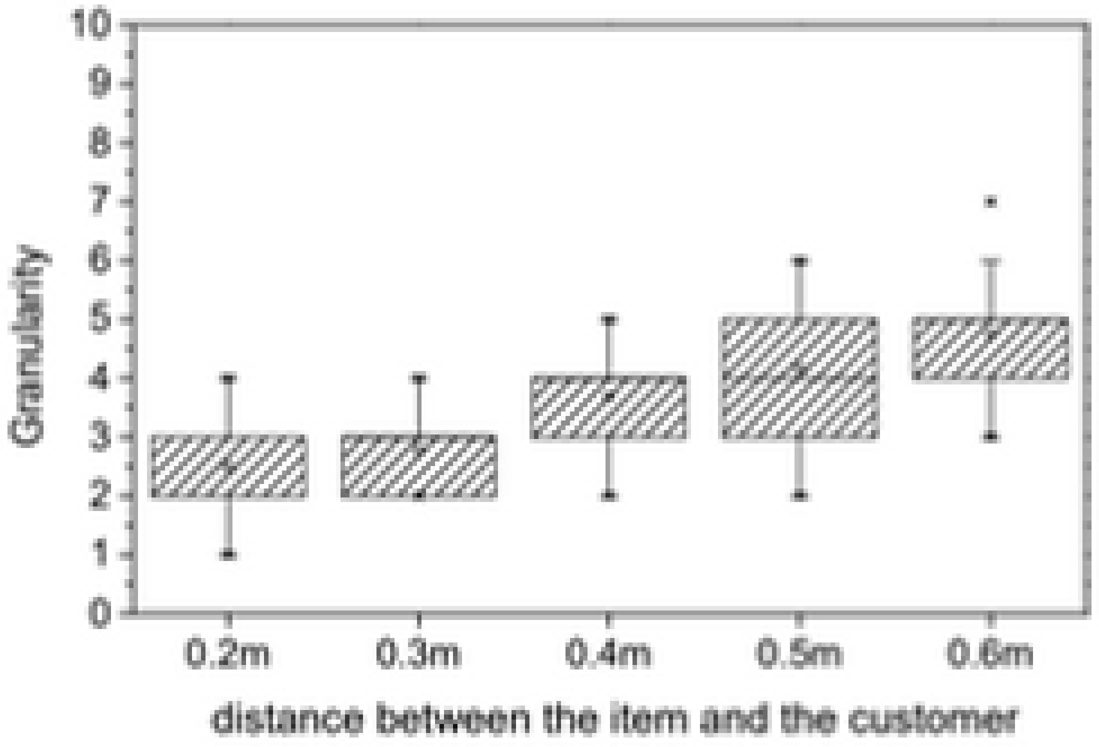


Figure 20.
Impact of multiple customers

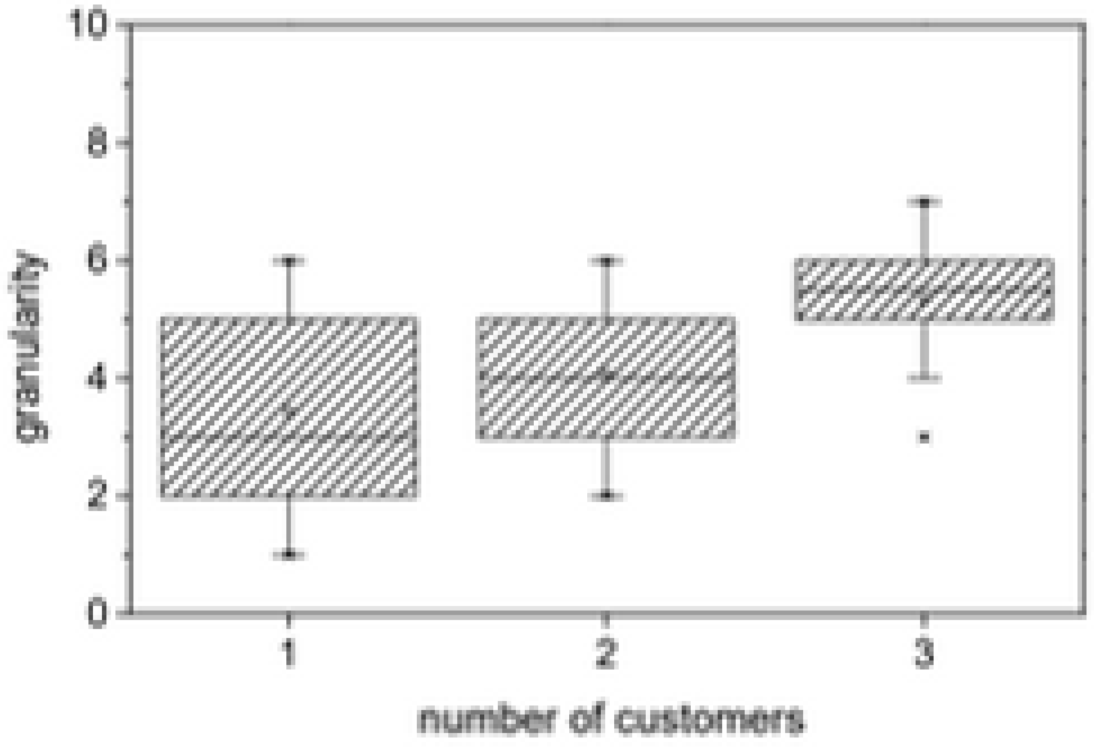
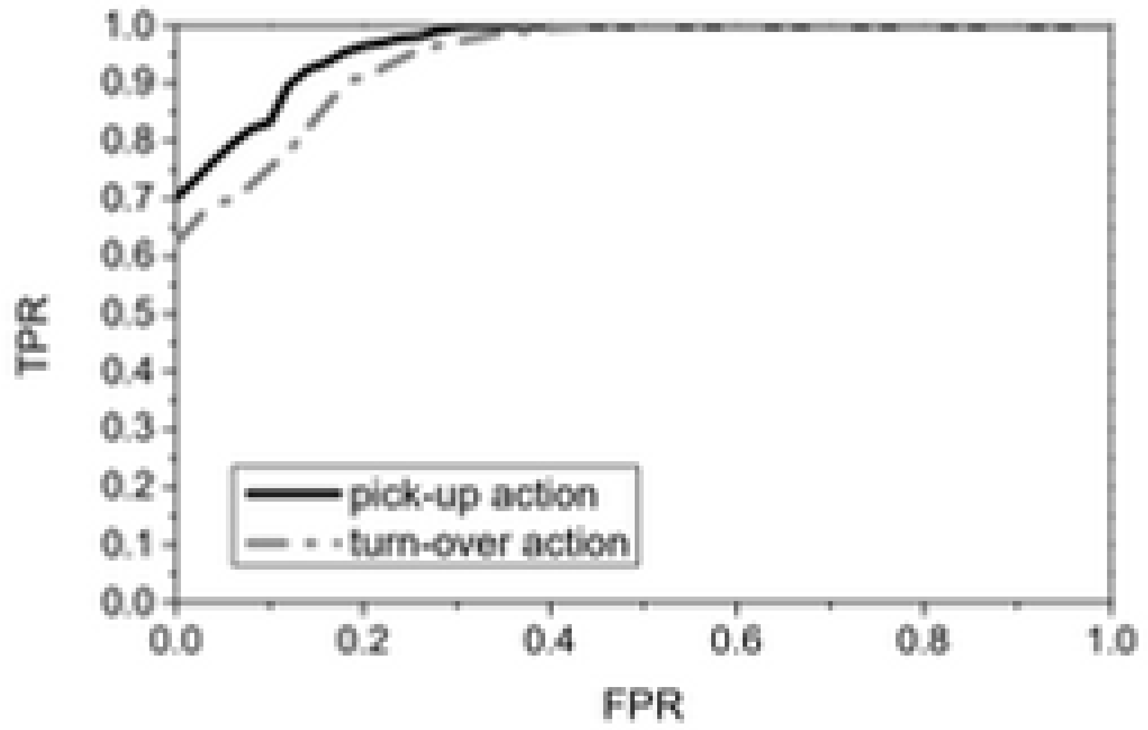


Figure 21.
ROC curve



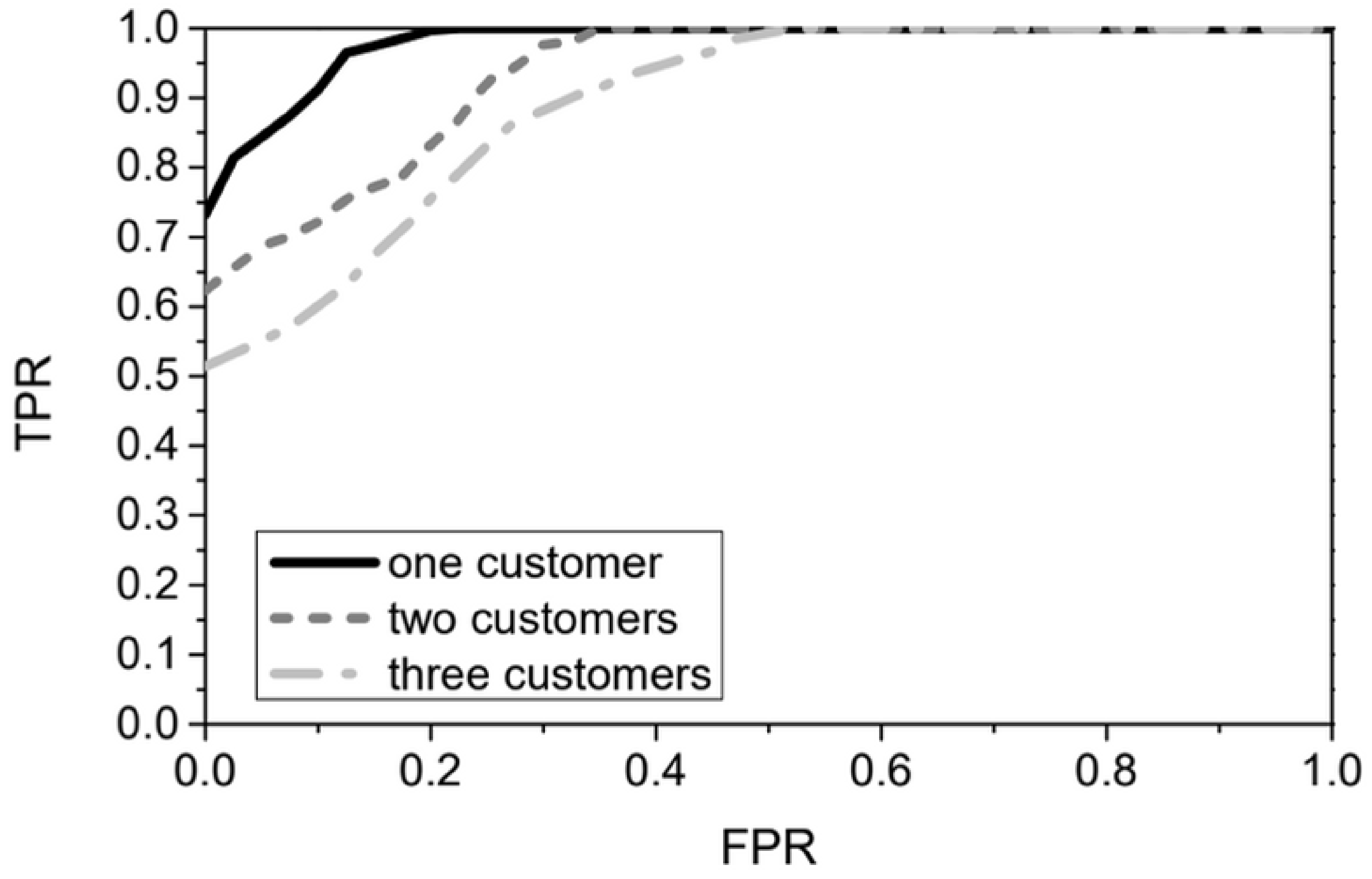
Ground-truth	Predicted	
	Turn over	Pick up
Turn over	187	13
Pick up	9	191

Figure 22.
Confusion matrix of action identification

- Detection precision decreases as the distance between the product and the customer increases

- As the number of customers increases decrease in detection precision due to the increasing LOS blocking

Evaluating ShopMiner's Performance



Ground-truth	Predicted					
	Turn over			Pick up		
	1	2	3	1	2	3
Turn over	187	184	178	13	16	22
Pick up	9	10	13	191	190	187

Figure 24.
Confusion matrix of action identification

Figure 23.
Impact of multiple customers

- Achieve an accuracy with an FPR of 13% when there is only one customer, but the accuracy tends to decrease as the number of customers increases
- Misclassification rises as the number of customers increases ➡ Multiple customers introduce a complex signal propagation environment and are expected to introduce phase disturbances to each item

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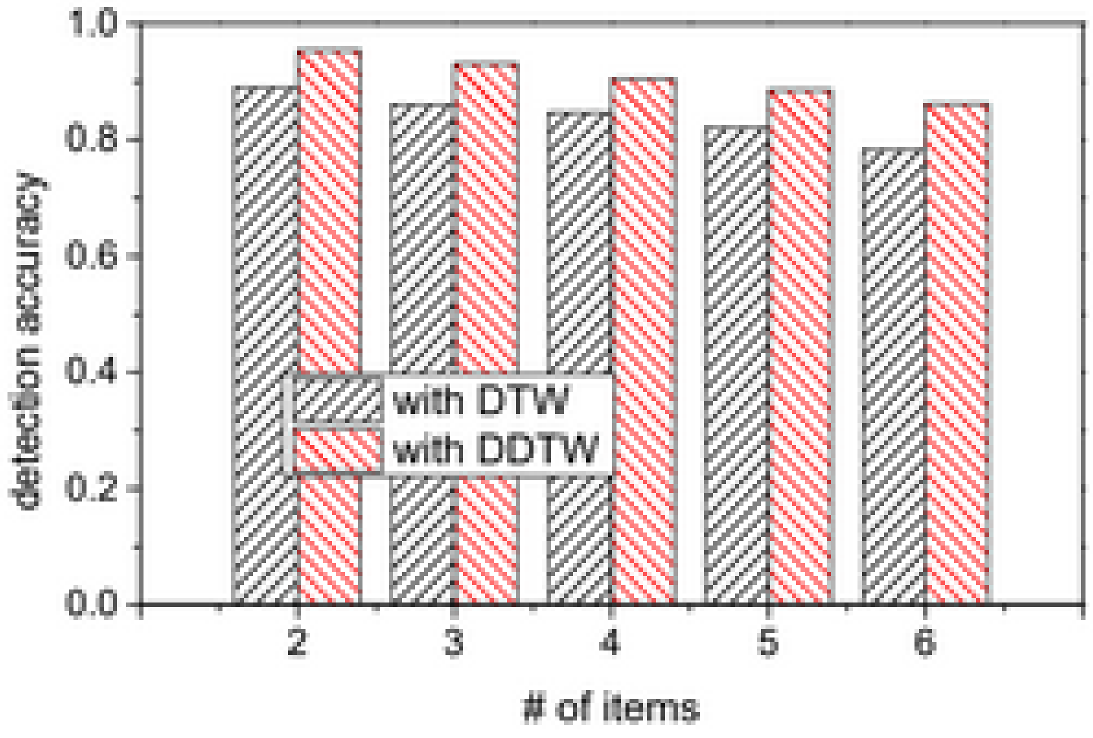
Figure 25.
# of items vs. detection accuracy



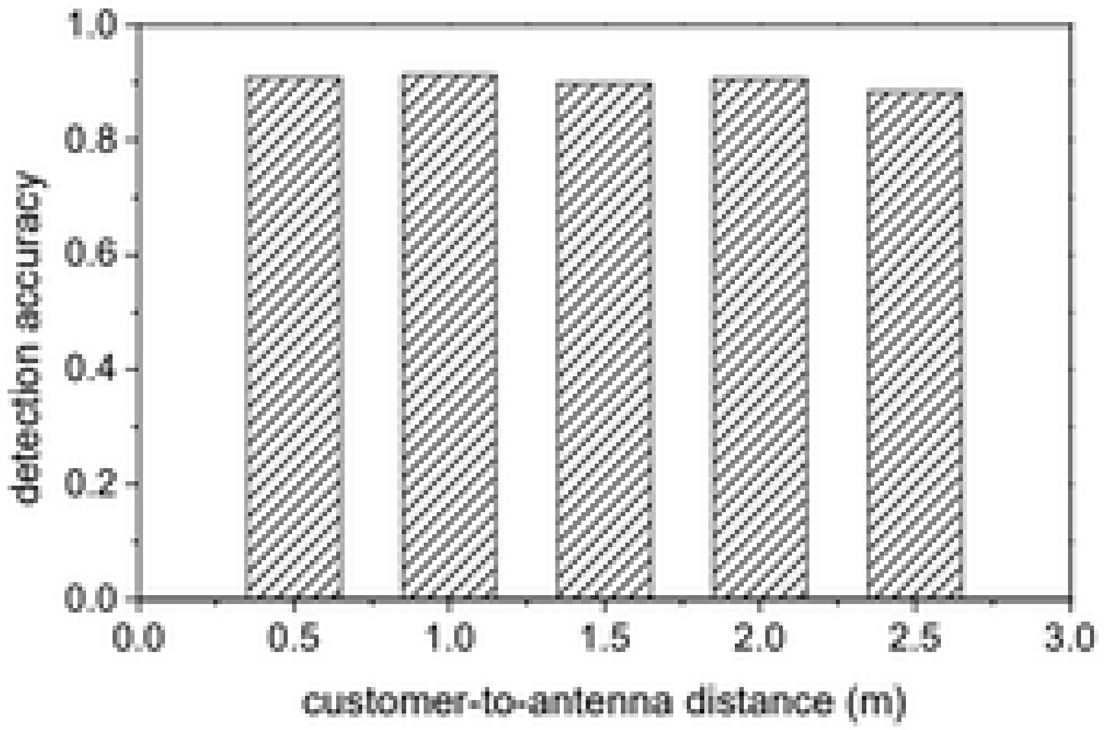
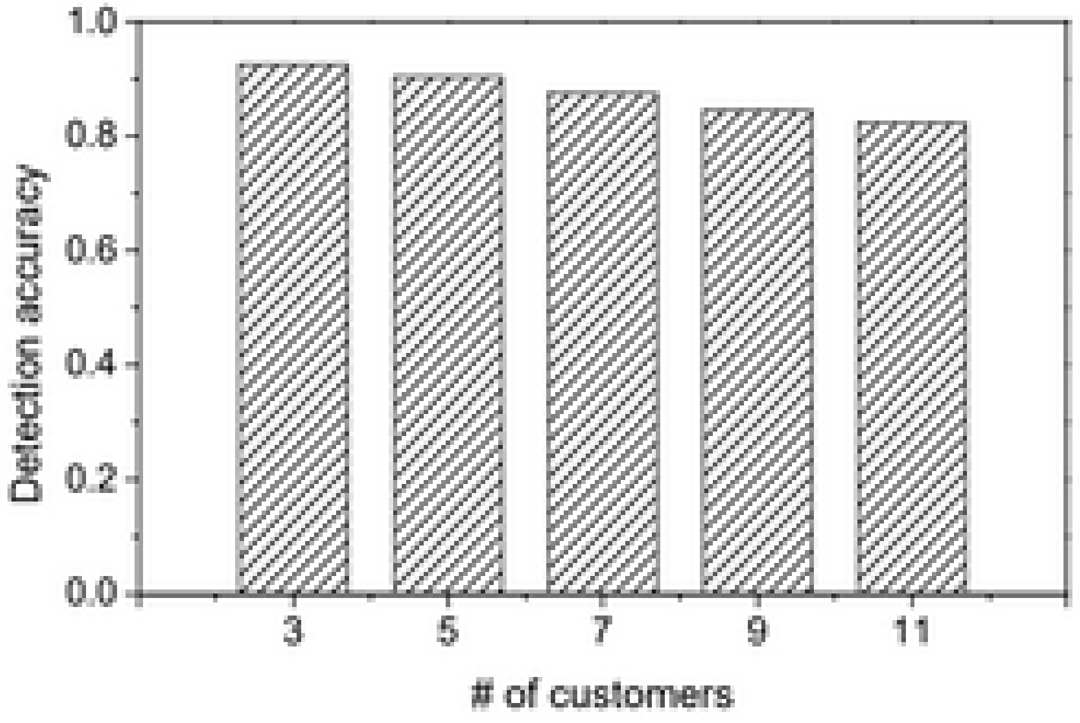


Figure 26.
Impact of customer-to-antenna distance

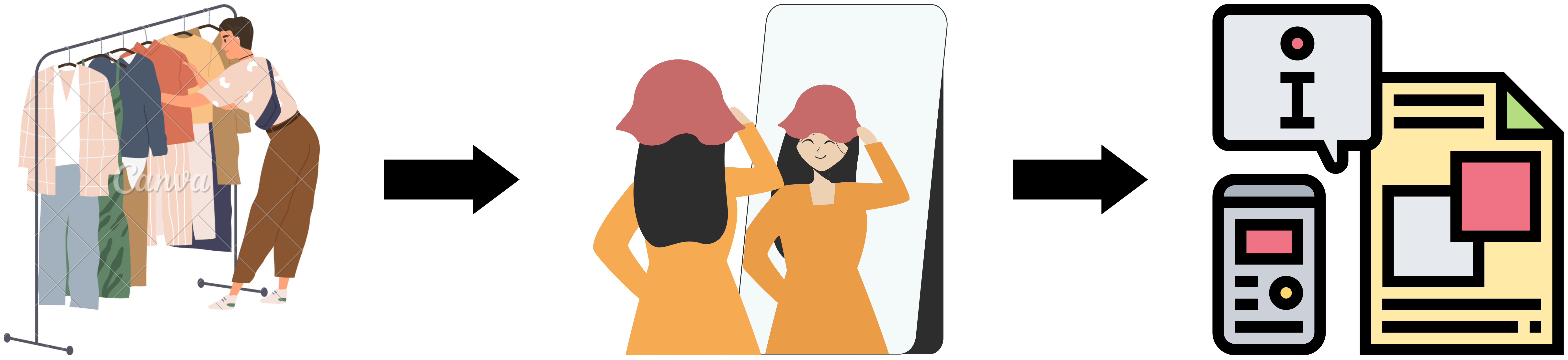
Figure 27.
Impact of customer populations



- Accuracy and the number of relevant items are inversely related
- Distance between the customer and the antenna has little impact on the accuracy
- The number of customers increases, the accuracy decreases

RELATED WORKS & CONCLUSIONS

- This thesis presented the design, implementation, and evaluation of ShopMiner, an RFID-based customer shopping behavior mining system that operates within a store
- By attaching RFID tags to each item of clothing, ShopMiner was able to "see" and detect how customers browse the store, which categories of items they are interested in, and which items they select
- This comprehensive shopping behavior data can help identify customer preferences, test new products, optimize commercial strategies, and more, and ShopMiner will be developed for widespread use in real-world applications



LESSON LEARNED

- Among the many sections, I found the section on **using the human shadowing effect as a measure of popularity** as the most interesting

- In the experiments in this paper, the measurement of phase values was a very important part of the process, and it was the key data for category determination

- In this situation, I would have thought that the human shadowing effect, which impedes communication by blocking the LOS link, is a distraction that needs to be eliminated

- However, the authors of this paper **took a different approach** and **used one of the characteristics of this effect**, large phase change, as a control to compare with other data

- The research direction of the authors of this paper made me think about what is meaningful and useful data, and what is the right way to treat information as a researcher
  ➡ Realized that **phenomena or data that seem useless from a one-dimensional perspective can be valuable** as a resource depending on how you look at them
  ➡ Furthermore, I learned that it is not only important to calculate information accurately, but **it is also very important to decide from which angle to look at the data obtained**

THANK YOU

Presentation by A Lim Han