ORIGINAL ARTICLES

Prediction of Consumers' Intension through their Behavior Observation in Ubiquitous Shop Space

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Abstract: This paper has studied and observed the consumer behavior by collecting all kinds of actions of consumers and applying the ubiquitous environment which are RFID and camera sensors to gathering log data. The consumer's behavior was automatically saved as a log file and analyzed by using artificial neural network. From neural network model allows us to categorize the consumers into 3 groups which are: A) the consumers who were certain in buying a product, B) the consumers who intended to buy a product but could not decide what to buy, and C) the consumers who did not intend to buy but stop by to view the product.

Key words: Consumer Behavior, Neural Network, Prediction Model, Shopping Behavior, Ubiquitous Shop Space

1. INTRODUCTION

At present, the advancement in technology that has mixed to be ubiquitous environment and RFID initiated various researchers to find and develop an application to support human life in ubiquitous environment. For example, in the current Business to Customer (B2C) e-commerce – the shop or the system is trying to find several methods in providing higher consumer satisfaction in order to attract consumer's interest in the products rendered by its shop. Those methods range from membership program, point collection program and information delivery through internet and mobile phone by pushing the information towards a lager group of consumers. That the number of consumers and a large number of information have augmented make pushing the information that matches the consumer's need much harder. The information has been presented broadly, meaning the real target group cannot be captured. Another case is the information is pushed based on the user profile filled in the membership application form. This case, compared to the latter, is scant. Besides, consumers do not prefer to disclose the personal information, therefore the pushed information does not hit at the right spot and it eventually turns out to disturb the consumer and becomes the spam mail.

This paper has studied and observed the consumer behavior by collecting all kinds of actions of consumers and applying the ubiquitous environment in gathering log data [6][7]. The consumer's behavior was automatically saved as a log file and analyzed by using artificial neural network.

This analysis allows us to categorize the consumers into 3 major groups, A) Those who were certain in buying a product, B) Those who intended to buy a product but could not decide what to buy, and C) Those who did not intend to buy but stop by to view the product.

Next, three models for these 3 groups of consumers were built to analyze each consumer – existing or new – and categorize him or her into the proper group so that the information can be pushed towards the right group or the group with the closest needs.

We would propose prediction of consumers' intension through their behavior observation in ubiquitous shop space. Background and related study were reviewed in section 2. In sections 3, we describe our shopping analysis in the project. A creation and analysis of a model are discussed in section 4. In section 5 implementation and experiment are explained. The conclusions with directions for future work are expressed in section 6.

2. BACKGROUND

2.1 Behavior pattern

Human beings possess fives organs which perform the sense of awareness. They are eyes, ears, nose, tongue and body. These organs are functioning for seeing, listening, smelling, tasting and touching. Though human beings were born with the same five senses of feelings, they have different interest. This research has observed the behavior of consumers. When they have interest in a product, they will stare at it or pick it up to take a glance. The breakdown of measurement and summary results has been constructed by current implementation actions – standing, viewing, touching, carrying and fitting. The definition of consumer behavior in our current implementation has been defined as Table 1.

Table 1: Definitions for Behaviors Pattern towards Items.

Actions	Definition
Standing	The state in which a consumer stops by at a certain distance in front of a certain object.
Viewing	The state in which a consumer looks at a certain object.
Touching	The state in which a consumer touches a certain object where the object does not separate from its shelf.
Carrying	The state in which a consumer separately picks up a certain object from its shelf.
Fitting	The state in which a consumer uses a mirror to match a certain object with his/her appearance.

We have been developing our ubiquitous shop space which we call "augmented space" in ubiquitous environment. The augmented space is composed of microscopic and macroscopic view devices. We can describe them as follows:

Microscopic view devices

Each shelf is equipped with (a) an RFID tag reader to identify each consumer around the area. The RFID tag reader can read the member IDs and the information recorded in RFID tags. (b) several cameras to detect their behaviors, related to the items, such as touching, grasping and wearing.

Macroscopic view devices

The ceiling of the shop is equipped with a camera array to cover the entire area, without occlusion, to detect the location of each consumer at each time slice.

In evaluation, we assume the time that consumers spent in front of products on the shelf may be a good predictor. We also assume that consumers will touch items in which they have an interest. We hypothesize that a consumer is interested in an item when he touches and stays in front of the item for a period of time. In the system process, we gather the consumer behavior, there must be a data summary so that we can use that conclusion for the following analysis (Table 2).

Table 2: Definitions for Evaluations of Actions toward Items

Evaluations	Definition
Period	The time that a consumer spends on a behavior measured in seconds.
Frequency	The number of times that a consumer behaves

2.2 Related studies

Recent developments in Information Technology are making electric household appliances more computerized and networked. If the environments surrounding us could recognize our activities indirectly by sensors, the novel services, which respect our activities, would be possible. This idea was initially proposed by Weiser as ubiquitous computing [1] and is emerging as Robotic Room [2], Intelligent Space [3], Easy Living [4], Smart Rooms [5], etc. One of the most important factors for such systems is the recognition of human intentions by using ubiquitous sensors. Intelligent Space detects the positions, which are recognizable from the external observation of a human, by using multiple cameras on the ceiling and drives a mobile robot to follow the human [3]. Easy living also detects the position of the human and turns on a light near the human [4]. These systems are considered as providing services by taking human intention into account on where the human intends to move.

In conventional retail stores, sophisticated RFID, GPS, and video based consumer tracking solutions have recently been developed that permit retailers to track how shoppers navigate through stores and respond to changes in the store environment [11][13].

For computer-based observational research to be widely adopted in retailing, several technical and behavioral challenges must be addressed. The first and most critical issue concerns the accurate collection of tracking data. Each of the available technologies has certain advantages and limitations that affect its suitability for different retail channels. For example, several companies have developed tracking systems that use RFID, GPS, or infrared sensors attached to shopping carts, hand baskets, or hand-held shopping devices to track the consumer's path through the store. These systems can provide reliable information on the shopping process, and the data are easily linked to individual-level consumer transaction and loyalty information. However, they are not effective in environments where consumers do not use shopping carts, leave their carts to shop in the store aisles, or otherwise choose not to use the tracked devices. Also, the cart-based technologies provide no information on the size or composition of the shopping party.

3. SHOPPING ANALYSIS IN THE PROJECT

The enforcement of answering a huge number of questionnaires on users is a bottleneck in modeling personal preferences. One idea is just taking their behavior log via ubiquitous sensors, without asking them, and mining some specific features by statistical analysis. Such a method is called passive observation. From the aspect of a ubiquitous information environment, future store projects [14], for instance, proposes a smart shelf to monitor their goods with RFID tags in real-time, communicating information with the store server as well as a consumer's shopping cart. The basic idea still remains in a passive observation scheme while it refers personal preference data of each consumer. The problem of this method is that it consumes long time and huge personal log to cover enough behavior data.

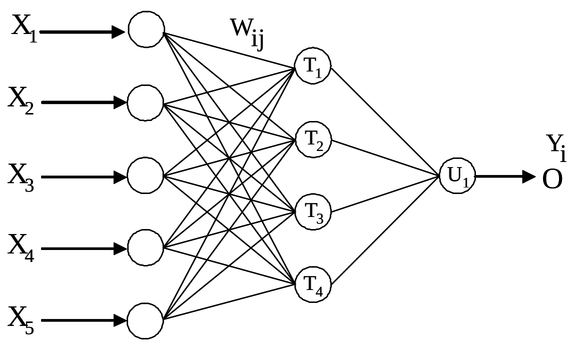
Our idea is to show several messages to each user, i.e., applying active observation, without expecting direct answers. If a message is informative and interesting to a user, he may pay attention, gaze, and follow the suggestion according to the message. In this process he is freely behaving by his intention without feeling any enforcement to answer to the system. In this case, monitoring each user's behavior, i.e., responses to the messages, via ubiquitous sensors enables us to attain enough behavior data effectively. This method corresponds to indirect interaction in active observation.

4. A MODEL CREATION AND ANALYSIS

4.1 Neural network for prediction model

Artificial neural networks are relatively crude electronic networks of neurons based on the neural structure of the brain. They process records one at a time, and learn by comparing their prediction of the record with the known actual record. The errors from the initial prediction of the first record is fed back into the network, and used to modify the networks algorithm the second time around, and so on for many iterations. Thus the neural network is capable to predict the result accurately and precisely with a nonlinear form. The back propagation method is the most popular among other methods used to predict the target value with learning background data of physical behaviors [9].

Back propagation (BP) model of the feed-forward multi-layer neural network is currently the most widely applied in the artificial neural network and it has significant practical worth in various manufacturing and informatics fields. BP network is usually a three-layer feed-forward network, which includes output layer, hidden layer and input layer. The structure of neural network used to predict consumer behavior group which consists of one hidden layer and one output is shown in Figure 1. The output is a prediction value of consumer behavior group. In this experiment, the Behavior pattern (standing, viewing, touching, carrying, and fitting) was initially utilized as a parameter in training and prediction. However, this time, we had increased the number of parameters to augment the effectiveness in prediction as shown in table 3 where X_1 is the number of times performed in standing and viewing per minute, X_2 is the number of times performed in touching, carrying, and fitting per minute, X_3 is times spent for the most frequently touched Item per minute, X_4 is screening item per minute, and X_5 is starting time period in viewing the first piece of product. Weight adjusting equation and sigmoid function for this neural network model is deduced in equation 1 and 2, respectively.



X: input; W: weight; T,U: Threshold; Y: Target value; O: output

Figure 1: Structure of Neural Network Model

$$\Delta W_{ij}(t) = -\varepsilon \frac{\partial E(t)}{\partial W_{ij}(t)} + \alpha \Delta W_{ij}(t-1) \qquad (1)$$

$$P(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

When, ε = learning parameter,
E = mean square error,
α = momentum,
t = iteration number, and
P(z) = sigmoid function.

Table 3: Input parameters for neural network model

Input Parameters	Content
X_1	Number of times performed standing and viewing per minute.
X_2	Number of times performed touching, carrying, and fitting per minute
X_3	Times spent for the most frequently touched Item per minute
X_4	Screening Item per minute
X_5	Starting time period in viewing the first piece of product

4.2 Training Process

We picked up the gathered data from nine samples of seven participants to test the model. We designated one minute of time as the starting point in projecting each consumer and categorizing them in the appropriate consumer group. Why one minute? Because one minute is the length of time that a consumer in this training set data spent which could be considerably the shortest time.

The projection reveals that the number of times spent to perform five shopping behaviors in one minute is comparable to the value of training set data because they both were adjusted into the same unit. Once the value is obtained, it will be plugged into the Neural Network Program to forecast the type of consumer group.

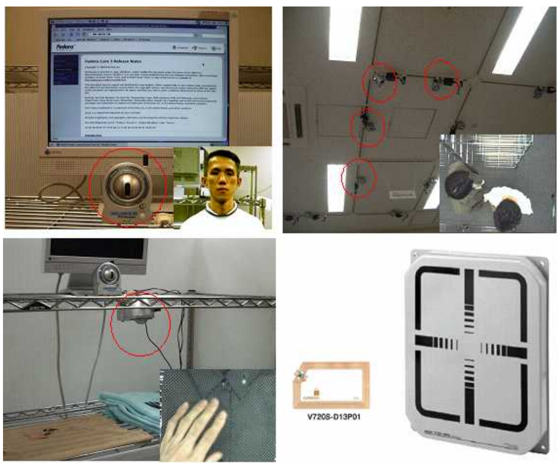


Figure 2: System Overview of Ubiquitous Shop Space

Finally, we had the consumers answer the questionnaire before leaving the shop in order to compare the difference or similarity between what the consumers have chosen and what the Neural Program has forecasted.

5. IMPLEMENTATION AND EXPERIMENT

5.1 Implementation

For the experiment, we have built a 30-square meter room to be an apparel shop which was functioned as a Ubiquitous Shop Space. There were 101 pieces of both men and women's apparel displayed on the six-floors shelf. Only 24 pieces were used in this experiment which meant each floor displayed four pieces of apparels. Each shelf, four cameras (Panasonic Network Camera BL-C31) were installed to monitor hand motions of the participants. There were 24 cameras altogether. Besides, 6 cameras were also installed in the ceiling and used to monitor location of the participant in the shop space. We applied the Fedora Core Linux operating system and the Apache web server utilizing PostgreSQL database. Moreover, RFID units (OMRON V720 Series) were used to identify participants if they approached the front of the shelf.

5.2 Experiment

In this experiment, there were seven female participants. These participants had to register with the system before the experiment. They were divided into 3 groups which consisted of:

Group A: Those who were certain in buying a product. They had already searched for the product from the internet. They were aware of the product availability but wished to experience the real product and try it on.

Group B: Those who intended to buy a product but could not decide what to buy.

Group C: Those who did not intend to buy but to stop by to view the product.

The experiment started from the point where they entered into the shop. As soon as the system proved that they were registered ones with RFID, they could wander around to view, to touch and to try it as long as they preferred. While they were in the shop, each camera would automatically record their five major behaviors as mentioned in the previous section. The data was saved in log file database.

Figure 3, 4 and 5 show the values of each group of consumer. The horizontal axis shows the five behaviors of the consumer while the vertical axis shows number of times to perform an activity of each consumer.

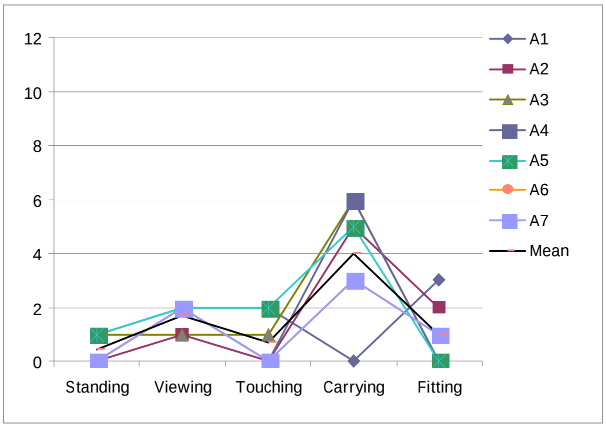


Figure 3: Number of Times Performed an Activity of Consumer Group A

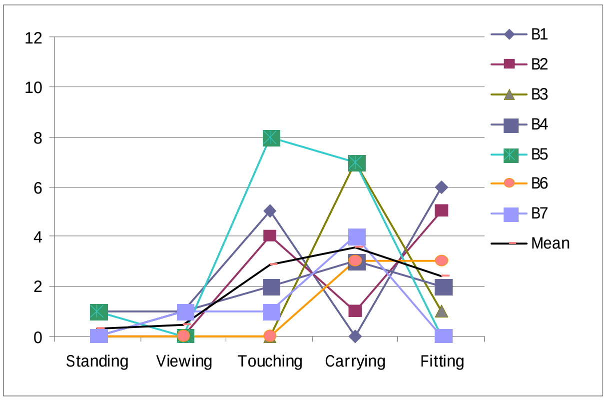


Figure 4: Number of Times Performed an Activity of Consumer Group B

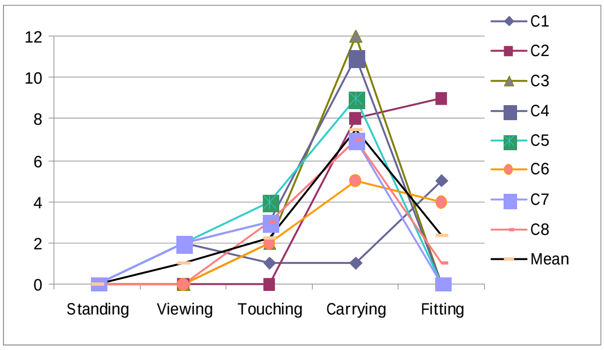


Figure 5: Number of Times Performed an Activity of Consumer Group C

Figure 3 shows the result of Group A Consumers, who stood and viewed the product first.. After that, they tried to hold it and to try it, whereas the behavior of consumer group B (Figure 4) is vague, cannot be explained about tendency. In group C (Figure 5), the consumer’s behavior tends to be linear increasing.

Afterwards, the normalized number of times to perform each activity and another parameter which is a training set data was put in neural network program. The learning of neural network model is completed by thirty-one samples from seven users (Table 5). From the neural network model, a test data from seven users will be plugged in to forecast the type of consumer group (Table 6). Finally, we had the consumers answer the questionnaire before leaving the shop in order to compare the difference or similarity between what the consumer have chosen and what the neural network model has forecasted.

Table 5: Result of Neural Network Data Training

Trainer	Input					Target Value	Output
	X1	X2	X3	X4	X5		
1	1.716	4.291	0.514	0.368	0.432	A	A
2	0.560	3.918	0.509	0.210	0.183	A	A
3	1.446	5.060	0.605	0.207	0.033	A	A
4	2.111	4.222	0.472	0.302	0.087	A	A
5	1.998	4.661	0.592	0.190	0.114	A	A
6	1.421	2.841	0.559	0.142	0.350	A	A
7	3.337	7.787	0.487	0.185	0.114	A	A
8	1.434	7.168	0.596	0.239	0.101	A	A
9	1.715	3.429	0.515	0.429	0.149	A	A
10	2.321	6.963	0.529	0.193	0.233	A	A
11	3.818	2.545	0.625	0.636	0.102	A	A
12	0.000	4.063	0.584	0.254	0.114	B	B
13	0.000	4.405	0.694	0.157	0.199	B	B
14	0.419	6.292	0.409	0.084	0.067	B	B
15	0.000	3.166	0.566	0.106	0.068	B	B
16	0.447	4.913	0.421	0.089	0.073	B	B
17	1.602	7.211	0.673	0.267	0.050	B	B
18	0.974	3.896	0.698	0.139	0.088	B	B
19	0.420	3.357	0.842	0.140	0.048	B	B
20	0.000	4.318	0.540	0.154	0.136	B	B
21	0.000	6.209	0.609	0.035	0.048	C	C
22	0.000	4.999	0.653	0.071	0.029	C	C
23	0.508	3.557	0.738	0.042	0.201	C	C
24	0.585	3.800	0.653	0.037	0.020	C	C
25	0.000	5.525	0.713	0.050	0.071	C	C
26	0.759	3.797	0.620	0.063	0.136	C	C
27	0.000	3.888	0.731	0.086	0.063	C	C
28	0.000	4.155	0.568	0.038	0.157	C	C
29	0.468	6.554	0.701	0.067	0.134	C	C
30	0.000	4.626	0.631	0.046	0.064	C	C
31	0.000	3.901	0.758	0.061	0.051	C	C

Table 6: Prediction of Consumer Predicted Data

Trainer	Input					Target Value	Predict Output
	X1	X2	X3	X4	X5		
1	0.000	3.119	0.575	0.267	0.103	A	B
2	0.889	1.778	0.186	0.296	0.312	A	A
3	0.901	4.507	0.498	0.100	0.187	A	A
4	0.480	5.281	0.538	0.137	0.060	B	B
5	0.764	2.675	0.664	0.109	0.062	B	B
6	0.462	3.231	0.811	0.173	0.051	B	B
7	0.894	3.130	0.618	0.134	0.070	C	B
8	0.000	4.024	0.549	0.069	0.036	C	C
9	0.000	6.657	0.625	0.047	0.036	C	C

The test results which neural network model has forecasted corresponded to hypothesis about 77%. Group A and C Consumers would have tendency to switch to Group B Consumers if they found a preferable product to purchase.

In this test, the results actually show the effectiveness of our approach in an actual Ubiquitous Shop Space environment.

The experiment explained that

Group A Consumers have made a purchasing plan before visiting the shop or shopping online. We can conclude as the followings.

In general situation:

1. Time would be used in searching for interested goods. They spent more time in viewing the first piece of product compared to other groups. If they can quickly find it, the searching time will become shortened, compared to other groups.

2. The number of interested or screened product is less than that of other groups.

3. They spent lengthy time on the extra interested product (or sometimes returned back to re-check it) which has been in advance decided to be purchased.

In some cases, when consumers found that the actual product did not match up with their intention; for instance, different color, material, etc, once they had searched them, they might change their mind not to purchase it.

Group B Consumers had an intention to buy but not decided on what to buy.

1. A portion of time would be spent in searching for the interested product and the product comparison. Time spending at the shop varied from the medium to maximum length depending on the strictness of purchase selection.

2. The number of interested or screened product is larger than that of group A. They spent lengthy time on the extra interested product (or sometimes returned back to re-check it) which has been in advance decided to be purchased. (Similar to Group A)

Group C Consumers were window shopping type

1. They, compared to Group A, and B, spent the lengthiest time in the shop with the exception that if the product did not attract their attention; they would view and step out of the shop very soon. When they started viewing the first piece of product, they would take a faster action than other groups.

2. The number of products viewed and touched exceeded that of other groups.

3. They would walk around without the goal of destination but would not go back to re-check the product. Except for the situation that they came across the intriguing product, they would spend more screening time or make a purchasing decision. This set of data was not brought to be used as a training set of Group C Consumer.

Some participants spent less time in the shop and had no substantial amount of activities which led to a complex prediction.

The starting point of time in selecting the first piece of product becomes significant because participants who made a buying intention beforehand would take up more time at the beginning to search for the targeted product.

Results of this experiment were recorded by the Video Camera as well as the ubiquitous sensor to examine the system accuracy. At present, Log System - a stand log, a view log and a touch log - can function reliably and would be improved to be more automatic in the near future.

6. CONCLUSION

This paper aimed to analyze the log data from different types of action of consumers in order to understand the consumer behavior. The analyzed data was processed through a Neural Network Model. The outcome of the experiment revealed that the data used in test set corresponded to the hypothesis about 77 percent. However, the observation of consumer behavior in this study was merely observing the external behavior which was automatically recorded by camera sensors and logged to database. In reality, it is inadequate to understand the actual consumer behavior simply by relying on the results of this experiment.

In addition, other factors will also need to be taken into consideration. The first example is the personality of each consumer which cannot be easily measured by the tool or program. Another example is the mood and feeling during their presence at the shop because it affects the process of viewing and choosing a product.

In the near future, we wish to apply this system to be implemented in the real shop so that it will render the convenience to consumers in daily life and build the utmost consumer satisfaction.

REFERENCES

1. M. Weiser, The computer for the twenty-first century, Scientific American, 94-104 (1991).
2. J.H. Lee, G. Appenzeller, H. Hashimoto; Physical agent for sensored networked and thinking space; Proceedings of the 1998 IEEE International Conference on Robotics & Automation; 838-843 (1998).
3. T. Mori, K. Asaki, H. Nogushi, T. Sato, Accumulation and summarization of human daily action data in one-room-type sensing system, IROS2001, 2349-2354 , (2001).
4. J. Krumm, S. Harris, B. Meyers, B. Brumitt, M. Hale, S. Shafer; Multi-camera multi-person tracking for easy living; Proceedings of 3rd IEEE International Workshop on Visual Surveillance; 3-10 (2000).
5. A. Pentland, R. Picard, P. Maes; Smart rooms, desks, and clothes: toward seamlessly networked living; British Telecommunications Engineering; 15, 168-172 (1996).
6. S. Sae-ueng, S. Pinyapong, A. Ogino, T. Kato; Consumer-friendly Shopping Assistance by Personal Behavior Log Analysis on Ubiquitous Shop Space, proceeding of 2nd IEEE Asia-Pacific Services Computing Conference; APSCCS2007, 496-503, (2007).
7. S. Sae-ueng, A. Ogino, T. Kato; Modeling personal preference using shopping behaviors in ubiquitous information environment; proceeding of 18th IEICE data engineering workshop/5th DBSJ annual meeting (DEWS2007), (2007).
8. D. Naito, K. Yamamoto, K. Yada, N. Matsumura, K. Ohno and H. Tamura, Does WEB Log Data Reveal Consumer Behavior?, Proc. of the Workshop Discovery Challenge in conjunction with ECML/PKDD 2005 (Oct 7 2005, Porto, Portugal), pp. 43-54, (2005).
9. MICHAEL A. Arbib, The Handbook of Brain Theory and Neural Networks, 2 Ed, THE MIT PRESS, Massachusetts: p.1344. (2002).
10. Montgomery, Alan L., Shibo Li, Kannan Srinivasan, and John C. Liechty: Modeling Online Browsing and Path Analysis Using Clickstream Data, Marketing Science, 23(4), 579-595. (2004).
11. Gogoi, Pallavi: Retailing, the High-Tech Way, Business Week Online, July 6, Special Report: Retelling's New Tech. (2005).
12. Osgood, CE 1957, The Measurement of Meaning, Univ. of Illinois Pr, New Ed. (1957/06).
13. Pereira, Joe: Spying on the Sales Floor, The Wall Street Journal, December 21, p.B1. (2005).
14. The METRO Group Future Store Initiative; - Retrieved September 1, 2007, from http://www.future-store.org