Understanding Customer Malling Behavior in an Urban Shopping Mall using Smartphones

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Abstract

This paper presents a novel customer malling behavior modeling framework for an urban shopping mall. As an automated computing framework using smartphones, it is designed to provide comprehensive understanding of customer behavior. We prototype the framework in a real-world urban shopping mall. Development consists of three steps; customer data collection, customer trace extraction, and behavior model analysis. We extract customer traces from a collection of 701-hour sensor data from 195 in-situ customers who installed our logging application at Android Market. The practical behavior model is created from the real traces. It has a multi-level structure to provide the holistic understanding of customer behavior from physical movement to service semantics. As far as we know, it is the first work to understand complex customer malling behavior in offline shopping malls.

Author Keywords

Customer behavior, shopping mall, smartphone

ACM Classification Keywords

H.1.2. Models and Principles: User/Machine Systems – Human information processing

Introduction

An urban shopping mall can be considered as a reduced form of a modern city. It includes not only shopping stores but also various amenities necessary for urban lives such as restaurants, cafes, bookstores, hospitals, and theaters. For example, COEX Mall, one of the largest shopping complexes in Seoul, has about 320 stores including a big bookstore, an aquarium and a multiplex movie theater and attracts more than a hundred thousand customers a day. In such complicated environments, customers definitely show different and diverse malling behavior depending on their visit purpose, companion and time of day.

Understanding customer malling behavior will be the fundamental basis of progressive research on urban shopping malls. Basically, it could give an opportunity to emerging advanced services developed for urban shopping malls. For example,

- *Mobile advertising*: Advertisers can target potential customers based on their malling behavior, in terms of preference and timing, more delicately than location-based advertising [4] (e.g. sending McDonald's coupons to a teenager group when they are likely to have a break after hanging around for a while);
- *Social recommender*: Systems can recommend customers of similar behavior and locations of interest, as like previous work in urban areas [5, 12];
- *Business alliance*: Store owners can explore business strategies by finding supportive or rival stores based on collective customer behavior analysis; and
- *Space planning and management*: Mall managers can utilize the understanding of major customer flows for store relocation and facility management.

This paper proposes a novel computational framework developed to understand customers' malling behavior, named *MallingSense*. The framework incorporates a comprehensive model of customer malling behavior. Based on the model, it is designed as an automated framework leveraging customers' smartphones. The benefit of the automated processing is obvious with respect to the scale and timeliness. Existing manual techniques utilized in marketing research, such as human shadowing of in-situ customers [7], could be used for customer behavior analysis, but they are so labor-intensive requiring huge cost that they cannot be performed frequently at a large scale. Our framework, instead, takes advantage of smartphone sensing capability for customer tracking and data collection.

As for a computation framework, the malling behavior of a customer is regarded and interpreted as a trace of her store visits. This is intuitive because customers usually hop across stores and enjoy services provided by individual stores while they are hanging around in shopping malls. From the store visit trace, we create the multi-level structure of customer malling behavior model as shown in Figure 1. In each level, the model characterizes the different features of customer malling behavior as follows.

- **Activity level**: we categorize the service semantics of diverse stores into six customer activities, i.e., shopping, eating, resting, seeing, reading, and playing. Then, we investigate the impact of service semantics on customer behavior by understanding the dynamics of customer activity transition.
- **Store category level**: we explore the effect of customer preference on the behavior, especially on store category selection, since customers often select

different store categories based on their taste while pursuing an activity.

- **Movement level**: we examine the intra- and inter-store movement of customers in terms of time duration and the degree of movement.

This paper presents the prototype of MallingSense developed for a real-world shopping mall, i.e., COEX Mall. Development consists of three steps; *customer data collection*, *customer trace extraction*, and *behavior model analysis*. First, raw data of smartphone sensors are collected from a number of in-situ customers in the mall. Then, customer store visit traces are carefully extracted from the sensor data. Finally, the meaningful features of customer malling behavior are extracted from the traces in each level of the behavior model.

The contribution of this paper is threefold: (1) it is the first work to model customer malling behavior computationally as a trace of store visits and develop an automated analysis framework based on the model, (2) we collect a large volume of sensor data of in-situ customers using their smartphones in an unsupervised manner. We identify and address practical issues that probably happen when collecting and processing such real-world data, and (3) the multi-level structure is proposed for comprehensive understanding of customer behavior, from physical movement to service semantics. In each level, we present interesting patterns happening practically in a shopping mall.

Related Work

Research in Offline Shopping Malls

Traditional marketing research has paid attention to shopping malls due to their business value. In many cases, they used videotape analysis at a few spots or human shadowing on a small number of customers to

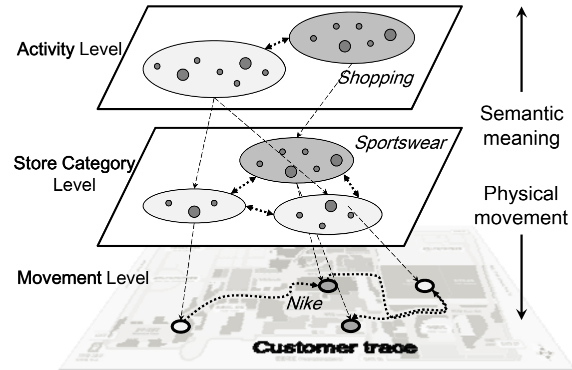

Figure 1. Multi-level structure of customer behavior model

study the customer behavior in offline shopping malls [7]. These manual techniques can provide more subtle and detail information about customer behavior. However, they are very labor-intensive requiring huge cost, so that they cannot be performed frequently in a large scale. It would be very challenging for academic researchers to collect large-scale customer trace data using such a method. Fortunately, the advance of ubicomp technologies enables automated customer monitoring via their smartphones. Our work can be considered as the initial step toward large-scale marketing analysis on the complex patterns of customer shopping behavior.

A few efforts in ubicomp research have been also made in offline shopping environments, which are categorized twofold: displaying customer activity levels on a map and tracking customer trajectories in shopping arcades. Kjeldskov et al. utilized Bluetooth to get the population density of multiple stores in a commercial square, and then transformed it into the level of social activities to display via mobile phones [8]. Meschtscherjakov et al. developed a prototype display that visualizes the transition of dynamic customer activity in a retail store on a map [9]. On the other hand, Rai et al. proposed a video-based solution for tracking customer shopping carts in retail shopping malls [10]. Leveraging video cameras attached in the malls, they focused on the cart recognition and identification accuracy. Kanda et al. developed a robot-based system that finds potential customers such as window shoppers by anticipating the customer trajectory [11]. All these have attempted to apply ubicomp technologies to better understand offline shopping environments and customer behavior. Our work is basically along the same line but significantly extends the scope in that we aim to understand customer behavior across *multiple* stores and amenities.

Customer Trace Extraction Techniques

The algorithm used for customer trace extraction is related to existing ubicomp techniques regarding meaningful place detection and indoor localization. Over the years, several techniques for discovering meaningful places have been invented for outdoor as well as indoor situations [2, 12, 13]. Recently, Kim et al. proposed a RF-based solution applicable to indoor situations [2, 3]. They examined the stability of periodically observed radio beacons such as Wi-Fi access points. Initially, we have tried using the technique, but found that, with a large portion of participants' smartphones, no Wi-Fi scan data were logged for several minutes occasionally, and no access points were visible in a couple of places. Moreover, the technique often works poorly in some areas where many small stores are located densely, since it was not designed basically to distinguish such fine-grained places. So, we need to come up with a practical algorithm which is carefully adjusted to be robust against those problematic cases.

Customer Trace Extraction

Our practical algorithm for extracting customer traces from raw sensor data is designed using a stay point detection algorithm proposed in GeoLife [12], which can deal with inconsistent Wi-Fi scan reports well. Also, we adjust the Wi-Fi fingerprinting method and the similarity formula to achieve the best performance in a given shopping mall environment.

The algorithm is comprised of three steps; *stay detection*, *store recognition*, and *post-processing*.

- **RF- and Movement-aware Stay Detection:** A stay in shopping malls is a probable indicator of a store visit or a rest on hallway benches. For stay detection, we adapt an algorithm which identifies spatial regions where a user spent a period exceeding a certain threshold [12]. It uses GPS coordinates to compute physical distance, but GPS is not available indoors. Instead, we devise the concept of *logical distance* between two time points, which is measured by RF state difference and physical movement for in-between duration. In practice, radio signal strength and acceleration values can be fluctuating and chaotic occasionally. So we utilize both measures together to make it more robust. We use the cosine similarity of Wi-Fi fingerprints as the measure of RF state difference and the standard deviation of acceleration magnitudes as the measure of physical movement.
- **Wi-Fi-based Store Recognition:** For each stay, we recognize the most probable store using Wi-Fi fingerprint-based localization, which is widely used for indoor localization [1, 3]. We compute the average Wi-Fi fingerprint of a stay and select the store whose reference fingerprint is the most similar to the average fingerprint. We collected the Wi-Fi fingerprint reference database for all 324 stores in COEX Mall. We also have

additional 64 places in hallways, especially near benches. Large stores such as a bookstore and family restaurants have multiple reference values.

- **Post-processing:** To compensate inherent errors in stay detection and store recognition, we apply two post-processing techniques. First, we merge consecutive stays of the same store. This reduces *divided* errors where a single store visit is detected as two or more visits; it sometimes occurs when customers wander near the edge of the store or sit on a chair adjacent to the hallway. Second, we validate the recognized store by checking the entrance time and the duration; we test if the visit time is outside the opening hours of the store or the duration is less than minimum meaningful duration, e.g. 3 minutes for retail shops and 20 minutes for fine dining restaurants. If it is invalidated, we select the next probable store.

To adjust and evaluate the performance of our extraction algorithm, we prepare a customer data set of 12 users with store visit ground truth. It shows fairly good precision and recall performance: 78.2% and 82.4% respectively. We also compute them by weighting visit duration, and get better performance: 86.3% and 89.2% respectively. Higher recall values indicate that the algorithm extracts most of *actual* visits well. The better performance of duration-weighted result shows that most of long visits are retrieved well and errors are mainly caused for short visits.

Real-World Data Collection

To collect customer data in COEX Mall, we use unobtrusive sensors such as Wi-Fi, accelerometer and compass, since they are regarded to well capture customer behavior in indoor situations and not to interrupt the natural behavior. Table 1 shows the data size and sensor parameters of the data sets. As shown in the table, we collect two types of customer data practically; *tracked* and *blind* data sets.

	Dataset		Tracked	Blind
Size	# of participants		12	183
	Date (DD/MM/YY)		11/06/11 ~ 03/09/11	27/10/11~21/03/12
	Age	Teenager	0	14
		Early 20's	10	81
		Late 20's	2	64
		30's	0	21
		Over 40's	0	3
	Gender(F/M)		7/5	98/85
	# of used traces		12	120
	Trace hours (total/avg/stdev)		46.5/3.9/0.9	431.9/3.6/1.1
	# of store visits		90	548 (estimated)
	# of unique store visits		51	156 (estimated)
Setting	Accelerometer (Hz)		FASTEST (24.3)	NORMAL (3.8)
	Compass (Hz)		FASTEST (15.5)	N/A
	Wi-Fi scanning interval		Every 10 seconds	Every 10 seconds
	Camera		Every 10 seconds	N/A

Table 1. Characteristics of collected data sets

- The *tracked* data set with ground truth information as like Figure 2(a) is utilized to develop and fine-tune the trace extraction algorithm. We recruited 12 users via the bulletin board of a university campus. We provided them with two Nexus One phones; one for recording sensor data and another for ground truth as shown in Figure 2(b). They were required to stay in the mall for at least 3 hours and visit more than 4 stores.
- The *blind* data set is used to build the customer behavior model. It contains sensor data only and customer traces are extracted by our extraction algorithm. It is contributed by a large number of real customers who installed our sensor application and visited the mall autonomously. They were only required to provide simple information; phone number, age, gender, visit purpose, and the number of companions. We texted an electronic movie ticket as incentive.

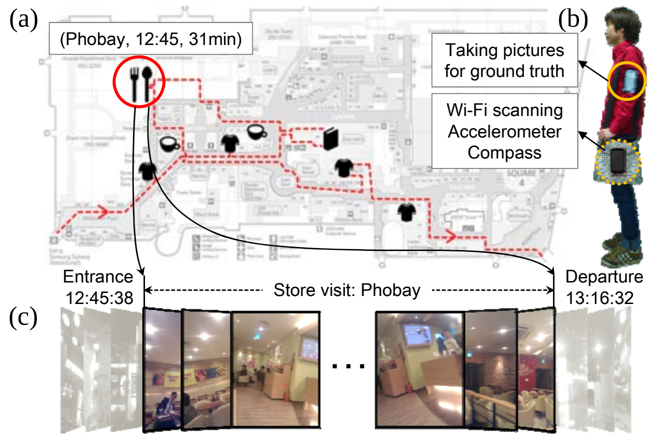

Figure 2. Data collection at COEX Mall: (a) ground truth trace, (b) phone position, and (c) ground truth tagging tool

Collecting the ground truth traces was a challenging task, since we do not want to miss any details of movement such as when, and how long they visit which stores. Also, we do not want to interrupt customer's natural behavior. Our solution is to use one more smartphone attached to users' upper arm and takes pictures of surround scenery periodically. This approach rarely interrupts their behavior and it provides accurate and detail information on their movement. Concerning the energy consumption, we set the resolution to 384×512 pixels and the shooting interval to 10 seconds. Then, we manually tagged the ground truth traces as shown in Figure 2(c).

Customer Behavior Model Analysis

This section describes the customer behavior model extracted from real customer traces with respect to COEX Mall. Table 2 shows the malling activity and store category classifications in the mall.

Activity	Store Category	Code	Sample Store	# of Store	
Shopping	Fashion Outlet	A1	Mille21, department store	5	138
	Clothes	A2	Bean pole, Uniqlo	48	
	Sportswear	A3	Nike, Adidas	10	
	Accessory	A4	Accessorize, Samsonite	31	
	Cosmetics	A5	Skinfood, The Face Shop	13	
	Electronics	A6	a#, Linko, Sony, Samsung	13	
	Stationery/souvenir	A7	Artbox, HummingJ	18	
Eating	Fast food	B1	McDonald, Burger King	4	94
	Food court	B2	Food court	1	
	Casual dining	B3	Korean, Chinese, Italian	82	
	Fine dining	B4	TGI, TODAI, UNO	7	
Resting	Coffee	C1	Startbucks, Caffe bene	19	67
	Dessert	C2	BR31, Smoothie King	13	
	Bakery	C3	Paris Baguette	6	
	Hallway	C4	Hallway(bench)	29	
Seeing	Cinema	D1	Megabox	1	2
	Aquarium	D2	COEX aquarium	1	
Reading	Bookstore	E1	Bandi&Luni's	1	1
Playing	Fun	F1	Game, karaoke	3	11
	Beauty care	F2	Hair salon, nail shop	8	
Misc.	Misc.	X	Medical, bank	40	40
Total				353	

Table 2. Activity, store category, and store in COEX Mall

Service Semantics – Activity Level

In the activity level, we investigate the dynamics of activity transition which gives a strong hint about why customers are moving in urban shopping malls. We have approached this question in two perspectives; the correlation between adjacent activities, and the influence of the time of day [6].

Table 3 shows the activity transition probability of real-world customers, i.e., the conditional probability of specific next activities from current activities. Basically, most customers go to shopping stores often, and more likely when they visited another shopping store before. Customers who have been involved in reading, seeing and playing activities seem more likely to go resting to take a break.

Figure 3 shows the activity probability over the time of day in our collected customer traces. Whereas the shopping, seeing and resting activities seem to be performed quite uniformly over time, the eating activity shows the peaks at lunch and dinner times as expected. The probability of the eating activity between lunch and dinner times is slightly higher than we expected, because customers sometimes go to fast food and food court for resting with some beverage or chatting with friends while sitting on the benches they provide. If we filter out such visits from eating, the peaks in lunch and dinner times become more remarkable.

Customer Preference – Store Category Level

In this level, we inspect the patterns of store category selection when customers do an activity, which are often determined by customer preference. We compare the store category patterns for customer groups of different demographics and visit purposes. We also present the association analysis results between store categories, similar to the market basket analysis widely used in marketing research [14].

Figure 4 presents store category probability distribution for shopping, eating and resting activities. Firstly, it shows the distribution of overall customers; on average, they often go to stationery/souvenir (A7) and clothes (A2) category for shopping, fast food (B2) and casual dining (B3) for eating, and hallway bench (C4) and coffee (C1) for resting. We focus on some groups of customers whose visit purpose is dating and killing time or customers who are teenagers and late 20's. The teenager group shows quite different distribution. They visited fashion outlet (A1), food court (B2) and bakery (C3) more likely. The figure also conforms to some general expectations. Customers for dating went for

Current	Next Activity					
Activity	Shopping	Eating	Resting	Seeing	Reading	Playing
Shopping	0.55	0.14	0.15	0.07	0.07	0.00
Eating	0.38	0.01	0.21	0.30	0.09	0.00
Resting	0.31	0.15	0.19	0.17	0.12	0.01
Seeing	0.35	0.19	0.31	0.00	0.08	0.06
Reading	0.36	0.26	0.31	0.08	0.00	0.00
Playing	0.00	0.17	0.50	0.17	0.17	0.00

Table 3. Activity transition table

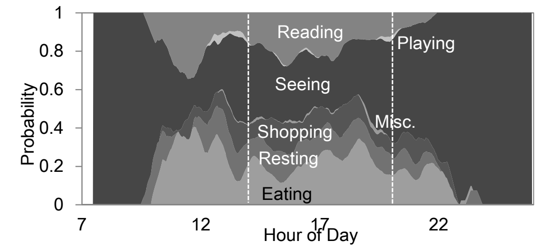

Figure 3. Activity probability over time of day

fine dining (B4) more likely, but customers for killing time never made such a choice. They are more likely to use hallway benches (C4) for resting.

To examine the association between store categories, we measure *lift* values. We only include store categories whose supply value is over 0.15, i.e., visited by more than 20 out of 132 customers. The higher value indicates strong positive association between two store categories. Value 1.0 implies that they are independent of each other. Table 4 shows representative results. Stationary/souvenir category has strong association with fashion outlet, clothes, and accessory, as expected generally. The association between food court and cosmetics seems the special case of COEX Mall; many of the cosmetics stores are located near the food court in the mall. Such positive associations can be utilized by store owners to explore business strategies and promote their stores. On the

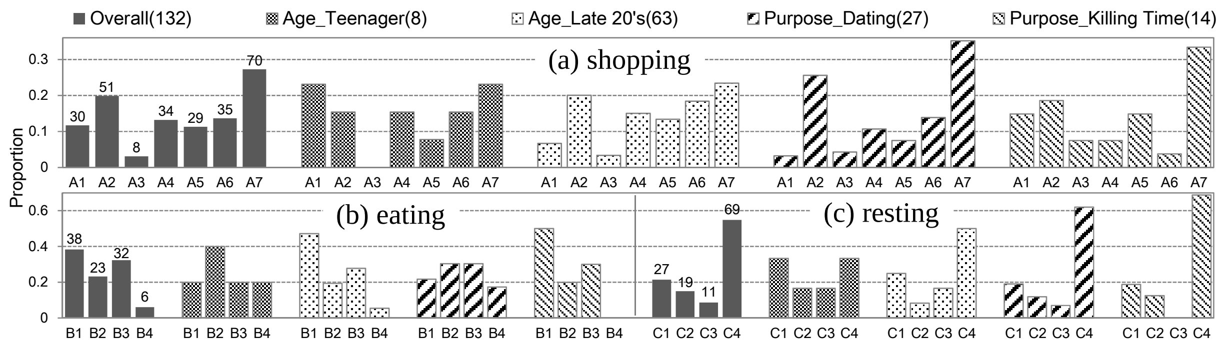

Figure 4. Store category probability per activity

Positive			Independent			Negative		
Category A	Category B	Lift(A, B)	Category A	Category B	Lift(A, B)	Category A	Category B	Lift(A, B)
Cosmetics	Food court	2.10	Bookstore	Fashion Outlet	1.05	Fast food	Cosmetics	0.45
Stationery/souvenir	Fashion Outlet	1.84	Electronics	Cosmetics	1.02	Casual dining	Food court	0.42
Stationery/souvenir	Clothes	1.77	Cinema	Accessory	0.95	Coffee	Fast food	0.40
Accessory	Fashion Outlet	1.69	Stationery/souvenir	Bookstore	0.94	Casual dining	Fast food	0.36
Electronics	Coffee	1.63	Fast food	Electronics	0.92	Clothes	Food court	0.20
Stationery/souvenir	Accessory	1.61	Electronics	Bookstore	0.92	Fashion Outlet	Food court	0.00

Table 4. Store category association (lift)

other hand, store categories in the eating activity show negative associations with each other as expected, since they are in the rival relation. Unexpectedly, the coffee and fast food pair also shows negative association. This might be because fast food restaurants sell beverages these days.

Physical Movement – Movement Level

In this level, we examine the physical characteristics of the intra- and inter-store movement. First, we figure out the temporal characteristics of the movement; the distribution of visit duration (intra-store) and moving time (inter-store). Then, we present the degree of movement from the acceleration data, while visiting the stores and moving around the hallways.

Figure 5 shows the overall distribution of visit duration and moving time. The duration represents how long customers are staying in stores and the moving time indicates how long it takes to walk to next stores from previous ones. As expected, customers spend much more time for visiting than moving. Store visit duration has a long tail due to some stores where customers sit long usually such as cinema and fine dining restaurants.

We break down the visit duration distribution to investigate different patterns by activity. Figure 6 shows that shopping has the shortest visit duration on average, while seeing is the longest due to cinema. Note that the distribution of seeing is separated into two groups clearly. The long visits are surely for

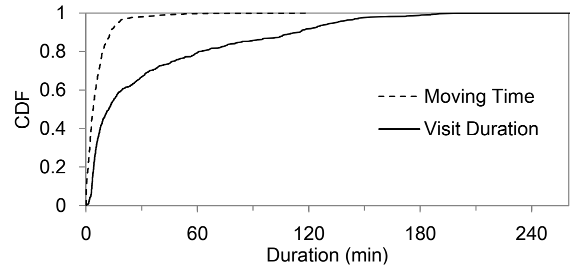

Figure 5. CDF of visit duration(stay) and moving time(walk)

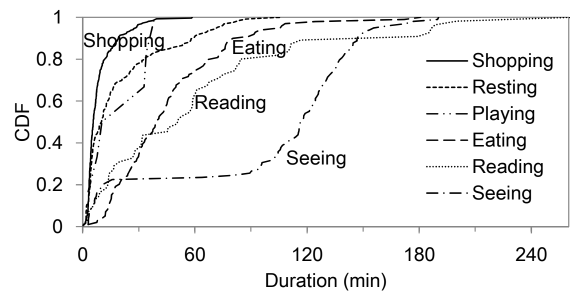

Figure 6. CDF of visit duration (stay) per activity

watching a movie in the theater, while the short visits seem for ticketing at the box office.

We also break down the distribution of moving time by activity. See Figure 7 for the results. As compared to the other distributions, that of eating is slightly shifted toward the right hand side, meaning that customers walk longer when they are looking for a place to eat. There may be some tendency on the mobility involvement of customers when they pursue different types of activities. Interestingly, the moving time distribution of the seeing activity is similar to that of others. Since there is only one place in the mall, it is supposed to take more time to arrive. This might be because customers wanting to see a move stay around intentionally near the movie theater.

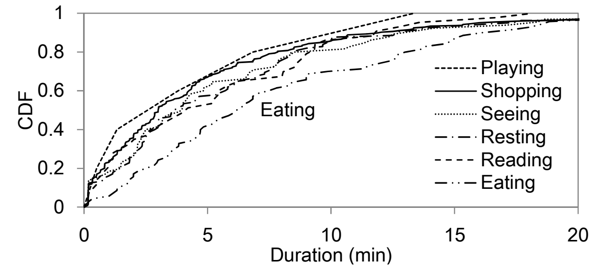

Figure 7. CDF of moving time (walk) per activity

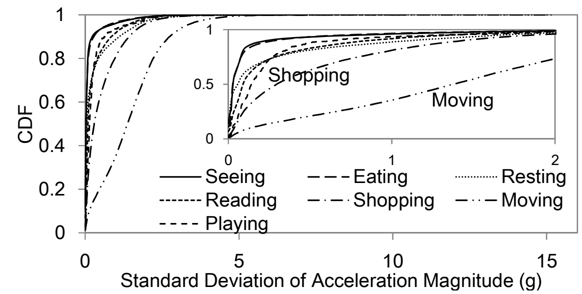

Figure 8. CDF of standard deviation of magnitude

We also investigate the degree of intra-store movement per activity. The customer movement is usually influenced by service semantics of a store [1]. We measure the degree of movement using the standard deviation of acceleration magnitudes; high deviation represents the high degree of movement. Figure 8 shows the CDF of the standard deviation. As expected, customers hardly move while doing seeing and eating activities, whereas they browse in the stores of the shopping activity. However, the higher degree of movement is clearly shown while they are moving in hallways. Such difference can be further utilized to allow the store recognition to distinguish better among adjacent stores and hallways.

Conclusion and Future Work

This paper presents MallingSense, a novel computational framework for customer malling behavior understanding. The automated analysis framework that utilizes customers' smartphones helps us understand the characteristics of customer behavior and provides the fundamental basis of future customer applications. We prototyped the framework in a real-world shopping mall. This work can be considered as the first step toward large-scale customer analysis in offline shopping environments. We believe that the proposed framework will be very useful for research on urban shopping malls and further city-wide areas. In future work, we intend to continuously gather sensor data from more customers and investigate dynamic changes in the behavior over time. Another direction would be to develop several advanced shopping mall services on top of the proposed framework.

Acknowledgements

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