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Mobile merchandise evaluation service using novel information retrieval and image recognition technology

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ABSTRACT

Consumers' purchasing behavior has obviously changed in recent years with developments in social economics. This change has been evident in the decreased ratio of planned purchases but not in the increase of planned (or spontaneous) purchases. This act of spontaneous or otherwise unplanned purchasing is called "impulse buying". However, buying under these conditions costs more money always comes with negative responses, such as complaints and regret. Therefore, we propose and have designed a new merchandise recommendation system, the Mobile Merchandise Evaluation Service Platform (MMESP). This is a three-tier system composed of Real-time Merchandise Identifying System (RMIS), Real-time Merchandise Evaluation System (RMES), and Real-time Merchandise Recommendation System (RMRS). With this system, Mobile Users (MUs) take pictures of merchandise and send them to MMESP, RMIS integrates Region Adjacency Graph (RAG) and Self-Organizing Maps (SOM) to gather information on the merchandise through those photographs, and. RMES and RMRS provide Intelligence Agents (IAs) and Multiple Document Summarization (MDS) to summarize recommendations on merchandise for MUs, all in real time.

1. Introduction

Consumers' purchasing behavior has obviously changed in recent years with developments in social economics. This change has been evident in the decreased ratio of planned purchases, but not in the increase of unplanned (spontaneous) purchases. This act of spontaneous or otherwise unplanned purchase is so-called "impulse buying" [2,18,21].

Consumers' purchasing might be very hurried because of work stress and the lack of leisure time. Furthermore, the purchasing environment, such as others' recommendations and special discounts lead the consumers to purchase on an impulse. Solomon indicates that more than 70% of cosmetics buying decisions are not on the plan and the impulse buyers make their shopping decisions very quickly [17]. However, buying under this condition is more expensive, and it always comes with negative responses such as complaint and regret [16].

The traits of impulse buying are:

1. Fast shopping decision making
2. Information deficiency
3. Expensive dealing price
4. Below expectations products

Based on all of the above, Mobile Merchandise Evaluation Service Platform (MMESP) oriented designing principles and functions should include:

1. Identifying the product instantaneously
2. Accessing the product's information immediately
3. Displaying the product's recommendations and evaluations from former consumers
4. Providing price comparison and recommendation

Therefore, this research was designed to integrate the Image Identifying System (IIS), Self-Organizing Maps (SOM), Intelligent Agent (IA), and Multiple Document Summarization (MDS) in the information system. Taking make-up and magazine as examples, we provide instant Merchandise Evaluation Service (MES). We designed a 3-tier structure of Real-time MMESP, including Real-time Merchandise Identifying System (RMIS), Real-time Merchandise Evaluation System (RMES), and Real-time Merchandise Recommendation System (RMRS).

The remainder of the thesis is structured as follows. In Section 2 we provide background knowledge through the description of

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related technologies, such as the concept of IIS, SOM, IA, and MDS. In Section 3 we propose the approach of the adaptable MES search combined RMIS, RMES, and RMRS. The complete structure and implementation of MMESP we proposed is explained in Section 4. Finally, conclusion and the future work are given in Section 5.

2. Related work

The Mobile Merchandise Evaluating Service Platform (MMESP) is designed to provide (i) real-time merchandise identification, (ii) real-time access to related information on the merchandise, (iii) instant browsing the product's information, and (iv) price comparison and recommendation. Necessary research background and relevant technology include: (1) Image Identifying System (IIS), (2) Intelligent Agent (IA), and (3) Multiple Document Summarization (MDS).

2.1. Image identifying system (IIS)

As a result of the rapid development of technology, the Internet not only provides a medium for transfer of text data, but also, more importantly, for multimedia. To deal with impulse buying, MMEPS integrates an image identifying system to help users evaluate products via picture taking.

A common feature in many application systems is the key component needed to do the image identification. Many recognition systems and algorithms have been proposed. There are some traditional methodologies in the image identification research area, such as dynamic programming, elastic matching, minimum distance classifier, string matching by correlation and deformable templates. Recently, some researchers have used genetic algorithm and hidden Markov mode. Today, the image identification techniques have made great progress in alphanumeric recognition. Moreover, there exist many improvements in image retrieval plus identification techniques and recognition algorithms. Yang et al. [22] and Perlibakas [12] used PCA for appearance-based face representation and recognition. Li and Tang [9] used support vector machines (SVM) to enhance Bayesian recognition. Therefore, we used SOM algorithm to improve the dynamic image retrieval and accelerate the recognition in this study. Furthermore, we implement the mobile merchandise evaluation service platform to facilitate its use by mobile users.

2.2. Intelligent agent (IA)

The definition presented here is adapted from Wooldridge and Jennings (Wooldridge, 1995). "An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives". The functionality of each intelligent agent is described as follows. (i) Blog Content Retrieval Agent (BCRA), (ii) Merchandise Information Retrieval Agent (MIRA), (iii) Geographical Information Agent (GIA), (iv) User Interface Agent (UIA), (v) Coordinating Agent (CA), and (vi) Resources Monitor Agent (RMA). Six intelligent agents provide mobile clients with the customized information.

The applications with MMESP are shown as follows:

2.2.1. E-commerce

MMESP is user friendly because it can automatically provide judgments and support decision-making from the viewpoint of user's preferences and requirements.

2.2.2. Information collection and retrieval

The current web information is too complicated, it is also time-consuming and labor-intensive in finding specific information for the user. Inference engine technology is becoming stronger so that data collection and retrieval are more convenient and intuitive. However, due to its inefficiency, the search will display accessed information repeatedly, and cannot accurately meet user needs. MMESP combines the agent mechanism to search out the desired information more accurately by storing an index value or the historical record of user browsing.

2.2.3. Information filtering

The intelligent agent uses pre-defined filtering rules to filter information in advance in order to reduce the amount of data and extract more useful information.

2.3. Multiple document summarization (MDS)

Blogs have increased greatly in recent years because of the rapid development of computer technology and broader access to the Internet. Users may receive a huge amount of information from blogs through the intelligent agency. However, it is difficult for the user to filter useless and repeated information. To solve this problem, MMESP uses Multiple Document Summarization (MDS) to simplify and eliminate repeated information, so the user can save search time and derive needed important information.

MMESP is combined with MEAD which is a public domain portable multi-document summarization system based on Linux. MEAD, whose process is shown in Fig. 1, is implemented by Perl programming language [15].

The main procedures of MEAD are:.

(1) Preprocess: The intelligent agent retrieves the contents of the Blog using HTML format to segment sentences in the original document in order to facilitate follow-up by the weight computing.

(2) Feature selection: In this paper, MDS is designed to consider several features to compute the weight of each sentence by words and phrases. The main three features are centrality, sentence length, and position [1,13,14,23,24].

(3) Classifier: The score of each sentence is computed as the total weight of each feature [8].

(4) Reranker: The Classifier only functions to score sentence similarity and sorting. This may lead to a problem when there is a high degree of similarity between sentences, especially in multi-document summarization. MEAD designs a Reranker mechanism to recalculate sentences with syntactic similarity and set the threshold to filter out important sentences to reduce the redun-

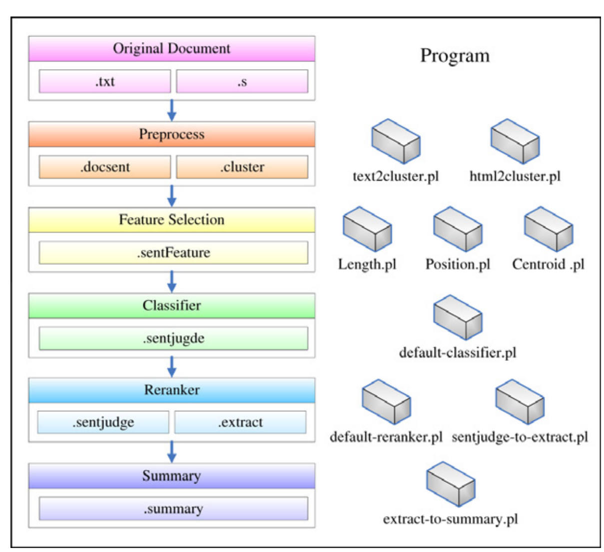

Fig. 1. The process of MEAD.

dancy ratio. Finally, a summary value is derived by extracting sentences from original document by the compression ratio [3].

(5) Summarization: Summarization retrieves and recombines words and phrases in the original document according to the ranking of the sentences by Reranker sorting.

(6) Evaluation: MMESP measures the performance of the text summarization system, including the effect of output results as well as users' satisfaction [11].

3. System structure

Mobile Merchandise Evaluate Service Platform (MMESP) integrates image recognition and relevant Information Retrieval techniques. It provides (1) thematic inferences, (2) merchandise optimization inferences, and (3) multi-document summarization, to recommend merchandise suitability to the user. The system design principles are followed. The MMESP which is designed with three-tier architecture is published to open platforms (e.g. Facebook, Google, Yahoo, and other application stores). As shown in Fig. 2, MMESP includes Real-time Merchandise Identifying System (RMIS), Merchandise Evaluation System (MES), and Merchandise Recommendation System (MRS). Users can use any kind of mobile device, such as 3G cell-phone, personal digital assistant (PDA), laptop, or tablet pc to access the merchandise evaluate service through application or browser.

MMESP includes intelligence agents, image identifying system, self-organized neural network, multiple document summarization, and merchandise recommendation system. The recommendation results would be presented on the hand set device, and a mobile user can receive the merchandise evaluation service supported by software and hardware in a wireless communication environment. MMESP is based on the 3G cell-phone platform providing wireless communication for a mobile user designed by Java. Users connect to a World Wide Web (WWW) server which is developed by Java Server Pages (JSP). System manager could build and manage the system in the back-end side.

3.1. Real-time merchandise identifying system (RMIS)

RMIS is at the front end of internet, it mainly processes multimedia and provides services such as image recognition, which includes Real-time Multimedia Transmission (RMT) and Image Identifying system (IIS).

When users rush to buy something, they can use cell-phone to take pictures of the product and send them through J2ME technique (MIDP2.0) via mobile communicate internet (3G or IEEE802.11b) to the server. RMIS will integrate the Region Adjacency Graph (RAG) and Self-Organizing Maps (SOM) as soon as it receives the image. At the same time, it processes and classifies the image in order to recognize the merchandise. The flow path is shown in Fig. 3.

3.1.1. Real-time multimedia transmission (RMT)

Text and pictures are transmissible media data. The user can use 3G cell-phone or PDA to take pictures of the product they are interested in. These pictures will be sent back to the back-end RMIS for image recognition, to provide real-time and convenient merchandise evaluation service.

3.1.2. Image identifying system (IIS)

RMIS integrates the Region Adjacency Graph (RAG) and Self-Organizing Maps (SOM) techniques to process the multimedia image. The procedures are (i) transformed to the RGB matrix (ii) fuzzy process (iii) color degrade (iv) histogram (v) region and

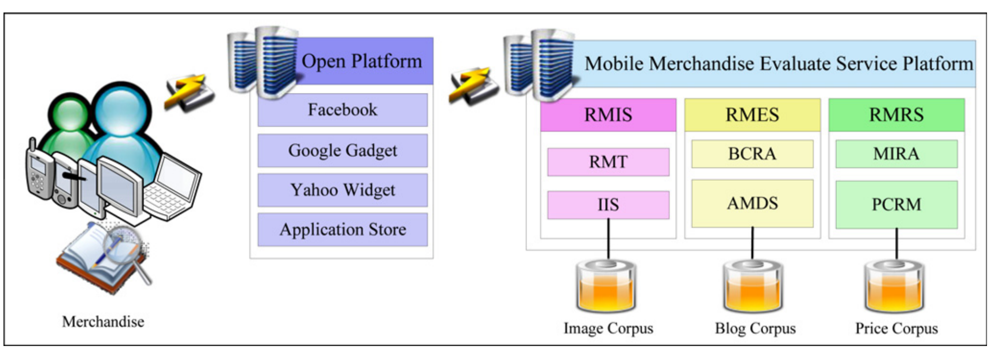

Fig. 2. System structure.

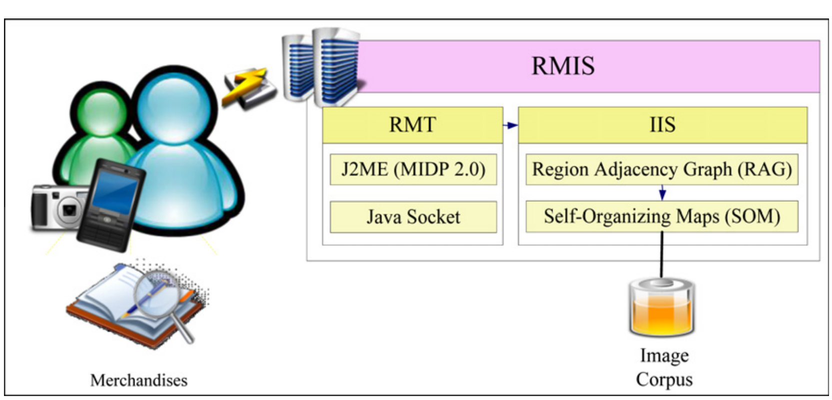

Fig. 3. The process of RMIS.

adjacent relation (vi) region merging (vii) Region Adjacency Graph (RAG) (viii) Self-Organizing Maps (SOM) and (ix) similarity determination.

First, RAG calculates the merchandise pictures and derives the merchandise characteristics, then puts them into SOM to train the Artificial Neural Network. When the system gets the image, it can compare and classify the image and recognize the merchandise in order to get the relevant information to do the commenting and recommendation.

This research is based on Java, and integrates image processing via Region Adjacency Graph (RAG) technology to prevent the image identification from being affected by the rotation, enlargement, or condensation of the image or the partial sub-image. The main processes are as follows [7].

(1) Transforming to RGB matrix: First, the input image I is transformed into RGB matrix to execute the calculation. For example, there is a cosmetic product "Clinique Moisture Surge Extended Thirst Relief" shown in Fig. 4.

(2) Fuzzy process: The input image I is smoothed by a linear, typically Gaussian, filter. This linear filtering eliminates any plateaus, defined as uniform regions, by converting the image to a floating point representation with a gradient magnitude operator and yields the gradient magnitude image (GMI). The numerous gradient operators of GMI can be utilized as follows:

$$I_{GMI} = \|\nabla(G(I))\| \tag{1}$$

where $G(\cdot)$ and $\nabla(\cdot)$ are the Gaussian filtering operation and gradient operator, respectively, and $\|\cdot\|$ denotes magnitude [6]. The GMI, shown in Fig. 5 can be viewed as a geographical surface where the largest gradient magnitude values are interpreted as watershed lines, and the regions separated by the watersheds as catchment basins. Thus, as a physical analogy, any water falling on one side of a watershed line will flow downhill until it reaches a local intensity minimum (LIM). To formally define the LIMs, let $i_g(n) \in I_{GMI}$ be a sample in the GMI image at index $n = [n_1, n_2]$, and define the $N \times N$ neighborhood (N odd) of samples centered at n as follow [5].

$$I_n^N = \left\{ i_g(m) \in I_{GMI} : m \in \Omega_n^N \right\} \tag{2}$$

where

$$\Omega_n^N = \left\{ \begin{array}{l} m \in Z^2 : \\ |n_1 - m_1| \leqslant \frac{(N-1)}{2}, |n_2 - m_2 \leqslant \frac{(N-1)}{2} \end{array} \right\} \tag{3}$$

Then a sample $i_g(n) \in I_{GMI}$ is a LIM if

$$i_g(n) < i_g(m) \forall i_g(m) \in I_n^3, \quad m \neq n \tag{4}$$

Fig. 6 shows the example image as processed by GMI.

(3) Color reducing: In this step, it reduces the processed image's colors from RGB value. For example, it can reduce the number of colors from 256 to 4 by dividing into 64, and the number of colors will diminish from $256^3 = 16{,}777{,}216$ to $4^3 = 64$. The example image of reduced color is shown as Fig. 7.

(4) Histogram making: It uses a histogram to display frequencies of pixels of 64 colors and examine the image process for failure or inaccuracy.

(5) Region adjacency relations: The adjacent points with the same color are brought into the same segments.

(6) Segment merging: In this step, we merge the fixed ratio segments with the larger segments around them because the fracture

Fig. 4. The input image.

Fig. 6. The image as processed by GMI.

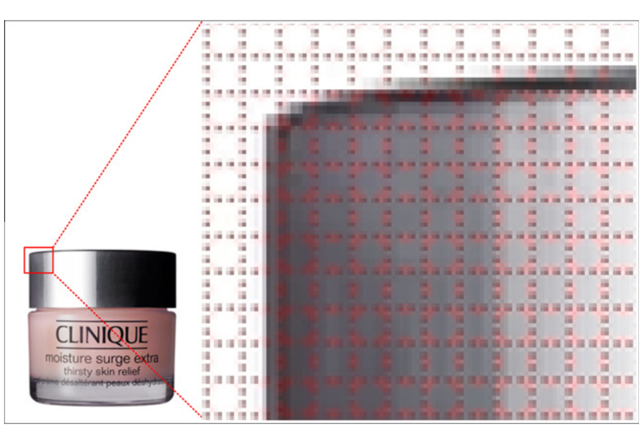

Fig. 5. The presentation of GMI ($N = 3$).

Fig. 7. Reducing color.

of segments might reduce the processing speed. Fig. 8 shows the example image after merging segments.

(7) Region adjacency graph (RAG) computing: After the above processes, it selects the top k large segments, which contain the colors, the measure of area, shapes, and the number of adjacent segments' into a two-dimensional array, and stores the k segments' neighborhoods in to RAG. Tables 1 and 2 show the results of example imaging after RAG computing.

Fig. 8. Segments.

Table 1
The RAG result of example image contains k segment and average RGB values.

Target	Value
Segments	1419
Average red	2.196912
Average green	2.025552
Average blue	2.045424

Table 2
The RAG results of segmentation contains the shape and RGB when the number of the largest segments (k) is set as 5.

Segment No.	$Shape = \frac{\text{Perimeter}}{\sqrt{\text{The measure of area}}}$	R	G	B
1	7.528407	3	3	3
2	7.785796	0	0	0
3	16.14663	3	3	3
4	7.850506	3	3	3
5	7.528407	3	3	3

(8) Experimental self-organizing maps (SOM): It projects the different RAG data into SOM and classifies the products' characteristic marks derived from SOM technique.

(9) Determining the similarity: Finally, we determine the similarity between the new incoming image and the classifications that have resulted from SOM algorithm. This research determines the similarity with Cosine Theorem, and determines the similar products for later computing service.

3.2. Real-time merchandise evaluation system (RMES)

RMES provides functions including Blog Content Retrieval Agent (BCRA) and Automatic Multiple Document Summarization (AMDS) and so on.

When the RMIS finishes the merchandise recognition, the system transmits the merchandise information to the RMES. BCRA will search the relevant blog content through the Google Blog Search, and save the Crawler and Parser as the Blog Corpus. Finally, the Multiple Document Summarization technique will retrieve the relevant Blog Corpus from the merchandise comment and summarize if for users in order to make their buying decision. The flow path is showed in Fig. 9.

3.2.1. Blog content retrieval agent (BCRA)

Blog Content Retrieval Agent (BCRA) provides functions such as Fuzzy Search, HTML Crawler, and HTML Parser; the details of the functions are as follows:

(1) Fuzzy search: It provides fuzzy arithmetic and judgment to build the relevant key word vocabulary, and it actively uses the key words to search through Google Blog Search.

(2) HTML crawler: It sends the content of blog after the Google Blog Search is finished, it also traces the relevant links and stores the HTML content.

(3) HTML parser: It interprets the HTML with HTML tag from HTML Crawler and derives the information. It also effectively deletes the relevant special characters (such as single quotation mark and double quotation mark) to avoids SQL injection attack, and it builds the Blog Corpus in order to do the multiple document summarization inference.

3.2.2. Automatic multiple document summarization (AMDS)

RMES combines the AMDS by instantaneously summarizing the blogs' relevant merchandise comments. It efficiently reduces the amount of information so the users can conveniently view the comment and experience from the previous buyers AMDS is done by the MEAD package, which puts the relevant merchandise comment from Blog Corpus based on MEAD module. The processing procedure is (I) Predefine, (II) Preprocess, (III) Feature Selection,

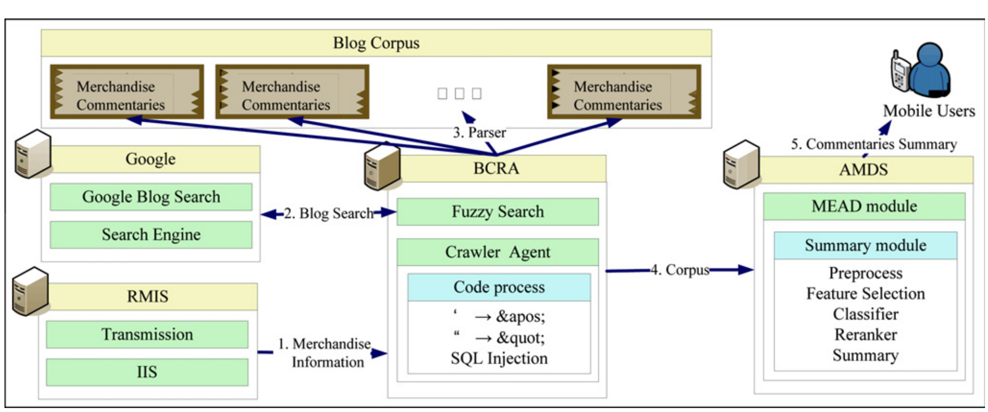

Fig. 9. The process of RMES.

(IV) Classifier, (V) Reranker, and (VI) Summary. The details are as follows:

(1) Predefine: In this section, we predefine and establish the Merchandise Comment Term Ontology (MCTO) which contains Merchandise Comment Term Set (MCTS) and Relevant Comment Term Set (RCTS) based on Natural Language Processing (NLP) and knowledge representation techniques for automatic summarization [20]. Fig. 10 shows the procedure for MCTO establishment.

I. Merchandise comment term set (MCTS): First, BCRA crawls and parses many merchandise blog articles from Google blog search engine (path (1) in Fig. 10). These articles are sent to several domain experts to generate the summaries as training data for MCTS establishment. Afterward BCRA uses the Stanford Log-linear Part-Of-Speech (POS) Tagger library [19] to analyze the POS (e.g. noun, verb, adjective, and adverb) from the experts' summaries (path (2) in Fig. 10). In this paper, we select noun terms and adjective terms to establish the MCTS (path (3) in Fig. 10).

II. Relevant comment term set (RCTS): For RCTS establishment, we use WordNet library [10] to find out the hypernyms and hyponyms of the noun terms and the synonyms and antonyms of the adjective terms according to MCTS (path (4) in Fig. 10), respectively. Finally, the MCTS is extended the relevant comment terms to establish RCTS (path (5) in Fig. 10).

(2) Preprocess: The preprocess transfers the format of original HTML documents from blog. Then it sets the document ID and Sentence ID sequentially in order to maintain the weight of sentences in each document and production.

(3) Feature selected: After that, MMESP uses several features, (i) Centrality, (ii) Sentence Length, and (iii) Position to calculate the weight of each sentence.

I. Centrality: We use the Vector Space Model (VSM) to carry out the similarity calculation. In this paper, the keywords which are contained by RCTS only will be considered. The maximum cosine value represents the centroid vector of the cluster. The following expression is used to calculate the value of the sentence *s*.

$$Score_{Centrality}(s) = \frac{|keywords\ in\ s \cap\ keywords\ in\ other\ sentences|}{|keywords\ in\ s \cup\ keywords\ in\ other\ sentences|} \times \forall keywords \in RCTS \tag{5}$$

II. Sentence length: If the length of the sentence is above a given threshold, it is 1. Otherwise, the sentence length is 0. The following expression is used to calculate the value of the sentence length.

$$Score_{Length}(s) = \begin{cases} 1, Length(s) > n \\ 0, Length(s) \leqslant n \end{cases} \tag{6}$$

III. Position: Position is to assign weight by the position of the sentence in the document. For this purpose the weight is divided into 10 levels: 0–9. 0: the sentence does not belong to a summary; 1–9: the sentence belongs to a summary. The importance: 1 is weakest, and 9 is strongest. The following expression used to calculate the value of the position of the sentence in the document.

$$Score_{Position}(s) = P(s \in S|Position_i) \times \frac{Average\ of\ Position_i}{9.0} \tag{7}$$

(4) Classifier: In the third step, we select some important features to set the different weight according to those features. We summarize those features and their weight to calculate the score of each sentence.

If Centrality weight is w_1, Position weight is w_2. The expression is as follows:

$$Score_{Overall}(s) = [w_1 \times Score_{Centrality}(s) + w_2 \times Score_{Position}(s)] \times Score_{Length}(s) \tag{8}$$

(5) Reranker: In this step, we judge the correlation in sentences which will decrease the redundancy. Next, we set the threshold for filtering, and set the compression to extract.

(6) Summary: After that, we get the extract from Reranker and map the extract to summarize from Document ID and Sentence ID in this step of preprocessing. Finally, Multiple Document Summarization technology provides a summary of comments for users.

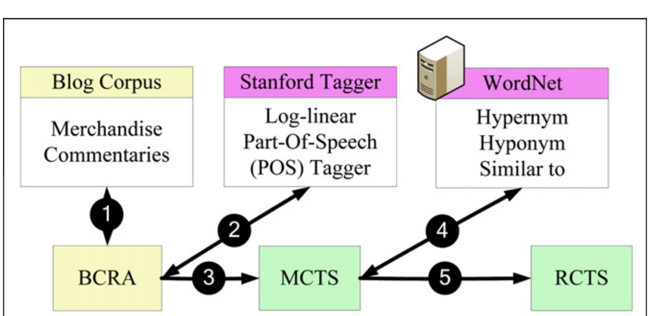

Fig. 10. The procedure for Merchandise Comment Term Ontology (MCTO) establishment.

3.3. Real-time merchandise recommendation system (RMRS)

RMRS provides functions that include Merchandise Information Retrieval Agent (MIRA) and Price Comparing Recommendation Mechanism (PCRM).

When RMIS finishes the recognition, it sends the data information to the RMRS, and it searches the price from the price comparing websites and the relevant website. According to the merchandise price information from a different e-commerce website, it saves the Crawler and Parser as the merchandise price corpus. Finally, it extracts the price information from the relevant merchandise price Corpus through the price comparing mechanism and recommends the better merchandise after price comparison. The user can learn the merchandise's reasonable price, avoiding wasting money. The RMRS procedure is shown as Fig. 11.

3.3.1. Merchandise information retrieval agent (MIRA)

Merchandise Information Retrieval Agent (MIRA) provides functions such as Fuzzy Search, HTML Crawler, and HTML Parser, the details of which are as follows:

(1) Fuzzy search: This provides fuzzy arithmetic and judgment to build the relevant key word vocabulary, and it actively uses the key word vocabulary in searching through Google Blog Search.

(2) HTML crawler: It sends the content of blog after finishing the Google Blog Search., It also traces the relevant links and stores the HTML content.

(3) HTML parser: It interprets the HTML with HTML tag from HTML Crawler and derives the information. It also effectively deletes the relevant special characters (such as single quotation mark and double quotation mark) to avoid SQL injection attack and it builds the Blog Corpus in order to accomplish the multiple document summarization inference.

3.3.2. Price comparing recommendation mechanism (PCRM)

RMRS provides Price Comparing Recommendation Mechanism (PCRM), which compares the price from different e-commerce websites through Merchandise Price Information Extracting Agent. It is a price-oriented recommendation so that the user can understand the price spectrum, determine the cheapest merchandise, and decide if he/she will to buy it.

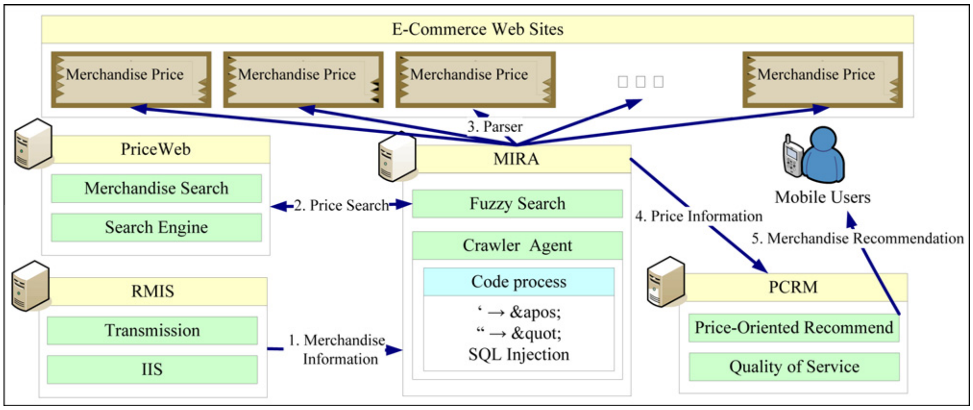

Fig. 11. The process of RMRS.

4. System evaluation and implementation

We report our experimental results and implement the architecture and approaches to merchandise evaluation service as an example in this section.

4.1. Evaluation

In experiments, we evaluate the merchandise identifying time, merchandise identifying accuracy, and merchandise evaluation accuracy in the following results.

4.1.1. Merchandise identifying time

The length of merchandise identifying time is according to the size of resolution. If the image size is bigger, the merchandise identifying time will be longer by IIS. Therefore, we compare the merchandise identifying times with different common formats of resolution (e.g. 240×320, 480×320, 640×480, 800×480, 800×600, 1024×768, and 1280×960). In experiments, the testing is performed 100 times per each format of resolution. Fig. 12 shows the average merchandise identifying times are 0.38 s and 5.46 s in 240×320 cases and 1280×960 cases, respectively.

4.1.2. Merchandise identifying accuracy

There are m images for n kinds of merchandise (such as merchandise image 1, merchandise image 2, ..., merchandise image m) in the domain of cosmetics, and those data are collected from several web sites or vendors. We measure the performance of our approach in the way called k-fold cross-validation [4]. In experiments, we focus on the moisture creams (e.g. Clinique Moisture Surge Extended Thirst Relief) and select 240 images for 24 kinds of merchandise. The training and testing are performed 240 times (i.e., $n = 24$, $m = 240$). In iteration i, merchandise image i is selected as the test corpus, and the other merchandise images are collectively used to train the values for each kind of merchandise.

In these experiments, the feasibility of applying Gradient Magnitude Image (GMI), Region Adjacency Graph (RAG), k-Nearest Neighbor (kNN), or Self-Organizing Maps (SOM) to merchandise image identifying is evaluated. Table 3 shows image identification by kNN or SOM combined with GMI and RAG. Consider kNN first; it can be observed that its classification performances are 22.08%, 36.67%, 43.33%, 47.92%, and 48.33% when the different numbers of the largest segments (k) are from 5 to 9. Second, we consider SOM to implement and evaluate that its classification performances are 76.25%, 78.33%, 80.83%, 81.25%, and 81.25%. The result of SOM algorithm combined GMI and RAG to improve accuracy rates is shown in Fig. 13. Therefore, we set the number of the largest segments as 8 and apply SOM with GMI and RAG in MMESP.

Table 3
The result of GMI, RAG, kNN, or SOM combination with the different numbers of the largest segments.

The number of the largest segments (k)	GMI + RAG + kNN (%)	GMI + RAG + SOM (%)
5	22.08	76.25
6	36.67	78.33
7	43.33	80.83
8	47.92	**81.25**
9	48.33	**81.25**

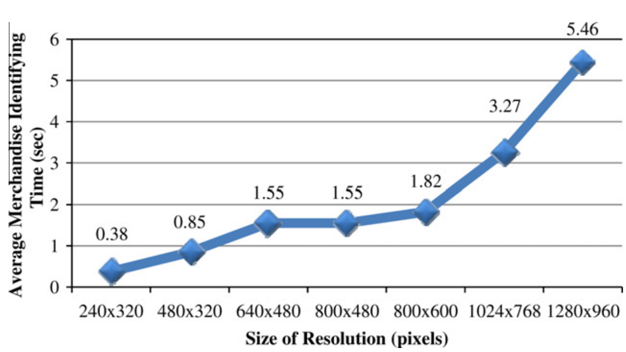

Fig. 12. The result of the merchandise identifying time with the different common formats of resolution.

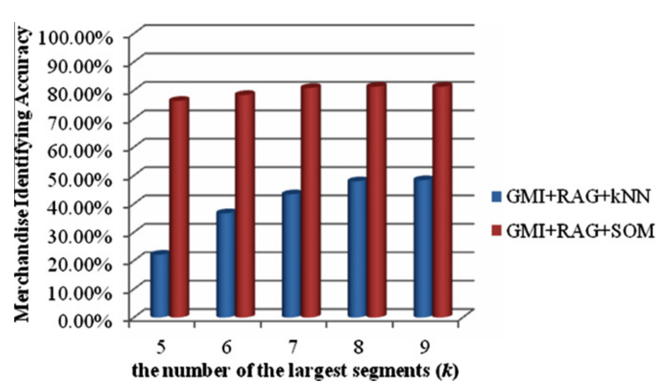

Fig. 13. The result of GMI, RAG, kNN, or SOM combination with the different numbers of the largest segments.

4.1.3. Merchandise evaluation accuracy

In this experiment, we randomly select 12 articles from Google blog search engine. These articles are sent to 4 domain experts for summarization. Moreover, we evaluate the performance of AMDS in the way called *k*-fold cross-validation [4]. In iteration *j*, blog article *j* is selected as the test corpus, and the other 11 blog articles are collectively used to train the values by the method proposed in Section 3.2.2. Table 4 shows the results of which the training and testing are performed in 12 runs. About 78% summaries which match with experts' summaries are enough to help users to understand the merchandise. Therefore, the result of the experiment shows that AMDS can be successfully applied to automatic summarization.

4.2. System implementation and case study

- Step 1: When a user would like to buy a particular product, he (or she) can photograph the product by cell-phone.
- Step 2: After taking pictures, he (or she) can upload the photos to MMESP, and connect to MMESP, as shown as Fig. 14a–c with different versions. Click the browse button of to choose the picture.
- Step 3: After receiving the photo, RMIS would automatically identify the merchandise, and then combine the two methods of Region Adjacency Graph (RAG) and Self-Organizing Maps (SOM) to process and classify the images. While identifying the mapping merchandise, MMESP would list the related information of the merchandise to users as shown in Fig. 15.
- Step 4: RMES accesses the judgment and use experience information from Blog Corpus.
- Step 5: Multiple document summarization technique would retrieve the recommendation to process the summarization of content, and send the result to the cell-phone of user shown as shown in Fig. 16.

Table 4
The result of automatic summarization accuracy.

	Total expert's sentences	Sentences match expert's sentences	Accuracy rate (%)
Expert 1	15	11	73
Expert 2	9	6	67
Expert 3	5	5	100
Expert 4	16	13	81
Total	45	35	**78**

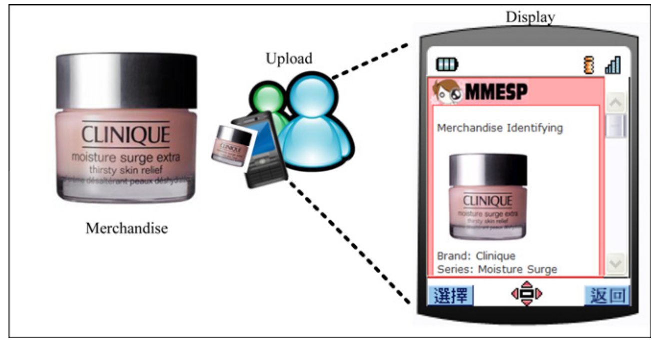

Fig. 15. Real-time merchandise identification.

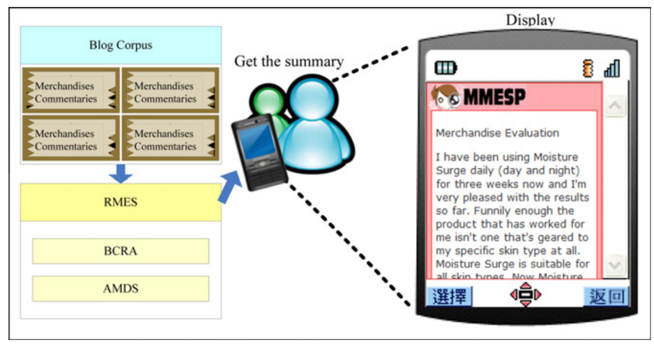

Fig. 16. Merchandise evaluation.

- Step 6: RMES retrieves the price of the merchandise from all the e-commerce web sites.
- Step 7: Price comparison and recommendation mechanism would list the price information. The same product may have different prices at several price comparison websites, which provides the merchandise price enquiry shown in Fig. 17. Users could learn the range of price information by querying the price to evaluate whether they wish to buy the product or not.
- Step 8: User clicks the photo, which would list information on the merchandise in detail.
- Step 9: After RMIS carries out the identification process, it would send the merchandise information to RMRS. Next, the merchandise price information retrieval agent would not only search the price of related products on a price comparison website and Internet, but also crawl and parse the price information into Corpus.

Fig. 14. (a) Real-time merchandise identification (mobile phone version). (b) Real-time merchandise identification (Facebook version). (c) Real-time merchandise identification (Google Gadget version).

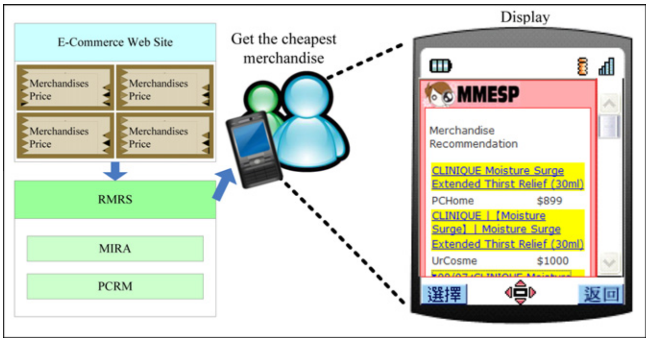

Fig. 17. Merchandise recommendation system.

Fig. 18. Merchandise price comparison.

Step 10: Finally, it activates the price comparison recommendation mechanism to retrieve the price information in Corpus, as shown in Fig. 18. RMRS would compare the price and recommend merchandise to the users, who can see the range of price and avoid wasting money.

5. Conclusions and future work

Because Impulse Buying is unplanned and happens quickly, the buying decision is always done without thinking and is easily influenced by the surrounding environment. MMESP can provide mobile transmission service, so that users can take pictures of the merchandise from their cell-phone and send the pictures to the back-end server to activate real-time calculation. MMESP will send back the merchandise's recognition information, consumer's comment and relevant merchandise price comparison to the user for a buying decision.

Through a portable device (such as 3G cell-phone and PDA) and a wireless communication network environment (3G or IEEE 802.11b), users do not need machine major computer processor but can derive useful information, such as merchandise evaluation service, from MMESP while shopping.

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