KI/OSK: Practice Study of Load Sensitive Board for Farmers Market

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Abstract

In recent years, the retail industry has increasingly gained interest in the ICT system for enriching the customers' shopping experience and is now being deployed in some stores. As the most common implementation method is limited with its high cost and large consumption of space, it is a challenge for smaller or temporal stores to install such services. In this paper, we explore the usage of a loadsensitive board to improve the retail shopping experience specifically in smaller and temporal stores. As a case study, we develop and examine KI/OSK, an easy-to-install modular table-top retail application using SCALE - a previously developed load sensing toolkit - specifically for the Farmers Market. Our study uses iterative user research including surveys with Farmers Market managers to assess design requirements, and testing and revising through a field study in a Farmers Market.

Author Keywords

Retail UX; Object Tracking; Load Sensing; Field Study

CCS Concepts

•Human-centered computing \rightarrow Human computer interaction (HCI); *Haptic devices;* User studies;







of KI/OSK using SCALE toolkit as a reflection of

[Step1] Assessment of

of KI/OSK via user interviews

Design and Requirements

in-lab studies & user interviews 2019.07

2018.09

[Step3] Field Study 1 Evaluation at an internal company pop-up store for verifying the system flow



armers Market store mainly for validating UX [Step5] Discussion of findings and challenges for the future improvement

Figure 1: This figure chronicles exploration of KI/OSK. Through the five steps including user research, in-lab user studies and field studies, the design and prototype have been revised.

Introduction

In recent years, there has been a growing interest for retail stores to implement the ICT system both for research and commercial services [1] [3]. By utilizing object recognition systems (for detecting items the shoppers picked up), such a system can dramatically improve the physical retail store experience for shoppers (by reducing the time for checkout), for sellers (by reducing the load/cost of check-out), and for marketers (to gather customer data by analyzing detailed activities in stores).

As such state-of-the-art systems can only be implemented in very few technologically equipped stores (e.g. many cameras, sensors, and computers), it is important to develop a way for retail stores to implement relatively simpler methods. Thus upgrading the system into a more portable, less technologically dependent version for small or temporal retail stores is imperative for full utilization (e.g. pop-up store).

In this paper, we propose KI/OSK, a shopping system enabled with relatively simple equipment consisting of a load sensitive board that is suited for small and temporal pop-up stores. The system of the load sensitive board is based on our previous research prototype SCALE (Figure 2)[5], comprised of a board equipped with load sensitive modules to track object activity (pick up, put down) on the board.

Specifically, in this case study paper, we will report our iterative user study based research targeting the improvement of customer shopping experience at a Farmers Market. We chose the Farmers Market as this scenario can potentially benefit from the SCALE platform for two reasons; 1. To implement a scalable and simple version of SCALE that can be used in small and temporal stores, 2. The weight detecting capability of SCALE matches the bulk selling style in a Farmers Market. Our iteration process is composed of the five steps as shown in Figure 1.

With our short cycle iterative design process utilized in a real-world retail store environment, we examine both technical research questions, [RQ1: What is the detection accuracy and speed?], as well as the UX research question, [RQ2: How can the system benefit from shopping UX in a Farmers Market for both sellers and shoppers?]. We believe the research and findings included in this paper will be a great and concrete instance for deploying a tangible and ubiguitous sensing technique (a popular topic in HCI) from the lab and into a real-world environment. This research also aims to allow for small and temporal retail stores to introduce digitally enhanced real-world shopping experiences with a simple and easy-to-install method.

Design of KI/OSK

The first step in the design exploration is to clarify the reguirements while taking into consideration the issues and needs from Farmers Market stores.

Issues and Needs in a Farmers Market

We conducted user interviews with seller-farmers and organizers of the Farmers Market event in Tokyo, Japan. Once concluding the interviews, there were three findings: First, one of the major issues of the system is that the seller's tend to obstruct the advantage of the Farmers Market, where shoppers are encouraged to easily communicate with sellers directly. For example, most shoppers and sellers usually enjoy casual conversations including how to choose good produce, how to cook such produce, when items are acquired or how long the term of ripeness will be. To naturally start these conversations, we came up with a way to spark discussion. Second, the seller tends to be bothered by unsupervised check-outs, packing operations, compilation of sales data and estimating shipping amount. Third, we found that although sellers usually sell pre-packaged produce for convenient access and poten-

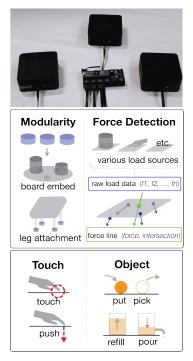


Figure 2: The SCALE tool kit which is shown in the top of the Figure, measures the intensity and direction of the applied force onto the weight sensing surface. Based on the force measurement, a designer can implement a variety of functionalities for touch detection and object status recognition. tial hygiene issues, they have required the bulk selling form to reduce the operation of sorting by size and packing in shipping. Whereas, we presume that many shoppers occasionally require bulk purchasing, after discussing with colleagues that are currently in charge of planning business related to Farmers Market. Shoppers basically need fresh food at a frequency depending on one's lifestyle.

Design Requirements

Based on the issues and needs for a Farmers Market, we set the UX design requirements for sellers and shoppers as followings, (1) Easy to install and easy to arrange, (2) Encourage bulk selling/selling by weight, (3) Reduce seller and shopper efforts.(4) Encourage in-store-communication between seller and shopper.

In order to realize the above UX design requirements, we define three functional requirements for KI/OSK: First, as a basic function, placement recognition (picking up, placing down) for the items on the shelf needs to be achieved. This is required to integrate item selection, measuring items and pricing into a natural purchasing sequence. For this, a recognition system with both accuracy and speed are required. For accuracy, we aim that the average detection error rate (not detecting the item at all, or detecting the wrong item) will be within 2% error. About the speed, the response of detection delay will be within one second.

Second, KI/OSK needs to recognize which item is taken based on the location the item was registered in. To register properties of items into the system, the system need to be designed in a way that sellers assign the position and area of shelving in which the item is placed in bulk.

Finally, the system allows shoppers to show the information of the item they grabbed. We assume that this interactive

feedback will become a trigger to encourage conversation between the seller and the shopper, and to make the shopper check their current shopping list.

System limitations

In this study, we aim to prototype a simple system for small and temporary stores. Thus, currently KI/OSK has several functional limitations. The first is that multiple shoppers cannot use the system simultaneously, due to a lack in shopper identification functionality. The second is that the system cannot detect if shoppers pick up/place multiple items from different shelves at the same time. This limitation had to be taken into account through our design process in this paper.

Implementation

While prototyping, the challenge is to find out how this system should be designed to work with a standard purchasing flow so as not to cause additional delay for shoppers. To fix this, we defined the range of the UX this study targets to evaluate the current functions of KI/OSK. Thus, this paper will focus on the grabbing item phase in Figure 4. Note that the software and device configuration below was decided as a result of the in-lab user study and Field Study1. The detailed configuration for the Field Study is described later in each User Study section.

Software Design

The system is comprised of the following three applications software: *DetectorApp*, which combines with SCALE software developed with openFrameworks, has functions of controlling the shopper's login and logout, identifies which item was taken from its designated shelf space, and sends the item list data including the item name(s), weight(s) and the price(s) to *DisplayApp* and *CalculatorApp* based on the signal data from SCALE devices. *DisplayApp*, which is developed with Unity, shows the item information on LCD1 in

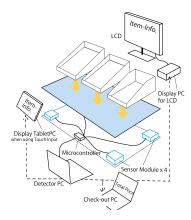
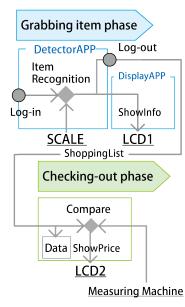


Figure 3: Base System Configuration.



real-time. *CalculatorApp* sums up the total price using the pricing data of each item and shows the total on the LCD2 when checking-out. *CalculatorApp* also processes comparisons with true values. When a weight from *DetectorApp* is larger than the true weight via scale, *CalculatorApp* adds the true weight into the calculation. When a weight from *DetectorApp* is smaller than the true weight via measuring machines, *CalculatorApp* adds the true weight into it on the condition that the difference between both of the weights is within 20% of the real weight.

Device Configuration

As shown in Figure 3, the device configuration is comprised of three PC's (SurfaceBook1 for CalculatorAPP and LCD2, SurfaceBook2 for DetectorApp and Intel NUC8 for DisplayApp), an LCD (Dell24-inch), a LAN network hub and SCALE tool-kit devices including a microcontroller(Teensy3.6), three axis load cells (FL100N, 4x) and its amplifier circuits (HX711, 12x). In addition to these, three regular scales (TANITA TL-280) are added into the Field Study 2.

Object Recognition Improvement for KI/OSK Through technical evaluations in-lab, we found that the object status detection of SCALE would need to be improved to recognize various items on various shelf types through various ways of handling. The accuracy of detecting the object and its weight varied in accordance with the condition of the shelves and ways of picking-up and putting-on items, because disturbance of the signals are often caused by them and the variation leads misjudging the handling of an object, for instance when distinguishing between touching or picking up the item from the shelf or the board itself.

The graphs in Figure 5 explain the sequences of item recognition in *DetectorApp*. When the process catches a fast rising of sampled signals like a square shape without fluctuation shown in (a) from 3-axis load sensors, the system judges picking-up/putting-down the object and returns the position and weight. When the process catches a gradual rising of signals or large fluctuations of signals shown in (b) or (c), the system judges an input by touching the board, shelves or items. Especially, we improved the accuracy through the basis of mathematical analysis of the waveform, and also, created a function storing signal data to detect picking-up/putting-down objects in a row in the same area.

Technical Evaluation

To verify the reliability of the recognition function, we conducted a technical evaluation on the following basic components: weight, position within an area pre-set and recognition time. The verification method is to randomly putdown and pick-up a lime(s), around 40g, and an orange(s), around 60g, on a tilted wooden box shelf for Farmers Market usage ($30 \times 48 \times 5$ cm) on an MDF board ($61 \times 61 \times 1.2$ cm) repeatedly, up to 15 times. As a result, the percentage of error in average weight difference is 1.095%, no errors for detecting an item in the located area and the speed of detection is fast enough to get feedback in real-time. The function of distinguishing forms of touching also works well while selecting an item within a mix of items.

User Study

We conducted two field studies, a preliminary study and a focused study. Toward the focused study in a real Farmers Market, we needed to research not only the accuracy of recognition and the design of KI/OSK, but also the selling operation sequence with purchasing.

Field Study 1

The preliminary study (Field Study 1) was conducted from 11:30 am to 1:30 pm on July 25th, 2019. The location was a company's internal store which often has experimental studies held. This condition is suitable for conducting inter-

Figure 4: KI/OSK Software Design.

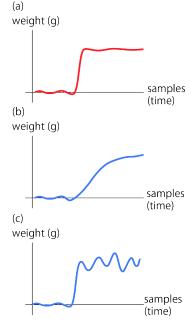


Figure 5: Object Recognition Sequence. The red line indicates the sequence of samples from the signal when picking-up an object. Whereas, the blue lines indicate the sequence of samples from the signal when touching an object or a shelf. views and receiving feedback. The study aims to evaluate (1) the accuracy of recognizing items picked up/put down and its weight, (2) the usability of purchasing for shoppers, (3) their preference for bulk purchasing, and (4) the smoothness of selling operations including the restocking of items.

System Configuration:

We stocked four items which are comprised of two bulk items (mushrooms and limes) and two packed items (buckwheat snacks and dried noodles) so that we can evaluate the system operations of common food items. Upon selecting the items, we had to consider seasonal and guality foods which our cooperation producers wanted to sell at the time. Each group of items are displayed in their own respective box (21 x 28 x 16 cm) located on two KI/OSK boards (MDF, 61 x 61 x 2 cm) side by side on a table (120 x 60 x 80 cm). There are two SCALE tool-kits in this experiment to test the servicing of two customers simultaneously. There are also two tablet-PC's (Panasonic RZ-5) in front of each board to show item information and control log-in/out by a shopper as shown in Figure 6. Regarding the staff, four sellers from this development team behaved as two instructors who are in charge of supporting the shoppers purchasing and accounts. Additionally, one interviewer and two observers are included as research staff.

Procedure:

First, instructors consent with the visitor after a simple brief on the evaluation of the weight based sensor system we are developing. The shopper can then purchase items with the additional help of the purchasing information on the tablet PC displayed in real-time without explanation of the mechanism. Second, a participant selects the board – the shelf selling mushrooms and limes, or buckwheat snacks and dried noodles - by logging into the system with the tablet PC. Then, the shopper selects and places the desired items in a basket while checking the item information: each item name, weight, unit price and total price. Thirdly, the shopper logs out and either continues to shop at the next board or proceeds to check-out at another table. Finally, the interviewer semi-structurally asks the participant, "How was the usability of this system?" and "What were the pros and cons of bulk purchasing?" with their consent. The observers mainly check the validation of interaction design between the shopper and the system.

Results and Findings:

20 individuals participated in this study, and we collected the data through logs of detection. From the log data, the average detection error rate (not detecting the item at all, or detecting the wrong item) was found to be 24.8% (out of 78 handling samples), and the average difference error of detected weight is 9.48% (out of 78 handling samples). The main causes are considered to be linked to extremely lightweight items such as noodles (around 20g). Additionally, the handling of lightweight items also affected the response speed of the detection through a delay of 1-2 seconds for identification of the item.

We received comments from nine participants that were semi-structurally interviewed (three male and six females), such as: "It was hard to see the item information on the LCD while choosing", "I was concerned about the misdetections", and "I prefer bulk purchasing because I wanted to taste a little bit of each item".

From our own observations, we noticed that sellers dedicated effort and time to explain what the tablet PC is, how to log-in the system and recover from errors of detection and operation, and that it is hard for the shopper to see the LCD's while selecting an item due to its small size and low position in front of the shelf on a tablet. We also found that participants tended to sift through items on the shelves to locate their preferred items. This handling may have caused the mis-detections. Additionally, the two KI/OSK configurations increased the sellers workload and operations when refilling items. Towards the next field study, we improved the Detector App for the accuracy of detection, and the system configuration for smooth operation flow.

Field Study 2

The second field experiment was conducted at the daily Farmers Market event in Tokyo Traffic Hall, from 11:30 am to 5:30 pm on September 21st, 2019. This focused study was basically programmed to respond to the RQs we set. We aimed to test (1) the recognition accuracy of identifying picked/put down items and measuring its weight, (2) the shopper's experience of bulk purchasing, including the usability and the quality of communication with sellers, and (3) the smoothness of selling operational flow such as setting up the system, refilling items, supporting shoppers purchasing and adding up sales. Upon evaluating the seller's operation flow, we aim to meet the limitations the event organizer set, e.g. the prep time is within 2 hours from 9:30 am, reporting sales until 6 pm, and the space (about 4 x 3 m) and two tables (150 x 80 x 90 cm) are assigned.

System Configuration:

We stocked mushrooms, red potatoes, and sweet potatoes in the same manner as the previous study. Note that the items were decided while considering size variation, quality to attract shopper's interest, avoiding extreme lightweight items, and produce freshness obtained one day before. They were displayed in their own box shelf (28 x 36 x 28 cm) located on a KI/OSK board (MDF, 120 x 61 x 2 cm), on a table as shown in Figure 7. Another table was used for check-out space. One of the main revisions from the last study is the usage of a large LCD screen (24-inch) in order to allow shoppers to more easily check item information, and to have the shoppers not use the system to reduce the sellers' efforts of instruction and alleviate shoppers confusion. Another main revision was the display of the feedback information on the LCD. When logging-in, the LCD displays short explanations of each item, and when an item is picked-up, it is changed to four cooking examples using the item being picked-up.

Regarding the staff, three sellers from our development team behaved as an instructor and two accountants. And, two observers are included as research staff and observed from behind the tables outside of the store. The observers also held the post of system operator who checks the system performance and operates the system when dealing with recovering from a detection error or quantity refilling.

Procedure:

First, the instructor receives the shoppers consent after a short briefing on the usage of our weight system currently under development, and then logs-in the system by touching a RFID card which the instructor has on the card reader. Second, the shopper selects and places their items in plastic bags while checking the item information including name, cooking recipes, weight, individual unit price and total price. Finally, the seller logs out using the RFID card and the shopper proceeds to complete the check-out process at the next table. The reason for using the RFID card to manage this system for e-money payment in the future. In this study, because KI/OSK does not cover payment systems and every shopper does not necessarily have e-money, a seller operates the logging-in and out.

Results and Findings:

We received 35 participants and collected data through logs of detections and observations. In the first half of the study, there were a lot of errors. The errors were mainly caused by the windy conditions that day. The difference er-



Figure 6: Field Study 1 is set up at an internal company store as a preliminary field study.

rors especially are related to the vibration noises created by the wind. From the log data, the average of detection error rate was 17.1%(76 samples) and the average of difference error of detected gram was 8.52%(76 samples). Therefore, we tried to decrease three item shelves to two item shelves (red potatoes and sweet potatoes) on a KI/OSK board to reduce the vibration noise by changing to a smaller board (MDF, 90x61x2cm). The average of detection error rate like not detecting or the detecting wrong item became 7.25%(126 samples), and the average of difference error of detected weight became 7.1%(126 samples).

From the observation, we received positive scenes where the LCD that showing item information had frequently triggered the conversation between sellers and shoppers. Also, the system allowed sellers to install the system within an hour, smoothly change the display layout when switching to smaller board and refill the items in the store. When changing the layout, basically we only had to put shelves out and refill items, change the parameters of position for the shelves and the four sensors, and calibrate the sensors with *DetectorApp*. On the other hand, issues were found when shoppers are in a group like a family. For example, when a member of the group picked an item up, the other member also picked the other item up or touched the shelf. The few seconds delay of detection caused by the vibration noises made the shoppers stressed.

Discussion

Based on the findings from the Field Studies, here we discuss the validation of our design concepts while focusing on two considerations based on our research questions.

RQ1: What is the detection accuracy and speed? From a technical aspect, we consider two findings, the accuracy of recognizing object status and distinguishing be-

tween touches. Although we have raised the accuracy of detections in Field Study 2, the result is not satisfactory to use it for selling by weight at present. Especially in outdoor conditions, where a vulnerability was found. Likewise, the response speed will have to be improved to have high robustness. For the future work, we should focus on designing the load sensitive surface with durability and robustness while developing a specialized load sensor module. The function of distinguishing from touches mostly worked well. However, the function created mis-detections and the delay of detection because the detected object is not identified while making the signal fluctuation by touching the items or shelves, or wind. On the other hand, the function of detecting touches is potentially capable pf providing various input methods to KI/OSK. For example, when a shopper touches a cooking sample image attached to the surface of the board or a shelf, the LCD comes to show the cooking ingredients and the appropriate amount recognition.

RQ2: How can KI/OSK benefit from shopping UX in a Farmers Market for sellers & shoppers?

Regarding another question from a UX design aspect, we consider the design of KI/OSK in according with the four requirements based on the issues and needs.

Easy-to-install and Easy-to-arrange:

As mentioned, installing KI/OSK finished within an hour. However, we mostly did the work with the help of three sellers. To efficiently set the system and the display up, building the set-up procedure, wireless-connection between Display PC, Detector PC and SCALE, and GUI for easy to edit parameters for the areas of shelves and the recognition processing in Detector App will be needed.

Bulk Purchasing:

As mentioned in Design Requirements, promoting bulk purchasing and purchasing by weight are needed to highlight a



Figure 7: Field Study 2 is set up in a Farmers Market event at the Tokyo Traffic Hall.

feature of the Farmers Market. However, measuring items including the arrangement of the amount and calculating prices obstruct the smooth flow of purchasing and seller operations. We found KI/OSK potentially allows to naturally shorten the process explained. However, the limitation that it is incapable of simultaneous recognition for multiple operating items should be improved for group shoppers.

Reducing seller's efforts:

In addition to that, KI/OSK has potential to help shoppers estimate amount of shipping items and arrange display layout. From the results of Field Study 2, we became able to grasp the trend of purchasing status on shelves. For example, the average purchasing amount of potatoes per shopper is 423.7grams (9 samples). We can assume that in that day, shoppers tended to purchase about four middle sized potatoes from our data. This simple in-store marketing is not easily brought excepting load sensing approach.

Encouraging Conversation:

As mentioned in Results and Findings, conversations were stimulated in Field Study 2, rather than in Field Study 1. Of course, sellers were encouraging shoppers to check item information not only to talk about the item itself, but to explain what the system they are using is. However, sharing item information on a large display supported the sellers who are unfamiliar with selling to keep their conversations going with the shopper. Whereas, for example, a function of interactively showing more detailed information via the web was needed because sellers could not answer some detailed item questions from the shoppers. To explore how to provide item information efficiently, KI/OSK should be designed by taking advantage of HCI studies to design a public display to interactively give shoppers production information in retail spaces[2][4]. This may begin to incorporate characteristics of online retail to physical retail.

Conclusion

In this study, we have repeatedly evaluated KI/OSK in Field Studies. We believe that this study contributes to provide an option of selling style for sellers. In the future, to deploy KI/OSK to actual stores, we need to continue our evaluation in the field while raising the practicality. Additionally, KI/OSK can utilize the potential of SCALE to enhance functions, for instance, by combining touch detection with object status detection, where the height position when the object is handled could be detected. With such function, KI/OSK can recognize items on multi-layered shelves.

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