Wi-Fi Human Behavior Analysis and BLE Tag Localization: A Case Study at an Underground Shopping Mall

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ABSTRACT

Techniques for obtaining customers' behavior (dwell time, count, and flow) in a shopping mall or large exhibit are highly sought-after by organizers or shop owners. Additionally, ways of effectively directing customers from cyber space such as the Web or smartphone apps to physical retail stores are also in high demand. "Online to Offline (O2O) Marketing" has recently been attracting attention to make these a reality. However, the know-how accumulated through "O2O Marketing" is not shared widely as it can be sensitive for business and customer's privacy. In this paper, we provide the knowledge obtained through the demonstration experiments held by the "O2O Digital Marketing Study Group" organized by NPO Lisra at a large underground shopping mall in Nagoya. 250 BLE tags and 12 Wi-Fi scanners were installed in this mall. We also organized a "coupon campaign" to increase the number of participants. We were able to effectively collect visiting customer count measurements via Wi-Fi scanners irrespective of the anonymization of BSSID, as our results showed similar trends collected by optical human detectors inherently installed at the venue. This paper provides preliminary insight into understanding the behaviors of retail shoppers and we believe this is a firm starting point for this area.

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CCS Concepts

• Information systems→Mobile information processing systems • Human-centered computing→Empirical studies in collaborative and social computing.

Keywords

Wi-Fi Localization, O2O Marketing, Indoor Localization, BLE tag, Human Behavior Analysis

1. INTRODUCTION

"O2O Marketing" has been attracting attention in its attempts to urge customers to actually visit retail stores using the information in cyber space. Based on the attribute information of customers, "O2O Marketing" attempts to prompt specific customers to visit retail stores. In recent years, with the development of indoor positioning technology that use Wi-Fi or BLE tags, it is becoming possible to obtain the behavior of the customers in the vicinity of the stores. By taking advantage of the results of the analysis of customers' behavior, more effective measures can be implemented. However, the know-how involved in "O2O Marketing" has not been shared widely, since it is directly linked to business, and contains sensitive personal information. In particular, even though all kinds of attempts for testing such new technology as indoor positioning are being made, no methods of application nor results have been published.

In September 2015, collaborating with about 20 companies in the private sector, we organized the "O2O Digital Marketing Study Group"(O2OMK) within NPO Lisra (Location Information Research Agency), for the purpose of dealing with this problem. By bringing together the technologies and knowledge that are the strong points of each member company, this Study Group aimed to share the knowledge about O2O Marketing through demonstration experiments.

The purpose of this paper is to share the knowledge obtained in the demonstration experiments of O2OMK at the underground shopping mall of Nagoya (with 100 stores, covering an area of 10,000 square meters) where 250 BLE Beacon tags have been installed. In particular, we describe the results of analyzing the behavior of the people by scanning Wi-Fi signals of Wi-Fi enabled terminals in the mall and location information of customers who have installed our smartphone app that incorporates a position estimation scheme based on BLE.

The contributions of this paper are mainly summed up in the two aspects given below: The first contribution is to confirm the fact that the count of the visiting customers by the Wi-Fi scanners in the actual environment, showed trends similar to the optical human detectors irrespective of the anonymization of BSSID. The second contribution is the experience behind developing the mechanism for obtaining the history of customer behavior that is linked to the customers' attribute information through smartphone apps. We estimated users' position indoors by using the BLE Beacon tags on both Android and iOS versions of our app.

2. RELATED WORK

There are several papers that report demonstration experiments using Wi-Fi Localization or Human Behavior analysis.

Meneses[1] had a large scale movement analysis for about 6,000 clients using Wi-Fi based location data. However, they used "Eduroam" Wi-Fi network mainly deployed in their universities and they only used "connected log". So they had no problem with "Anonymized BSSID". Musa[2] tried to monitor unmodified smartphone using Wi-Fi and obtain more than 60,000 MAC/BSSID addresses. They used "AP Emulation" and "RTS injection" technique to increase the number of transmission from each smartphone. They also reported the existence of "Unlisted OUI" of MAC addresses. However, they just excluded these MAC addresses from their report.

Poter[3] provides a real-time arterial travel time estimates using Bluetooth devices. They deployed Data Collection Unit (DCU) at road-side. By using two DCUs, they can calculate the travel time of the certain area. They also discuss about privacy issues on the data collection. Jard[4] reported the difference of Bluetooth based scanner with Wi-Fi based one. They reported that for the road-traffic monitoring, Bluetooth is better than Wi-Fi at the time and location.

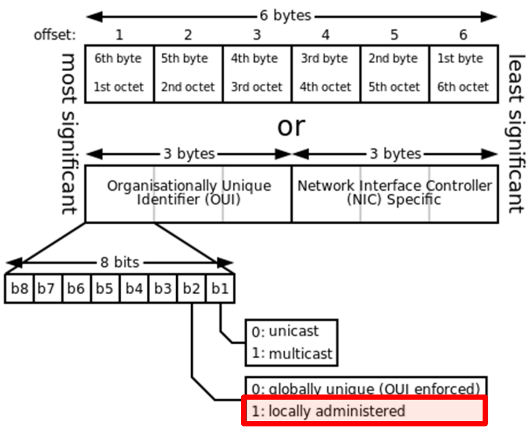

Figure 1. Locally Administered Bit of OUI (figure from Wikipedia:MAC address)

Figure 2. DF.sensor (WiFi / BLE Scanner)

Fukuzaki[5] reported the pedestrian flow analysis from Wi-Fi packet in the real environment. They developed Anonymous MAC Address Probe Sensor(AMP sensor) to collect MAC Addresses and anonymize it. They did a demonstration experiment using 6 AMP sensors. They also report in [6] a statistical analysis of Wi-Fi Packet-based pedestrian flow sensing using comparison with movement sensors. By calculating the factor of the Wi-Fi usage from the real number of the passengers, they estimate the actual number of pedestrians at the error rate of less than 7.9%.

3. BEHAVIOR ANALYSIS USING Wi-Fi

Currently, the mainstream of Wi-Fi based indoor positioning technology is the method using the strength of the electromagnetic waves of the Beacon Packets, sent by Wi-Fi Access Points. However, this method requires the customers to install a specific app, so the coverage rate of actual customers becomes an issue.

In this paper, we used Wi-Fi probe packets sent by the customers' terminals. Due to the fact that the signal intervals of the probe packet differ (from 30sec to 500sec), depending on the OS or the setting of the terminals, one has to remain in the same location for some time in order to observe a packet. However, if we are able to collect data on a certain number of people, the difference in the signal intervals of the terminals will appear as trends based on probability and the number of signals received. As a result, it will be proportional to the number of actual people at that location.

iOS9 and Windows10 anonymize BSSIDs in the probe packets. In the IEEE802.11 specifications, BSSID/MAC address is "locally administered" if the 2nd bit of the 1st octet is set (Figure 1.). We considered the BSSID to be anonymized if this bit is set. If the BSSID of a terminal is anonymized, it is possible to evade "stealth marketing" that can potentially be linked to personal information and buying behavior detection even as the customers are unaware. However, Vanhoef[8] revealed it is not enough.

On the other hand, when the objective is to analyze the customers' behavior, there is the problem of not being able to obtain their path of movement, due to anonymization. When the objective is to count the number of people who are passing through a certain location, the number of people counted could be more than the actual number of the terminals. In this demonstration, we observed Wi-Fi probe packets to ascertain whether or not it was possible to grasp the trends of the number of people who are passing through, even if BSSID is anonymized.

Figure 2. shows our Wi-Fi Scanner called "DF.sensor" developed by Koozyt Inc. The name DF.sensor is taken from the words "Dwell and Flow". It is based on Raspberry Pi2 with a battery backup real time clock. So, even under conditions where there is no

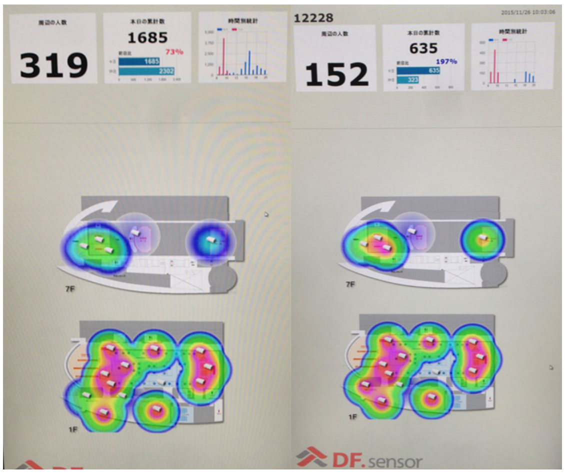

Figure 3. Sample Display of DF.sensor Information

network connectivity, the DF.sensor can collect Wi-Fi / BLE data with precise time information. It has a function to count the unique number, dwell time and flow of Wi-Fi/BLE terminals. Figure 3 shows sample display of DF.sensor information.

3.1 Experimental Field

We organized a demonstration experiment at the underground shopping mall "Central Park" in Nagoya, Japan. The mall has 100 shops and has an area of 10,250 square meters for shops, and 14,751 square meters for walkways. Figure 4 shows deployment location of DF.sensors in the shopping mall. We installed 12 DF.sensors all of them situated inside the shops(No.7 was not installed). Unfortunately, we could not obtain proper legal documents to install them in walkways and obtaining power was also an issue. Violet dots in Figure 4 depict BLE tags. We asked each shop for permission to install the DF.sensors and BLE tags. Each DF.sensor has a Wi-Fi connection to the Internet. Unfortunately, the connection was not stable, so we could not remotely monitor the sensors and continuously collect data over the period of the experiment. We salvaged what we could from the SD cards equipped in the sensors, and were able to collect most of the data. We collected the Wi-Fi data from February 16 to March 31, 2016.

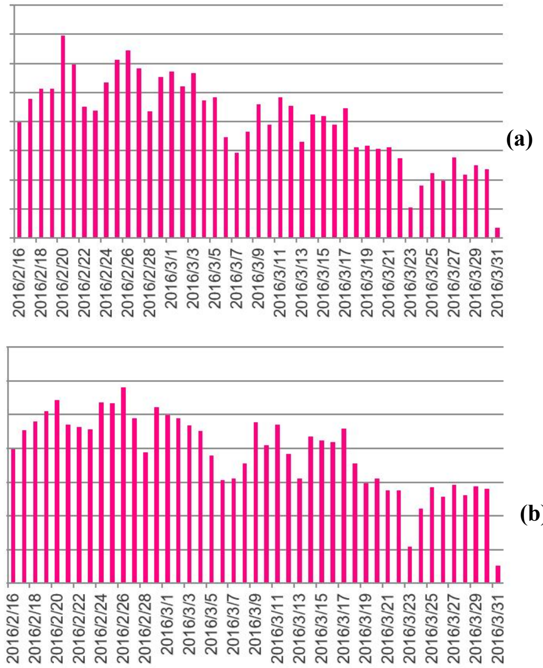

Figure 5. Relative Daily Unique Terminal Count

(a)non-anonymized (b)anonymized

During this time, we posted several posters announcing the Wi-Fi data collection experiment and contact information for any customer who wish to opt-out due to privacy concerns. The posters also provided notice about the privacy issues and anonymization of the BSSIDs collected by the DF.sensors. This kind of announcement and notice is necessary when conducting such experiments.

3.2 Experimental Result

Figure 5 shows relative unique terminal count of each day from the 12 DF.sensors. Due to business concerns, we are unable to show the absolute number of the terminal counts. However, it is enough to see the relative fluctuations of the terminal counts to understand

Figure 4. Deployment Location of DF.sensors at the Underground Shopping Mall

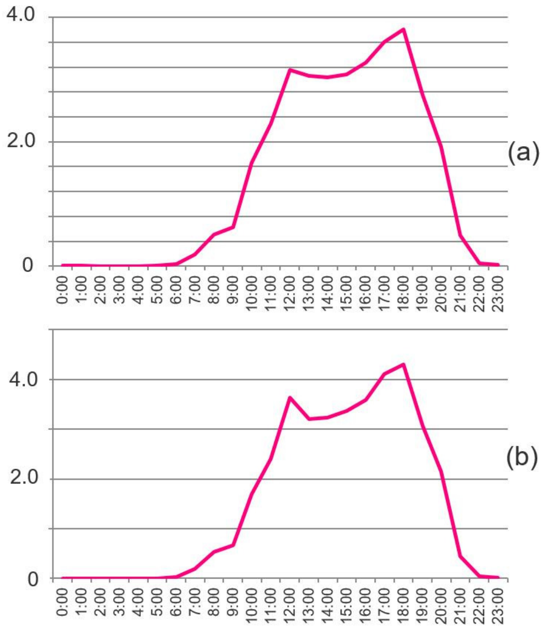

Figure 6. Hourly Relative Unique Terminal Count (a)non-anonymized (b)anonymized

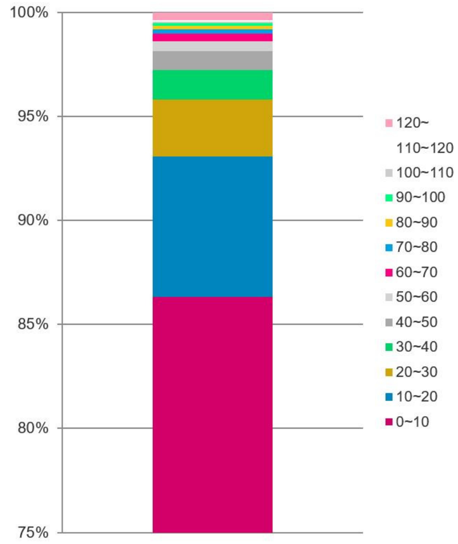

Figure 7. Total Dwell Time of each Unique Terminal

the human flow and behaviors (dividing factor is same across all relative count values). Also, there are some periods where the data is missing as we were unsuccessful in monitoring the sensors over the entire period of the experiment. Fig.5(a) shows non-anonymized count of terminals and Fig.5(b) shows anonymized terminal count. Over the period of 45 days, 36% of the count was from non-anonymized terminals and 64% from anonymized terminals. From the figure, even if the BSSIDs are anonymized, we can confirm that the proportion of the terminal count is relatively the same compared to the non-anonymized terminal count.

Figure 6 shows the hourly relative unique terminal count from all collected data with the Y-axis being the relative terminal count. Fig.6(a) shows non-anonymized count and (b) shows anonymized count. As can be observed from these two graphs the proportion of the count fluctuations are relatively similar. From these results, we can confirm that BSSID anonymization does not affect human behavior analysis via Wi-Fi scanners. From both figures, we can observe that people start moving about the mall starting at 6:00AM until 10:00PM, which is closing time. Also there are two peaks in the terminal count, one around 12:00PM and the other at around 6:00PM. Since the mall is close to the center of Nagoya, many office workers visit the mall for lunch. In the evening, they can be seen shopping after work or just walking through the mall. By using the Wi-Fi scanner scheme, we can observe these facts without asking customers to do anything, such as installing apps.

Figure 7 shows total dwell time of each unique terminal. Anonymized BSSID terminals are not included, as we cannot infer the dwell times of such terminals. The figure shows more than 85% of the terminals just stay less than 10 minutes. Sensor placement may be a reason for the low dwell time observation. For this period, we were limited to shops that would cooperate with this experiment. From the point of view of O2OMarketing, dwell time is very

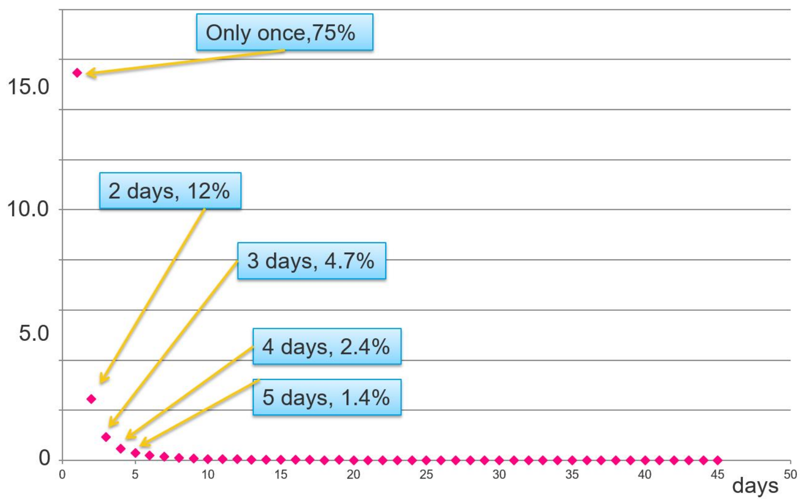

Figure 8. Number of Days each Unique Terminal Appeared

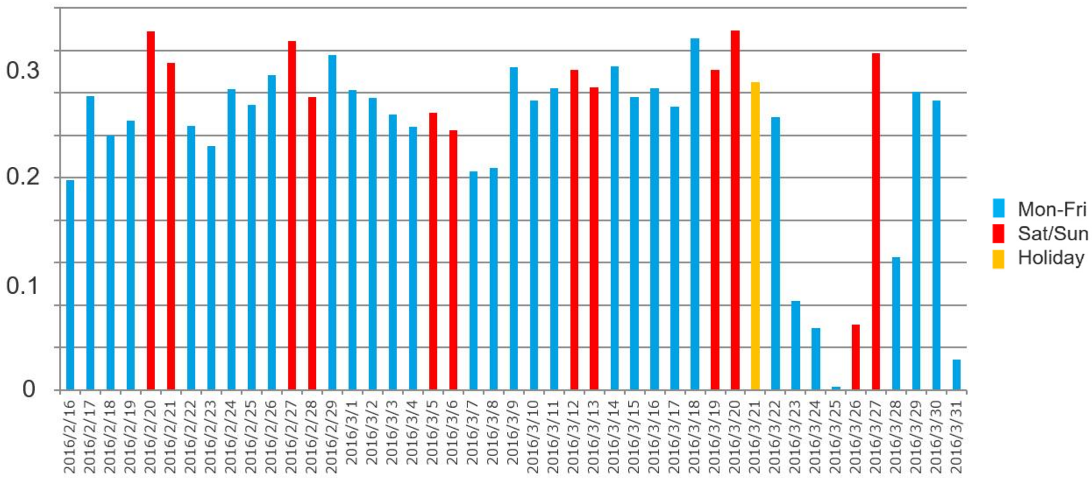

Figure 9. Relative Daily Unique Terminal Count from Single DF.sensor at Location 12

important. There might be a positive correlation between the shopping activity and dwell time.

Figure 8 shows a plot of repeat customers. The X-axis depicts of the number of days a terminal was observed at the mall. The Y-axis shows the relative number of the terminals for each day. This plot also excludes anonymized terminals. From the figure, we can see that 75% of the terminals just appeared only for a single day. 25% of the terminals appeared several times. However, we observed several terminals that appeared almost every day. Customers who work close to the mall may own these terminals.

Figure 9 shows the daily relative terminal count from a single DF.sensor at location 12 in Figure 5. Again, the Y-axis shows the relative terminal count. Around March 23~28, apparently there was a problem with data collection for this sensor as can be seen from the graph. From this figure, we see no particular weekday trends on the number of customers. For the weekends, it seems there are more customers on Saturday than Sunday.

In Figure 5, there is a decreasing trend in terminal count. However, from Figure 9, this trend cannot be seen, as we had a problem towards the end of our experiment. So, we can guess the decreasing trend in Figure 5 may have been caused by the failure of several sensors in the latter part of the experiment. Long-term stability and an effective mechanism and infrastructure to remotely manage and monitor the sensors are needed.

Figure 10 shows hourly relative terminal counts from a single DF.sensor at location 12. The terminal counts plotted for each hour are averaged over the duration from Feb. 22 to Mar.13. Fig.10(a)(c) depict plots for weekdays, and (b)(d) depict plots for weekends. Also Fig.10(a)(b) count only non-anonymized MAC terminals, and (c)(d) depict only anonymized terminals. From this figure, we can infer the different trends of customers on weekdays and weekends.

For weekdays, we already mentioned from Figure 6, that there are two peaks. One peak is seen at around 12:00PM and another at 6:00PM. On weekends, there is only single peak at 4:00PM.

Figure 10. Time-dependent Relative Number of Terminals from single DF.sensor at location 12

(a)Weekday, non-anonymized, (b) Weekend, non-anonymized (c) Weekday, anonymized, (d)Weekend, anonymized

Location 12 is an optician's shop, so there is no peak observed at lunchtime.

Anonymized terminals represented 64% of the data collected during the entire experiment, but at the location 12, the number of anonymized terminals are less than non-anonymized terminals. We have yet been able to confirm the reason behind this result. However, the proportions of the terminal count graphs are almost the same between anonymized and non-anonymized terminals, whether it is weekday or weekend. Thus we conclude that Wi-Fi scanners can reveal some trends in customer behavior even if the BSSID is anonymized in probe requests.

3.3 Comparison with Human Detectors

In our experimental field, the mall owner had already installed 6 optical human detectors at various places in walkways of the mall. By comparing the detection count form these detectors; we can confirm the usefulness of our Wi-Fi scanner scheme. Also, we may gain some insight regarding the ratio of the real customer count and Wi-Fi observed count.

Figure 11. Daily Relative Terminal Counts from DF.sensor and Human Detector

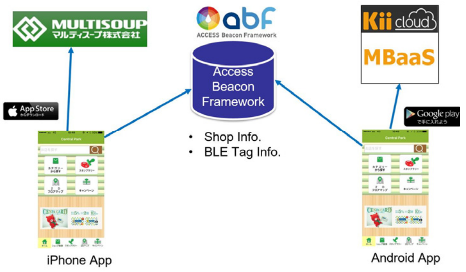

Figure 12. Configuration of Coupon Campaign System.

Figure 13. Steps involved in the Coupon Campaign

In Figure 11, we show plots of three different pairs of DF.sensors and human detectors. We paired a DF.sensor to the closest human detector.

Fig.11(a)(c)(e) show daily relative terminal counts at location 1, 2, and 13 respectively. Fig11(b)(d)(f) show daily relative counts from human detectors near each DF.sensor. We can easily confirm that the fluctuations of the graphs of (a) with (b), (c) with (d), and (e) with (f) are relatively similar. However, the actual ratio of (a) with (b), and (c) with (d) are around 60%. But ratio of (e) with (f) is only around 40%. The detection ratio of the DF.sensor with the human detector thus is not constant. However, the ratio seems stable with time. So if we obtain the detection ratio of the DF.sensor, we can continuously use that ratio for some portion of time. The optical human detector is actually counting customers. Our Wi-Fi scanner technique counts Wi-Fi terminals. Thus, there is a discrepancy. Not all customers carry Wi-Fi terminals, some smartphones may not have Wi-Fi enabled, and for some, we might not have observed a Wi-Fi probe packet in the window that the customer is in the vicinity of a DF.sensor. It is also interesting to note the difference in ratio according to DF.sensor. DF.sensor placement and how it is installed in a particular environment may be an influencing factor for the differences in ratio.

We observed that the BSSID anonymization ratio, at the location 1 and 13, terminal count was almost the same. But in location 2, shown in Fig.11(c), anonymized BSSID is little less than the other locations. This result shows even BSSID anonymization ratio might be dependent on the location.

4. COUPON CAMPAIGN

Wi-Fi scanners detect the number of terminals, but we have no other insight to do more analysis such as the demographic information of the customers because we cannot obtain any information about Wi-Fi users. In the experimental field, we also deployed 250 BLE tags. So we planned a coupon campaign to utilize these tags and to obtain demographic information along with customer's location information.

4.1 Design of Coupon Campaign System

To obtain demographic information of the subjects, we used a smartphone application named "Cenpa Navi" that customers can use as a guide for the shopping mall. The iPhone version of the "Cenpa Navi" was already on the market. So, we modified it to suite our experiment and also developed the Android version from scratch. We used BLE tags for positioning in the underground mall. These days, there are a lot of campaign apps or apps in general, so it was not easy to have customers install our campaign app. So, we decided to distribute 500 Yen (about $5) coupons in exchange for the installation of the app.

To bind the coupon with the customer's terminal, we printed serial numbers on each coupon. When a customer comes to the Information Counter at the mall to receive a coupon, installation of the app is checked and the serial number on the coupon is bound to the application by the support staff. We also design a questionnaire to collect demographic information through the app very carefully. There is a trade off in the number of questions and how serious a user will complete the form. For this experiment, we incorporated the following attributes: age, gender, job, transportation, accompanying person, objective of the visit, and favorite magazines (only for women). The reason why we included favorite magazines is that the mall's major shops are for women's fashion.

Figure 12 shows the configuration of coupon campaign system. Master data of shops and BLE tags are stored in ABF (Access Beacon Framework). However, logging data is stored on different servers. Multisoup Co. Ltd. developed the iPhone version, so the data was stored to the Multisoup server. The Android app was developed at Nagoya University. The logging data of the Android app was stored to MBaaS (Mobile Backend as a Service) called Kii

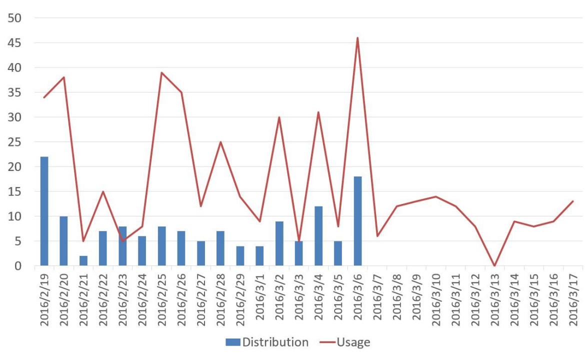

Figure 14. Distribution and Usage of the Coupons

Figure 15. Gender and Age based Location Analysis

cloud. Kii is also the member of the O2OMK and we had their full cooperation for this experiment.

4.2 Experimental Results

The "Cenpa Navi" coupon campaign (distribution of the coupons) was held from Feb. 19 to Mar. 6, 2016. The coupons could be used until Mar 17th. Figure 13 shows the steps involved from downloading the app to actually using the coupons at the shops in the mall. Initially, subjects are required to install the "Cenpa Navi" app. When they push the "campaign" button, they are prompted with the questionnaire mentioned previously. After they answer the questionnaire, the "coupon" page is displayed. Subjects are required to visit "Information Center" to show this display. The staff at the Information Center checks the display and registers the coupon serial number into the app. Finally, the coupon is handed to the subject. When subjects want to use a coupon at a shop in the mall, they are required to show the app and hand over the coupon to the shop clerk.

Figure 14 shows a result of coupon campaign. Unfortunately, for this experiment, we were not able to obtain the number of subjects as we had expected. We prepared 1,000 coupons but only were able to distribute 139 of them. In our review meeting, we concluded there were several reasons for the low number of subjects who participated in our experiment. We had only posted several posters at the mall, and did not heavily use SNS or Twitter to distribute information regarding the campaign. We thought that a 500 Yen coupon was enough benefit for users to install the app. But it was not true. For our next trial, we need to provide a method to create a "buzz" or viral marketing. So, unfortunately for this experiment we could not see any correlation between the smartphone app coupon campaign and logs observed with the DF.sensors mentioned previously.

Even though the coupon distribution rate was low, there were more users who installed the app and answered the questionnaire. We received 196 answers for questionnaire. This means 71% of the users who installed the app and answered the questionnaire, obtained the coupon. Also, from the questionnaire, 43% were male and 57% were female. This result also shows the characteristic of the shopping mall.

The 500 Yen coupons were distributed as a book of five 100 Yen coupons. In our experiment, 463 100 Yen coupons were used. Since, 139 coupon books were distributed, out of a total of 695 separate coupons, 67% were used. We think this usage rate is very high. So our forecast is that if we can gather more subjects, we will observe more general results with higher coverage.

4.3 Location based Analysis

Figure 15 shows one example of location based analysis with demographic data obtained through our questionnaire. In this figure, the left plot depicts female subjects' location logs, and the right plot depicts male subjects' location logs. We render each location log with a radius proportional to the number of log counts at each location. Also we changed the color of the marker by age. By using different attributes of the users, we can perform different types of analysis.

For example, Figure 16 shows gender and frequency based visualization. Gender is visualized with color (red: female, blue: male). Frequency of the mall visit is grouped in different columns. From this visualization, we can see the coverage area of "first time" and "weekend" groups are limited compared to other groups. Also, "once a month" and "once a week" groups heavily visit the lower part of the mall. This area mainly houses "women's fashion" shops. By specifying a customer attribute, we can easily create this kind of cross attribute visualization using the software called Tableau.

Unfortunately, due to the low number in participation for this experiment, we could not find general trends in customer behavior. More experiments and a larger data set are required.

4.4 Time-Dependent Analysis

Customer behavior can be characterized as dynamic movement within the shopping mall area along with coupon usage. Figures 15 and 16 do not depict the dynamic behavior of the customers. Of course, we can divide the row with time. But it is not easy to observe all aspects of customers' behavior.

We developed a visualization tool using WebGL to perform a time-dependent analysis of the customers' behavior. Figure 17 shows the current status of our tool. We can visualize dynamic

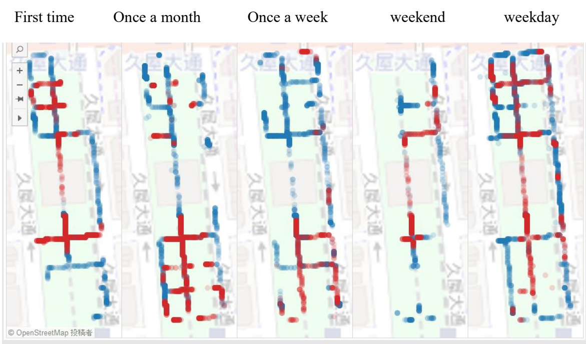

Figure 16. Gender and Frequency based Visualization

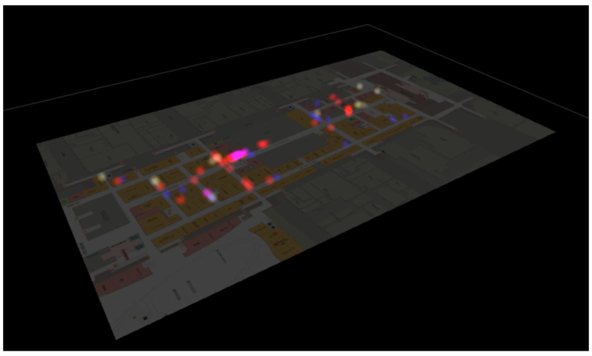

Figure 17. Time-Dependent Visualization and Analysis

movement of the customers in color for any attribute. We are planning to extend the system to support various types of time-dependent analysis.

5. Conclusion

In this paper, we described the knowledge and results obtained from the demonstration experiment held by the “O2O Digital Marketing Study Group” within NPO Lisra at a large underground shopping mall in Nagoya. In the mall, 250 BLE tags with 12 Wi-Fi scanners were installed to collect user location data and dwell tendencies. We were able to effectively collect visiting customer count measurements via Wi-Fi scanners irrespective of the anonymization of BSSID, as our results showed similar trends collected by optical human detectors inherently installed at the venue. We also described how we tried to attract customers to the venue through a “coupon campaign” using a smartphone application. A questionnaire was incorporated in the app to obtain various customer attributes along with location data. Further analysis is necessary combining attributes, time, and location. We also presented a visualization tool that depicts movement dynamically. We hope that the knowledge and insight from our experiment can be applied to the future experiments or real world deployments of O2O marketing systems.

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