Revealing the Retail Black Box by Interaction Sensing

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Abstract

Today a huge variety of methods to track and analyze the customers' behavior in e-commerce systems is available. However, in traditional retail stores such systems are not widely known and therefore the customers' behavior is considered as a black box in this domain. This paper presents the Smart Shelf technology able to track basic simple actions, such as take, return and remove, which are performed on items by the customer. These actions form the interaction context replacing the black box. We will show that this context can be used to enhance existing data mining and store management systems as well as the customer will benefit from recommendation systems comparable to those used in e-commerce systems of online stores.

1. Introduction

Today a huge variety of methods to track and analyze the customers' behavior in e-commerce systems is available. Most of the current e-commerce Web sites use these methods to find out in which products their customers are most interested. For example, they record how often information about a certain product is requested, how long the customer deals with this information, and finally how often a product is bought. This information is used to quantify the popularity of the offered products by means of various metrics like the average time-on-page or the click-buy-ratio, which is the ratio between the number of clicks on the link to information about a certain product and the number of actual sales of this product. The e-commerce vendors use such knowledge to optimize their advertising and product placement strategies as well as for recommendation systems, which help them to increase cross-sales and customer loyalty.

In real world retail stores however things are different. The only quantitative information the retailers usually have is the number of products coming into their stores from the suppliers and leaving them at the checkouts. Thus the retail store itself is a complete black box with respect to quantitative information about the customers' behavior and interaction with the products on sale. The most interesting moment where a customer decides whether to buy a product or not is often completely unobserved. Of course some simple crutches exist to find out something about the customers' behavior. For example, stores are periodically rearranged to get information about the influence that the location of a product within the store has on its popularity. This is also a very weak form of a recommendation system. While a customer is looking for the products he wants to buy after a rearrangement, products that he possibly has not known so far are recommended to him, especially those which are located where the customer expected to find the product that he is looking for. Similar a product can be recommended to the customers by bundling it with a popular one. Compared to the possibilities that the vendors in e-commerce systems have, those of the retailers are obviously weak and might even bother the customers rather than helping them.

The Smart Shelf technology we propose in this paper makes the shelves in retail stores aware of the products that are placed on top of them. The shelves can determine a unique identifier and the position of each product that is placed on them. In addition each shelf can recognize when products are placed on it or removed from it. Thereby we provide a means to track the customers' behavior on a quantitative basis. We can determine how often a product is removed from a shelf without being bought or how long a customer has hold a product in his hands before putting it back on the shelf. Thus we can bring some light into the retail black box that we face today.

As we will show in this paper the information provided by Smart Shelves can also be used to realize recommendation systems comparable to those used in e-commerce systems. Additionally some valuable store management applications like an out-of-stock watchdog or a plan-o-gram compliance check become possible using the Smart Shelf technology.

This paper is structured as follows: in Section 2 we analyze the situation we have in today's retail stores using an abstract model of the product flows in such stores. Based on this analysis we illustrate the potential benefits of Smart Shelves. Subsequently we discuss alternative technologies in Section 3 before we introduce the Smart Shelf technology in detail in Section 4. In Section 5 we describe some Smart Shelf applications. After an evaluation of the Smart Shelf in section 6, we finally discuss the related work in Section 7 before we conclude the paper in Section 8.

2. Analysis

The product's history within a retail store is drawn as a line from the injection into the store as the first step to the its history within the store as the second step and the end is represented by the checkout at an electronic cash point. We name this the input/output model, because these are the both sets where already information is available from. The step in the middle, the history of the product within the store, is unknown to us and therefore considered as black box.

In this section we decompose the input/output model for retail stores. We address stores starting from the size when they need a warehousing software system.

The input in our model represents all products that were ordered by the retail store. Those are held in the stock or are already in the shelves and ready to buy for the customers. All products are identified and registered in the warehousing software when they arrive at the store and so it is exactly known what the input of our model is.

The output is formed by the set of all product which are bought by store's customers. Electronic cash points based on laser scanners are used to identify a product via a printed barcode. They are connected to the backend system, the warehousing system, containing the price for each product which is then displayed. This information is used to determine how many products of each kind are sold and helps the manager to set up the order coming in as input into the model.

Apart from that obvious use this systems allows other evaluations. Ex post it gives coarse-grained information about what customers prefer. This becomes even more crucial when a new product is introduced. But, the reasons for the preferences can't be derived, because at this point the customer already did his decision for buying a certain product. In particular, if a product introduction fails there is a strong need to work out these reasons. To explore them the store's manager rearrange the products within the store or bundles a certain product with a popular one. In the first case, the rearrangement, he hopes to stimulate the buying behavior by guiding the customer to other products while in the second case, the bundling, he tries to benefit from the effect that one product recommends another one. But these approaches are trial and error approaches and do not result in quantitative predictions. On the contrary, often they result in annoyance of customers, especially when the products are rearranged. And even if a change can be seen in the output, it is questionable whether it is directly connected to measures the manager took.

2.1. Looking into the Black Box

As a consequence of this consideration we state that more fine-grained information is needed in order to understand why a customer behaves in a certain way while buying a product. This information, represented as the customer's buying behavior at the point of time when he makes his decision, is contained in the black box of the input/output model. The understanding of this stage opens the potential to exert influence on a crucial point. However, it is not easily measurable. A direct measurement would demand that one asks the customer all time about his current preferences. We believe that the buying behavior in the decision stage can be derived when observing the customer's interaction with the offered products. This results in a modified input/output model where the black box is replaced by the knowledge of customer-product interaction, which is further referred as the interaction context.

2.2. Requirements

As an interaction we consider a physical interaction based on the changing of location, which is imposed on an item. We refer to items as a more abstract view on products. This leads to the requirement of knowing the location of the item and what happens with the item at its location. To know on which item an interaction is performed an unique identification is required. In the end we demand that interaction observation and item identification converge in the retail store's backend system, in order to embed this fine-grained information into the process of evaluation of coarse-grained information.

We recognize customers' interaction with the items by observing three simple basic actions. The item's location is limited to a position on a planar surface, which makes it easier to sense. The first action we want to sense is "Item A taken from position (x,y)". Consequently, we also want to sense the second basic action "Item A returned to position (x,y)". The third one is "Item A removed from position (x,y)". A *remove* action is considered as a *taken* action whereby the item becomes a member of the output set. Latter is introduced to connect the interaction context with the output set of the model. This strongly demands a connection to the retail store's backend system.

2.3. A greater Picture

The simple input/output model of a item's history in a retail store where we started from was added by a customer-item interaction knowledge replacing the unknown black box. This knowledge is referred as interaction context, which is not personalized and therefore not bound to a certain customer. It is derived from sensing three simple basic actions a customer can perform on an item while he is in the decision stage of his buying behavior. These actions are *take*, *return* and *remove*. It requires a unique item identification and determination of a item's location. Furthermore we demand a connection to the store's backend system, where data from the input and output sets and the interaction context converge in order to derive better predictions of customers' buying behavior. In the World Wide Web observing the customers' interaction within the online shop is used to obtain fine-grained information about their buying behavior. The same approach is used by sensing the basic actions in the retail store. For instance, what is named as the click-buy ratio in online shops can be mapped as the take-remove ratio in retail stores. Our approach enables us to re-use methods from the business-to-consumer (B2C) e-commerce in the real world of a retail store. In addition it provides an increased customer experience and an optimized store management.

3. Technologies

For an appropriate interaction sensing it is required that the customer interacts implicitly with the sensing technology. That means, that the technology's integration into customer's interactions is done in a unobtrusive way, which results in less distortion of the entire buying process. The deployment of the technology should not cause higher prices of products caused by the costs of the technology and maintenance reasons. This might not be accepted by the customers. Therefore the sensing technology has to be cheap and reliable. Enabling a feedback to the customer while he is performing his action imposes a system reacting in real-time to the customer.

In the next paragraphs we have a short look into two technologies marking the edge points of sensing interaction contexts. Finally, it motivates our approach of the SmartShelf.

3.1. Video Systems

These kinds of systems are very common in many retail stores. According to their usage for theft observation video systems are made to see of what the customer is doing and they can watch many of them in parallel. An image recognition system can estimate kind of action, kind of item and also a clue of item's position. But such systems are very expensive and need lot of computing power for each camera, especially when it comes to real-time applications. On the other hand a review process by a human being can identify respectively interpret the customer's action more accurate. But, data needs to be re-entered, which needs an additional interface. Also, a close-to real-time behavior is not possible. Furthermore, a human being is not all the time available which weakens the reliability and the systems may loose its objectivity.

3.2. Augmented Items (Smart Items)

In this approach there is no sensing infrastructure. All kinds of sensors measuring interaction are on the item itself. Additionally, the item's identification is also held on it. For communication the item provides an interface, preferably wireless for not limiting the interaction. Sensors on the product obtain very fine-grained data about the interaction context, such as which side shows to the potential buyer, number of item's rotations, how strong is the item touched and so on. The item saves its complete history of interactions in its own memory to compute the interaction contexts. However, Smart Items need their own power supply and are too expensive to be deployed in huge numbers.

3.3. Smart Shelf

The considerations in the last paragraphs showed that the most fine-grained data is obtained when the interaction measuring is situated on the item itself. The less we augment an item, the more we have to interpret the obtained data from sensors outside the item. In the Smart Shelf approach we bridge these approaches to benefit from both. A item is only slightly augmented such as it does not become more expensive. This utilizes the sensing of our in 2.2 predefined basic actions.

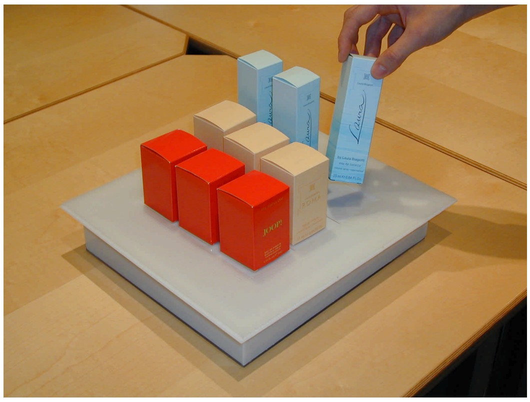

Figure 1. The Smart Shelf.

4. Smart Shelf Technology

In the Smart Shelf approach we augment products by RFID transponders to give them an unique identification. Furthermore we embed a transponder detection system into a shelf. In order to obtain the position of the product we declare the position of the transponder detection as the position of the product. The challenge in our prototype implementation, seen in Figure 1, was to have a very fine-grained detection and to be able to differentiate between various items standing close to each other.

4.1. Technical Design

The shelf is decomposed into the antenna system, the reader units and a central communication unit. It has to perform the following tasks: detect all transponders in range and read their identification, map the position of detection to an absolute position on the shelf, communicate the retrieved Ids and their position to an external system by request.

The detection and reading task is done by the antenna system and the reader units. The antenna system consists of a 6x6 grid of 36 smaller coils antennas based on an experimental design creating an electromagnetic detection field by overlapping of their separate fields, which covers a surface of 400 cm^2 almost uniformly. The core of a reader unit is RFID single chip reader MicroRWD [2]. It can detect and read 125kHz EM Marin compliant transponders augmenting test items. A MicroRWD reader is surrounded by 12 optical switches to address 12 separate antennas of the antenna system one-by-one. This multiplexing capability was introduced because a single chip reader costs an order of a magnitude more than the coil antenna with the switching circuit for this antenna. The reading of a transponder takes 130ms in average. However, in order to achieve an acceptable response time of the entire shelf there are 3 reading units working in parallel, but each for a separate detection area of the shelf. They operate most of the time independently from the central unit, except for the time of synchronization. Latter is needed because is has to be avoided that two antennas beside of each other are used to detect transponders simultaneously. Their detection fields would overlap and the attempt of reading would result in collision when there is a transponder on one of them. That's because the MicroRWD system is not an anti-collision system. The central communication unit is responsible for this synchronization. It also performs the task of gathering all detection data from the reader units and hold the pre-configured information of the position of each coil antenna. As a consequence the central unit is able to create the overview of all items with their position on the shelf. An external application can interfere the shelf's operation by a request on a standard RS232 interface. The shelf respective the central unit then replies with the last recent detections and their positions. The Figure 2 concludes this paragraph with a schematic of the shelf.

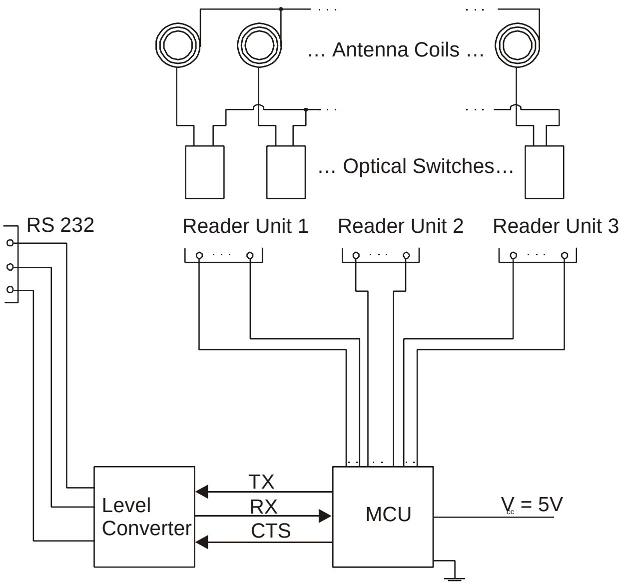

Figure 2. Smart Shelf Schmatic.

4.2. Performance

During our long-term tests we figured out some general problems with RFID technology and introduced some techniques to deal with them. By design the detection fields of the 36 coil antennas overlap each other on the 6x6 grid to avoid detection holes. In principle this results in 36 possible for an item, but at the same time this introduces multiple transponder detections, which are not stable over the time. As a consequence the grid was scaled down to a 3x3 grid and multiple detections were summarized to fit in this new grid.

The tests showed further that the RFID technology is not reliable as we assumed. When there was a static item configuration on the shelf we figured out up to 30% of missed reads, although the hardware was successively refined to cope with this problem. We implemented an additional memory function in the reader units. This function remembers at each attempt of reading a certain coil antenna the result of the previous attempt. If there was a previous detection and now there is none, it will start a schema of retrials to find the detection again. Long-term tests showed that the rate of read-misses could be decreased down to 0.3%. If there are lots of changes in the configuration of items this will slow down the operation of the shelf noticeable. The memory function works well when the configuration of items is mostly static which is true for normal application scenarios because people use to act with just one item a time in a time period of some seconds.

To address the slow response time of 130ms of one transponder a fast-update mode was introduced. It enables the central unit to update the current configuration when there was just half of the shelf's detection area re-read by the reader units. With this technique an average shelf response was achieved after 1.5s.

With the Smart Shelf we augmented items by cheap RFID transponders to identify them uniquely. The detection of the transponder on a shelf embedding the detection technology returns the positions of the item. The implementation operates standalone without any administration and replies with the last recent positions of all items by external requests. Additionally there is a configuration option allowing tweaking of timing parameters in order to be able to adjust to different characteristics of items.

5. Applications

As mentioned before the Smart Shelf can report the three basic actions *take*, *return* and *remove* to a backend system. In this section we give an overview of the applications that can be built on top of these actions. Basically these applications can be classified into three categories: data mining, store management, and recommendation systems.

5.1. Data Mining

Obviously the actions can serve as additional input for data mining and business intelligence systems. Hence they can provide a means for more detailed analyses of, for example, trends in customer behavior or the impact of advertising campaigns. In particular the interesting moment when the customers make their decision about buying a product or not can be revealed to such systems using the Smart Shelf technology. For example, we can observe how often a product is taken from the shelf without being actually bought or how long a customer holds a product in his hands before returning it to shelf. Thus we can deploy metrics similar to the click-buy-ratio or the time-on-page, which are widely used in e-commerce systems. Thus we can provide a means to quantitatively evaluate the effect of advertising campaigns and other measures undertaken to increase the sales of a certain product.

5.2. Store Management

Additionally the actions can be used to build various store management applications like a shelf out-of-stock watchdog or a plan-o-gram compliance check. That shelf management is a non-trivial task can be seen from figures telling that approximately 8% of all out-of-stock situations occur although there are enough products in the back-store, just because of missed shelf replenishments [3].

The Shelf Watch application that we built integrates both an out-of-stock watchdog and a plan-o-gram compliance check. This application manages a virtual model of the shelf representing its current state, i.e. the current location of the products on the shelf.

The application processes the messages received from the Smart Shelf. As described above these messages contain for each position on the shelf the identifier of the product located there or “0” for the positions where no product is located. By receiving a message describing the complete status of the shelf every 1.5 seconds, the model can be updated almost in real-time.

The application is connected to a backend system that stores the product information and the mapping of product identifiers to the appropriate product information. This backend system also holds the plan-o-gram stating which type of product is expected at each shelf position.

The application shows a graphical representation of the shelf’s state (see Figure 3) and checks the compliance of that state with the plan-o-gram. If there are any misplaced products they will be marked by a red frame in the graphical representation allowing an operator to easily recognize misplacements. If necessary a misplacement alert message can be sent out to other applications. Similarly the Shelf Watch application can generate an out-of-stock alert message, if a certain type of product is missing on shelf. Empty fields and fields with an unknown product on them are also especially marked in the graphical representation.

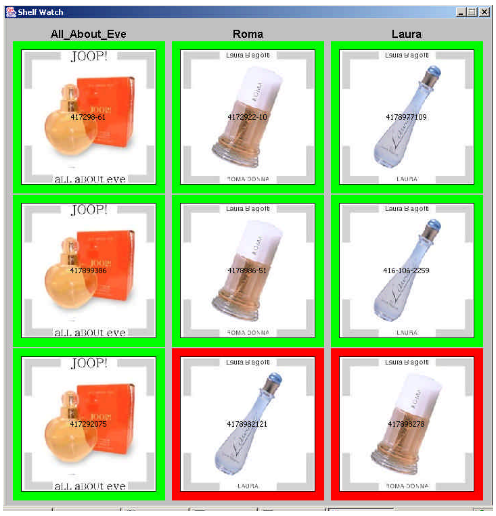

Figure 3. Graphical representation of the shelf.

5.3. Recommendation Systems

Finally the Smart Shelf allows a more direct interaction with customers. When a customer performs a certain action, like picking a product from a shelf, a backend system can immediately react to this action and trigger an appropriate response action. In this section we will show how this direct customer interaction can be used to realize recommendation systems in retail stores.

For such systems we also need some technology to communicate recommendations to the customers. The technology we have in mind here are electronic price labels as they are already available on the market today. Such labels consist of a LCD and a wireless communication interface. They are mainly intended to ease price adaptations, since new prices just have to be transferred to the electronic labels over the wireless communication interface, what makes a manual relabeling obsolete. Besides the price information today’s labels can also display small texts, e.g. 2 rows of 16 characters. Of course it would be technologically no problem to have more advanced labels that can also display graphics and play sounds.

In the e-commerce world recommendation systems are a well-known technique to increase cross-sales and customer loyalty. Consequently a lot of such systems are already in use today. The best known is probably Amazon.com’s “Customers who bought” –system. In [7] an overview of e-commerce recommendation systems is given. For almost each kind of system introduced there, we can find a reasonable equivalent in the retail world that can be implemented using Smart Shelves and electronic price labels.

For so-called non-personalized recommendation systems, i.e. systems that recommend the same products to all customers independent of their own personality, we would not even need a Smart Shelf but only the electronic price labels with a backend integration. The price labels could, for example, display a special message, if the respective product is under the three best selling products of a certain category and thereby recommending the customers to buy this product. However, if we also use a Smart Shelf we can direct the customer’s attention to such messages exactly at the moment when he is picking the product from the shelf, e.g. with a small beep emitted by the price label. This will certainly increase the number of customers who read the message.

Item-to-item correlation systems are another type of recommendation systems. They base their recommendations on the knowledge about a customer’s interest in one or more products. In order to realize such systems in a retail store we can use the Smart Shelf to recognize when a user is picking a certain product from the shelf what certainly indicates an interest in this product. At that moment the backend system can identify related products and recommend them to the customer through the electronic price labels. For example, we can inform customers picking a mobile phone from a shelf about the appropriate cases that are also available in the store. Less obvious correlations between items can be determined by analyzing the data provided by the checkout systems, i.e. the output set in our model. From this data we can see which products are often sold together and should therefore be considered as correlated.

6. Discussion

In order to discuss the Smart Shelf technology and their applications we compare it to other approaches from section 3 regarding the obtained information, costs, obtrusion, response time and scalability. These characteristics are ranked from “+” (positive) meaning that the requirements are met very well, over "O" (neutral) meaning that the approach needs further improvements, and finally down to "-" (negative) meaning that the requirements are hardly met.

We appraise the obtained information regarding the requirements for determining the basic actions *take*, *return* and *remove*. Therefore item's identification and position are needed. They can be obtained from the Smart Shelf and Smart Items very precisely, while video systems have problems with the unique identification. Costs are seen as higher prices for products because of the technology itself and maintenance reasons. Here, the Smart Shelf performs very well, because of the low cost augmentation, while Smart Items and video systems are more expensive because of their effort in hardware (Smart Items) and software/human review (video sensing). Obtrusion considers the side effect on the customers' behavior. Smart Shelf is a technologies where the customer is not aware of the acquisition of the interaction context. Smart Items need a certain complexity, so the customer is probably aware of them and video systems may create a feeling of being watched for the customer. The response time describes the time the technlogy can detect the basic actions. In particular, the Smart Shelf and the Smart Items response very fast, because they are directly involved into the actions. Video systems use the additional step of image recognition, which will delay the response, especially when done by manual review. Finally, the scalability provides information about how many actions at the same time can be performed. Smart Shelf was tested with three actions while still remaining an acceptable response time. The same performance and even better can be achieved by the Smart Items and the video systems.

Table1. Discussion of the Smart Shelf

	Smart Shelf	Smart Items	Video Systems
Obtained information	+	+	O
Costs	+	-	-
Obtrusion	+	-	O
Response Time	+	+	O
Scalability	O	+	+

7. Related Work

So far a lot of work has been done on the deployment of RFID technology to improve the data acquisition in business information systems as well as on customer tracking in e-commerce systems. However, to out best knowledge, we are the first who integrate the benefits from both worlds by using RFID technology in order to apply e-commerce techniques in real world retail stores.

Most RFID research has been focused on the physical layers, the protocols between tags and readers, and the development of appropriate software infrastructures [4]. There also have been some pilot projects on deploying RFID technology for supply chain tracking, e.g. in the consumer products industry [5], and to increase the shopping experience in retail stores [3, 6]. But in none of these projects the consumers' interactions with the products have been observed with a granularity that would be sufficient for a detailed analysis of the customers' behavior.

The methods that are used in e-commerce systems to track the customer behavior, like analyzing path traversal patterns [1], and metrics to quantify the consumer preferences, like the click-buy-ratio and time-on-page, are well understood. The same holds for recommendation algorithms [7]. But so far none of these valuable techniques has been applicable in real world stores, since an appropriate method for gathering information about the customers' behavior has been missing there.

8. Conclusion

In this paper we introduced Smart Shelves as a new technology that allows to track customer behavior in retail stores at a higher level of detail than it has been possible so far. Especially the interesting moment when the customers make their decision about buying a product or not can be observed better with Smart Shelves than with existing technologies.

We gave examples for the manifold applications that can be built on top of the Smart Shelf technology, which include data mining, store management applications as well as recommendation systems. Thus we showed that Smart Shelves will not only be advantageous for the retailers but also for the customers who may benefit from an increased shopping experience.

For the near future we plan to enhance our RFID-based Smart Shelves by load sensing technology [8] in order to decrease the response time of the shelves. The idea is to use the load sensing technology to detect the area on the shelf where something happened and to only read the antennas in this area. We expect that this will allow us to handle complex changes on bigger shelves almost in real-time.

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