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COLOR IMAGERY FOR DESTINATION RECOMMENDATION IN REGIONAL TOURISM

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Abstract

This paper presents a novel recommender service system that considers the image as a uniform representation for tourists' expectations, destinations, and local tourism SMEs. Images carried by each stakeholder role is modeled and managed by several system modules, and they also evolve to reflect the real time situations of each entity. In addition, the system is dynamic in terms of its emphasis on the dynamic relationships among these roles and entities. When interactions occur, image mixing will be conducted to derive extra image attributes for the adjustments of the images. Besides, since colors can be mapped onto emotions, this paper adopts colors to operate the image matching and mixing process in order to find good matches of destinations for the recommendations meeting the tourists' emotional needs. Although this image related approach we proposed is used in tourism domain, we believe our method could also contribute to other areas of either practical applications or academic studies.

Keywords: Recommender System, Image Modeling, Image Mixing, Destination Recommendation, Color Science.

1   INTRODUCTION

It has been widely recognized that gaps often exist between customers' expectations and their perceptions of service performance provided by SMEs (Robledo 2001; Quader 2009). This is especially true in destination tourism (OECD 2008). In order to close that gap, recommenders have to understand what tourists want, i.e. the customers' expectations. Capturing the expectations from tourists is an essential step to derive the customer satisfaction of recommenders that aim at providing desirable destinations and tourism SMEs (e.g. restaurants, hostels) in tourism destinations.

However, reviewing destination recommendation information systems or platforms in tourism nowadays, instead of capturing customers' expectations, most suggestions were done by various content mining methods (Weng et al. 2009; Göksedef & Gündüz-Ö güdücü 2010) based on the functional attributes of destinations, i.e. popularity, location, *etc*. In this way, it's hard for customers to discover the destinations, especially those not well-known ones, which can fulfill their emotional needs (because the emotional information and experiences of tours occur and are confined to only individuals). Without capturing customers' expectations or tourists' minds in recommendations, tourism recommenders would find themselves only satisfied restricted market segments that people favor popular attractions.

In the previous research, measuring customer expectations were only implemented with a questionnaire (Robledo 2001; Quader 2009). But for an efficient recommendation information system, there have to be a uniform representation which can stand for customer expectations, destinations, and SMEs so that we can manipulate them to do the matching through a uniform comparison of their similarities. We argue that images can serve as the uniform representation since image is an output of the mental picturing process which human will execute before starting a trip, and images have been commonly used in the marketing of tourism destinations (Robledo 2001).

For the competition in the flourishing tourism industry, the images perceived by consumers play an important role to destinations and SMEs. Images convey experiences that consumers are likely to gain from a journey. In the decision making process, consumers can reduce the number of alternatives through comparing their expectations with the images of destinations and SMEs. Images can also be a key component in the destination positioning process (Echtner & Ritchie 2003). Destinations and SMEs can also create their own positive images in order to differentiate themselves from competitors by modifying their operations and policies through diagnosing their own images.

The aim of this paper is to demonstrate a recommender system that uses images to capture tourists' expected destination images or perceptions, and recommends those destinations and SMEs which can meet their emotional needs. In addition, the design, method and architecture of this system could be domain-independent and applicable to a wide range of services. It recommends people things what they can be satisfied based on images which represent both objects and humans' minds. The results of the system are dynamic which evolve over time through the expected changes derived from the stakeholders' role interactions and the unexpected changes caused by casual events of society. With this approach, we can find good matches between human and objects (tangible, intangible) based on emotional needs.

In addition, none of the field of information system studies has ever utilized images as the representation of customer expectations, and recommended people the destinations and SMEs according to their images. It is difficult because images are psychological related. In this paper, we investigate two research questions. The first is how to devise a systematic method to measure and model images. The second is what will happen to these images when roles interactions and social events occur. This paper proposes a resolution method and system in response to the two questions and the method has two main components—Image Modelling and Image Mixing— that will be illustrated later.

Our system is also in line with Service-Dominant Logic (Vargo & Lusch 2004), which is a mindset distinguished from Goods-Dominant Logic. Service-Dominant Logic highlights several perspectives such as service exchange, operant resources, co-creation of value, and value in-use. With these concepts, people can rethink role relationships, resources integration, IT facilitation, etc. to gain

profound understanding about the service system. In the end, they can be innovative means with a combination of integrated operand and operant resources to fulfil demands. In this research, the recommendation information system is also a dynamic service system which evolves over time. Images of tourists, destinations, and SMEs will change according to the interactions between each other. The active image, therefore, can be regards as an operant resource. Moreover, the good matches can only be found when customers have a willingness to provide their expectations of destinations and to be involved in the image modelling process, e.g. attendance of trips and feedbacks, which correspond to the concept of value in-use.

The paper is organized as follows. Section 2 presents the basic concepts of our method, followed by the descriptions of the method's system architecture and its component modules shown in Section 3. Section 4 then offers a system scenario to demonstrate the contributions of our method. The conclusion is then provided in Section 5.

2 THE CONCEPTUAL FRAMEWORK

The underlying conceptual framework (i.e. the main ideas) of our method is shown in Figure 1 prescribing the interrelationships (arrow (1)~(4)) of the basic concepts (destination expectations, destination images, image modelling, image mixing and destination alternatives). The underlying theories of this framework include (1) Destination Image Theory: an important role in the various models of travel decision making rests on destination image that has the core components as functional characteristic attributes, psychological characteristic attributes and holistic imagery impression (Echtner & Ritchie 2003) (2) Color-Emotion Theory: colors can evoke emotional feelings (Ou et al. 2004), and emotions can be mapped to colors (Nijdam 2010).

In Figure 1, we assume destination expectations and destination images are the targets to be processed to attain the matching, that is, pairs of destination expectations and destination images being the outputs of the recommendation process.
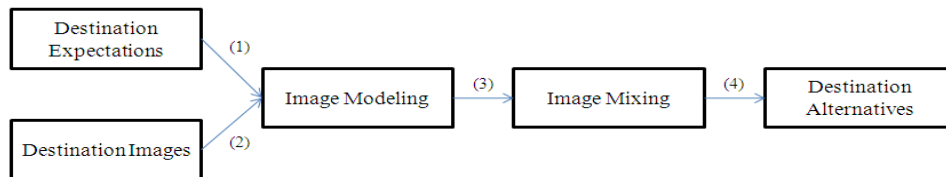

Figure 1.   Conceptual framework of the destination recommendation system

Destination Expectations: The expectations come from customers. People often do traveling to fulfill their emotional needs. In the planning stage of the journey, they have some expectations for the destinations and SMEs (i.e. local stores, like restaurants or hostels). For example, in the hot summer, people may want their vacations are hold at a cool and refreshing mountain; a couple just married might want to spend their honeymoon at a paradisiacal island with a sweet and romantic hotel room.

Destination Images: It includes not only images of attractions but also those of SMEs. As mentioned in Section 1, an image can deliver perceptions, feelings, or experiences that customers may have while visiting a destination and a SME. Images can then assist customers to decide a destination through the comparison and analysis between the images and the expectations. Although everyone may have different versions of impressions of a destination or a SME, it is believed that there are common impressions of a destination that can be accepted by the public, such as sunny California, romantic Paris, diligent Asia, and natural wild Africa. Hence, we view images as attributes of a destination and of a SME in our system.

Arrow (1) and (2): For the matching between destination expectations and destination images, customer expectations are regarded as demands and destinations are the candidates for these demands. Image as a medium is capable to express both expectations and destinations. In order to find the matching image pairs, the images at both sides are represented with the same format for simple comparison computation. Eventually, each entity in the system will carry its own image in a specific format, and the image can be obtained from varied data resources which need further analysis with

massive computing at the system backend before the matching process.

Image Modeling: To make images, a uniform representation of customer expectations, destinations, and SMEs, which can enhance the efficiency of the recommendation process, is required and the Image Modeling component could be particularly designed to represent and measure the images in a systematic way.

For representing an image, we propose a representation based on Echtner & Ritchie's definition (Echtner & Ritchie 2003). In our research, an image is composed of only psychological characteristics (e.g. pretty, casual, or mysterious) in contrast with those functional characteristics (e.g. prices, locations, or activities) that can be processed simply by condition filters (Echtner & Ritchie 2003; Mackay & Fesenmaier 1997). The timing for the usage of these functional filters can be after the recommendation (i.e., provided as an optional service executed by customers themselves). The psychological characteristics are referred as "image attributes" or "image elements" to avoid the confusion between the word "images" as mentioned in previous discussion which indicate the holistic perspective. Given the ingredients of an image are psychological words, we can map these psychological words onto colors separately (e.g., red for dazzling, yellow for bright) according to color emotion researches and color psychology studies (e.g., Ou et al. 2004). An image can then be composed of either psychological words or single colors as the uniform representation used in our system.

Another issue here is to model the image through analysis of data from various sources, which is also a process of searching for appropriate psychological words which are going to be fit into an image. There are three kinds of images corresponding to each role in the system. For the sake of comprehensiveness, all of the actors' opinions, behaviors and interactions are tracked and analyzed over time to extract the required image attributes. This is where the massive computing required at the system's backend (that leads to the creation or updating of the image models vital to our system).

The advantage of using color notations to represent images is its capacity for reducing the burden of computation at the front stage during matching that involves the characteristics of both physical and psychological. As color science is a mature discipline, scholars have done a lot of efforts to make color computable and adaptive in various uses, i.e. abstract mathematical color models and inter-convertible color spaces like RGB, Munsell, CIE XYZ, etc. In addition, there are already many applications about semantics in color (John et al. 1998), i.e. mapping emotions onto colors in a space, from which we can attain the benefit. In addition, there is no foundational works that are wildly accepted to clarify the distances between two distinct emotions, i.e. no one can really tell how far it is between happy and sad. Therefore, we can use color notations to measure, monitor, manage, and most importantly, to match images.

Arrow (3): Destination regions have different scales in reality (e.g. Taiwan is comprised of 25 administrative divisions). There is a need to consider what the image will be for a big destination which is a union of several regional destinations. A drink could be a good example—a scene in an extravagant castle will flash into one's mind when he is drinking a tea named "Wedding Imperial" whose image is given by just a few ingredients. This implied the union of images does not only equal to the sum of them. The alliance of SMEs who collaborate to complement each other for pursuing a better profit with better services provided can be viewed in the same way. We argue images can be mixed, no matter how different they are. A realistic example is a fashion style called "sweet pink." Therefore, not only the region unions and SMEs alliances but also interactions between different roles will have their images changed. For instance, a bar people thought it cool, crazy, and alluring, when more and more elders come to be their guests, the style of this bar would then turn to be classic day by day, while it is still charming and a new romantic feeling floating around.

Image Mixing: In order to understand what is the extra image a union of interactions may derive, the Center of Gravity Law for Color Mixture (Lucchese & Mitra 2000; Lucchese & Mitra & Mukherjee 2001) in color science can be adopted. That is, there can be different levels of mixing, from simple compositions to well-mixed, depends on how accurate the results we want. Sometimes, losing some preciseness can gain extra surprises.

Arrow (4): Finally, the matching of destination expectations and destination images can then be realized and the recommendation can be accomplished in different levels with destination alternatives as system outputs.

3 METHODOLOGY

3.1 System Architecture

The architecture of our destination recommendation system is presented in Figure 2 that is based on the underlying conceptual framework as mentioned in Section 2. That is, Image Modeling corresponds to Modeling Module; Image Mixing corresponds to both Interaction Module and Adaption Module. The following is the whole picture of the recommendation system with four modules involved.
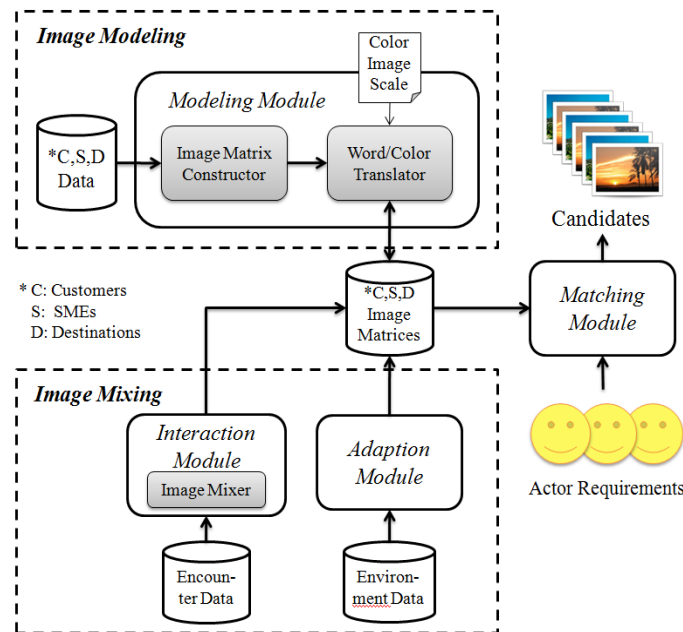
Figure 2.   Architecture of the destination recommendation system

In the system, all data from customers, SMEs, and destinations are the materials for the image matrix constructor. Through Modeling Module, we then have the first versions of image matrices consisted of either words or colors. Since this is a dynamic system evolving over time, images will vary with each entity's active movements (e.g. customers' images alter as he makes a journey) and inactive movements (e.g. destinations' images alter as feedback received).

Interaction Module monitors the contacts between stakeholder roles and direcly adjusts their images, because every kind of image interactions will influence with each other. It can be expained by the fact that images of SMEs which resides in a region will collectively decide their belonged destination's image. In addition, this influencing process is unceasing and the images are updated upon the interactions over time.

Adaptive Module detects ocassional events that happen in the real world and bring impacts to a region. For example, people would like to visit and do business at the site where a popular movie was shooted, and this makes destination image change.

The last one, Matching Module, receives customers' expectations converted from their inputs made in a searching box every time when they want a tour. After these instant expectations are added into the original customers' images, Matching Module will find the apposite destinations and SMEs to realize the recommendation. The following subsection will then detail the design and operation of the four modules.

3.2   Modeling Module

Image matrix constructor and word/color translator form this module whose input is the data from customers, SMEs, and destinations and output is the corresponding image matrices for each role. The ways about how the data is retrieved from data sources and converted into each kind of images are then described as follows:

- Data Source for Customer Image

(1) Classification: We assume customers are categorized into four tourist types—Organized Mass Tourist, Independent Mass Tourist, Explorer, and Drifter (Cohen 1972). Images of each type are predefined based on their characteristics correspondingly and a customer's classification can be attained from a simple questionnaire.

(2) Learning from Customer Behavior: As the initial images for every customer are established, they can start to grow based on four main tracks of customers' behavior. First, those on our recommendation system platform e.g. searching and browsing history. Second, information about the journeys they attended includes destinations and stores they chose, and the time they spent on each site respectively. Third, feedback they gave, e.g. emotional words which convey their impressions about some places can stand for customers' preference; and service index scores they gave can show their emphases. Forth, expecting destination images that we gain from customers' inputs every time when they are planning a trip. This one is distinct from others because it has the immediacy. Before the matching process, we will prepare an image which is the combination of a long term customer image (i.e. the one that has been growing) and a short term one (i.e. the customer's expectation to a destination).

- Data Source for SMEs Image

(1) Initialization: SMEs managers establish their own images by giving emotional words (e.g., owners can edit their profile anytime when their services alter). If the object is an alliance of SMEs, its image will be constructed by Interaction Module through mixing members' images.

(2) Rolling: 40% (this weight varies with regions) of an image will be decided by their customers' feedback. Besides, the image of the destination where they reside will also influence their own images (Interaction Module's responsibility).

- Data Source for Destination Image

(1) It is constructed by the emotional words given by SMEs and customers, and changed dynamically over time. The image of a bigger region is composed of its sub region images. Similarly, it will be influenced by images of SMEs and their customers (Interaction Module's responsibility).

As mentioned in the conceptual framework section, the representation of images is composed of psychological words. These words come from Color Image Scale (Kobayashi 1992) and all of them are adjectives. We devise an ontology as shown in Figure 3 to illustrate those image attributes taken to construct an image within our system. There are 15 categories, and image attributes having similar meanings will be arranged in the same category. Every image attribute is represented by a psychological word and has several properties: item numbers, color notations including Munsell and RGB value which will be used in the image mixing process, and coordinates in the Color Image Scale that will be used in the matching process. Since some of data from customers and SMEs owners are open answers, we can use tools like WordNet, a large lexical database of English, to identify the meaning of words, so that they can be translated into the words within the boundary of the Image Attributes Ontology.

Since images can be represented either by words or by colors, either form has three matrices as shown as Figure 4 which contain words, RGB values (r, g, b), and their intensity values (the value which equals the count of a particular psychological word divided by the total number of the psychological words in percentage terms) separately. The number of image elements we use is 180. These words are categorized into five adjective factors: evaluative, sensitive, emotional, dynamic, and scale (Kobayashi 1981). Thus, every matrix has 5 rows and 36 columns, and values within it can be zero.

After the image matrix in the word format is constructed and accompanied with intensity values, the word/color translator will map those words onto colors (Figure 5) according to our version of the Color Image Scale that we have adopted and slightly modified based on Nippon Color & Design

Research Institute Inc. (NCD)'s research (Kobayashi 1992 & 2001). In our version, for simplicity the relation of word and color is one to one, that is, every image attribute has its own meaning, and it can be presented either by one word or one single color.
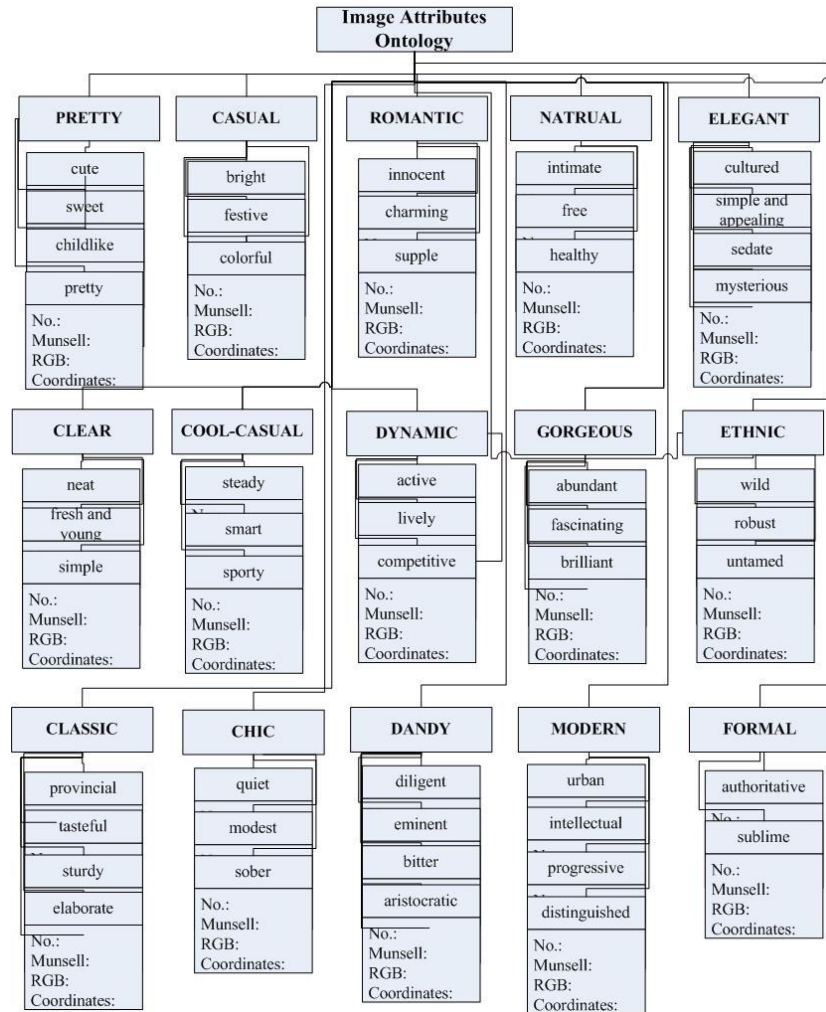

Figure 3. Image Attributes Ontology

$$\begin{bmatrix} W_{0\,0} & \cdots & W_{0\,36} \\ \vdots & \ddots & \vdots \\ W_{4\,0} & \cdots & W_{4\,36} \end{bmatrix} \quad \begin{bmatrix} C_{0\,0} & \cdots & C_{0\,36} \\ \vdots & \ddots & \vdots \\ C_{4\,0} & \cdots & C_{4\,36} \end{bmatrix} \quad \begin{bmatrix} I_{0\,0} & \cdots & I_{0\,36} \\ \vdots & \ddots & \vdots \\ I_{4\,0} & \cdots & I_{4\,36} \end{bmatrix}$$
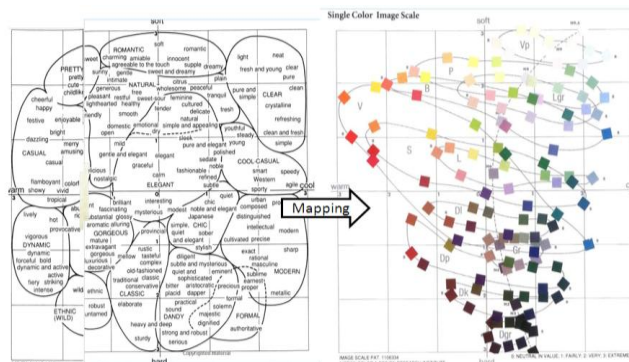
Figure 4. Image Matrices in three formats

Figure 5. Concept of mapping emotional words onto colors (Kobayashi 1992 & 2001)

3.3 Interaction Module

Since each kind of stakeholder role's image has influences on others to a certain extent, Figure 6 depicts this mutually influencing concept considered in our recommendation system. Those numbers in the chart stand for the relative strength of the influences between the images of roles (bold lines are those above six). When interaction contacts occur, the images of the involving entities would slightly change in accord with the influences from the other's images. For example, a man with red image visit a place with yellow image, the man's image will turn to more orange, because this fact reveals the man's preference in an implicit way.

Customers are less powerful on the influences than the other two because choices convey humans' preferences. We believe destinations have more significant attraction to customers than SMEs in regional tourism, or SMEs would devote to collaboration to thrive a destination. This is also the reason we gave 10 points to the relative influence from SME images to destination images. That's why we give a higher value to the relative influence from destination images to customer images than that from SMEs to customers. But why does the 3 points is given to the one from customer to SME images and 1 point from customers to destination images? For the 3 points, it's quite common that the types of customers will affect a person's decision about whether to enter a store, i.e. customers is one of the impression sources that people will perceive for a store. In contrast, we deem destinations as strong entities. A destination should be able to welcome various kinds of customers, at least not narrowly restricting them. So the destination images will be only slightly adjusted by their tourists' images. Meanwhile, SMEs attract people only if they have their own differentiated features which are often contributed from environmental resources (e.g., destination images). Accordingly, destination images as well as customer images are considered to have similar influences to SME images.
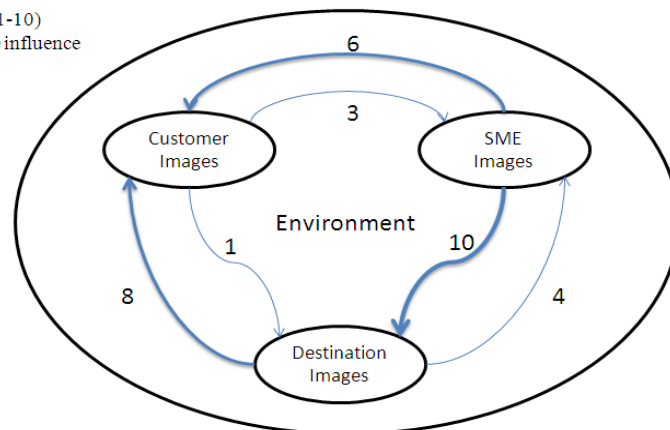

Figure 6.   Influences of the interactions among stakeholders' roles.

When the interactions occur, more than the sum of all the image attributes within each entity, we mix their images to realize the influences on their image matrices. The alliances of SMEs and a union of destinations can be viewed as a kind of interaction in which every member's influence is regarded as equal. In our research, we provide two levels of image mixing as below:

- Level 1 – Most Precise (Figure 7 is given as an example):
  (1) Select image elements of every destination whose intensities are higher than 10% (that can be modified in applications).
  (2) Combine the image elements from step 1 to form the alliance image. Each image element in the alliance will have a raw value which equals the sum of the percentage values of the referred same word, e.g. in Figure 7, the raw value of the word 'traditional' in the alliance is equal to the sum of '36' in Pounded Tea and '24' in Bull Cart. The intensity values of an alliance image are the results of normalization to these raw values.

Pounded Tea		Bull Cart		Kiln BBQ		Alliance		
healthy	10.00%	simple	4.00%	nostalgic	20.00%	healthy	10	4.27%
traditional	36.00%	natural	8.00%	earnest	4.00%	traditional	60	25.64%
nostalgic	20.00%	nostalgic	32.00%	sweet	4.00%	nostalgic	72	30.77%
aromatic	10.00%	rustic	8.00%	mild	20.00%	aromatic	10	4.27%
convience	2.00%	deligent	12.00%	traditional	4.00%	amusing	50	21.37%
cool	6.00%	hot	4.00%	amusing	40.00%	diligent	12	5.13%
classic	2.00%	traditional	24.00%	happy	4.00%	mild	20	8.55%
amusing	10.00%	sound	4.00%	intellectual	4.00%	Total	234	100%
mild	4.00%	casual	4.00%					

(Pounded Tea) + (Bull Cart) + (Kiln BBQ) = (Alliance)

Figure 7.   *The image mixing process for an alliance comprising the images of 3 SMEs (Pounded Tea, Bull Cart, And Kiln BBQ)*

- Level 2 –Most Surprising:
 (1) Categorize all images elements into 5 groups: Evaluative, Sensitive, Emotional, Dynamic, and Scale (Kobayashi 1981).
 (2) Mix those 5 sub-groups of all attendances' images separately to produce a new 5 image elements for the alliance. These 5 elements are treated as additional ones which can be added into the image union which is composed of all attendances' images.

Since we have intensity values, images which have less influences will be like 'filtered' during the mixing process. Therefore a threshold value is not necessary here; meanwhile, we *keep the 'nature'* of the alliance image forming process. In addition, image mixing *increases the possibility* with which we find image elements that differ from anyone within all alliance members' images.

We use additive color mixing method (normally used to do the light mixture) to facilitate the mixture of images. One of the reasons why we chose this method is that image or impression is virtual and we don't have to worry about its spectral composition, which is a consideration when mixing pigment or printed colors which use subtractive color mixing (Broackes 1992). Another reason is we use the RGB color model and CIE XYZ color space whose value are convenient to be extracted and converted (Fairman 1997; Lucchese et al. 2001; Pei et al. 2004) from NCD's Hue and Tone system (Kobayashi 1992 & 2001). Here we introduce the 4 steps of the image mixing process:

(1) Choose i numbers of emotional words or colors as targets, and find their RGB values in the Color Image Scale (Kobayashi 2001).

(2) Convert those RGB values into CIE xyY color space representations (Fairman 1997; Lucchese et al. 2001; Pei et al. 2004).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.49000 & 0.31000 & 0.20000 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00000 & 0.01000 & 0.99000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \Rightarrow x_i = \frac{X_i}{X_i + Y_i + Z_i} \text{ and } y_i = \frac{Y_i}{X_i + Y_i + Z_i} \quad i = 1, 2, 3 \ldots$$

(3) Use the Center of Gravity Law for Color Mixture to find the result (x_r, y_r) of color mixing (Lucchese et al. 2001; Pei et al. 2004).

$$x_r = \frac{\sum_0^i x_k \frac{m_k}{y_k}}{\sum_0^i \frac{m_k}{y_k}} \text{ and } y_r = \frac{\sum_0^i m_k}{\sum_0^i \frac{m_k}{y_k}} \quad m_k = \text{ percentages of the same reference luminance}$$

(4) Look up the image word represented by the result of color mixing. If there are no words for the mixed color, use a fuzzy method to gain surrounding words (e.g., if there is a major color, the mixed image will be like "pretty casual" in which the "casual" is in the main image).

Table 1 illustrates the computing process of the image mixing by above steps. Table 2 then exemplifies some results of the image mixing experiments.

Table 1.   *Computing of image mixing*

Munsell	R	G	B	CIE Color Space			CIE xyY color space			After Mixing			Mixing Result
				X	Y	Z	x	y	Y	R	G	B	
R/S	184	28	16	102.04	55.4798	16.12	0.58765	0.31951					amusing
YR/S	216	128	0	145.52	142.213	1.28	0.50351	0.49206					bright
R/D1	168	104	96	133.76	115.241	96.08	0.38762	0.33395					glossy
YR/Dp				127.107	104.311	37.8267	0.47209	0.38742	104.311	189.333	86.6667	37.3333	aromatic

dazzling	+	cheerful	=	bright
pretty	+	casual	=	cute
eminent	+	classic	=	formal
emotional	+	sweet and dreamy	=	feminine
dazzling	+	alluring	=	luxurious
peaceful	+	simple, quiet and elegant	=	calm
distinguished	+	neat	=	youthful
pretty	+	sound	=	fascinating
charming	+	precise	=	stylish
romantic	+	extravagant	=	glossy

Table 2.   Experiment of image mixin g

3.4 Adaption Module

Similar to Interaction Module in considering the influences of interactions, the interactions considered in this module however happens only in between the environment and all entities in the system. The image mixing component will be used here as well. When dynamic events occur, the whole region may be influenced. For example, when the Taiwan movie "Cape No. 7" was a fad, many hostels and restaurants in Kenting were decorated with the characteristics related to that movie. How we detect those occasional events in the system is to utilize the power of crowd. This can be done by using a text mining technology to uncover a surge of particular phrase among content provided by customers and SMEs. This is, the adaption module is done by some Web 2.0 content analysis, while Interaction Module then focuses on the interactions between stakeholders roles.

3.5 Matching Module

With the fundamental element, images, being comprehensively cultivated, this module can process them to find the good destination matches to fulfil customers' expectations. The recommendation procedures are shown as the following steps:

(1) Attain customer images: Analyze the customer's inputs on the system platform which stands for his expected destination image, and mix it with his existing images (the former is the leading part).

(2) Recommend destinations and SMEs to customers: First, select several colors which have relative large intensity in the customer's image and destination images. Then we use the type I in the concept of color harmony (the similar colors on the color wheel) (Cohen-Or et al. 2006) to calculate the similarity of each pair of them. Within each destination, this module can then attain the service provider recommendations. There is one thing to note: Why we don't compare the whole images is because we want to encourage SMEs and destinations to be differentiated.

(3) Obtain destination image graph: For each destination attained from step 2, we use Flickr API to search for a picture which is able to represent its image for customer evaluation.

(4) Filtering (optional): we provide the filter function after recommendation, like budget, preference, etc. We expect more people will see destinations and SMEs that are barely known before in this way.

4   SCENARIO

Mr. Yang was always busy at work. He noticed the conversation between him and his wife became less and less. So he logged into our recommender system named *iVoyage*, with a hope that a vacation could bring them happiness. As he typed a word phrase "a place like paradise" into the search bar (as depicted in Figure 8), it appeared numerous sentimental graphs that represented images of destinations on the screen in seconds. Through a quickly browsing, his eyes were caught by a country place named Nanpu, where he'd never been to and never heard before. But it still seemed a pleasing

place after viewing other tourists' sharing. Mr. Yang couldn't wait for this trip in Nanpu, where this couple could comfort their relationship and enjoy the peace.

On the other side, Peter, a hostel host lived in Nanpu, was building the image for his business on *iVoyage*. The hostel was a small, clean, and warm house, but its revenue was relatively low compared with its neighbors. Through the image diagnosis on the system, he found the hostel's image was not appealing enough for there were many similar accommodation service providers in the same region. Therefore, Peter seized the opportunity to make an alliance with his business partners who were a pounded tea restaurant host, a bull cart owner, and a kiln BBQ manager. Since then, their image became rich and meaningful whose image attributes are nostalgic, traditional, and amusing, just like a grandmother's farmstead.

On a Sunday morning, Mr. and Mrs. Yang arrived at Nanpu to be Peter and his partners' guests. They all had great memories on that day. Peter's alliance successfully left a good impression to the couple that made Mr. Yang bring his positive feedback to *iVoyage*. Most importantly, instead of a tropical island, Mr. and Mrs. Yang found their belonged paradise, a warm place close to their hearts.

Figure 8.   iVoyage scenario

5   CONCLUSION

This paper presents a novel recommender service system to capture tourists' expectations (emphasizing on emotional needs) and to meet their satisfactions by recommending desirable attractions and SMEs in destination regions. Image, as the fundamental element and an operant resource, has been cultivated to be the uniform representation for tourists' expectations, destinations, and SMEs. In the system, the modeling module constructs the images in three formats through the analysis of data; the interaction module and adaption module monitor the expected changes to images through the interactions between roles, and the unexpected changes caused by occasional environmental/social events respectively. They use image mixing to realize the changes. The above three modules also manage the life cycle of the images to ensure that the images can reflect the real time situations of role entities over time. Last, the matching module prepares images of customer expectations to find the good matches of destinations. The color format offered is to facilitate the image mixing and matching with its traits of correlations with emotions and the accompanied mathematical theories. Our contribution is proposing a new approach to model-based recommendation considering the psychological emotion needs of customers. The future works include evaluate the method and system on the aspects of the recommendation quality, the impacts of the evolutionary roles interactions, the sensitivity of the color-based computational recommendation, *etc.*

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