Color Imagery for Destination Recommendation in Regional Tourism

應用於區域觀光產業之色彩意象化目的地推薦研究

by

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Abstract

This research presents a recommendation service system that considers the image as a uniform representation of tourist images (include self-image and emotional needs), destinations, and local SMEs. Images carried by each stakeholder roles are 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 relationships among these roles. 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, we use colors to operate the image matching and mixing process to find good matches of destinations for the recommendation. This image related approach we proposed is domain-independent. We believe our method could contribute to other areas of practical applications and academic studies.

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

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CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

Over the past twenty years, the supply and demand of tourism have transformed for the dynamism of the global economy and the evolution of technology. These changes include the severer competition between destinations, more and more international tourists, and the increased frequency of short trips for people (OECD, 2010). Besides, experience economy is a trend emerging into tourism. Innovation occurred in the service delivery and the product development for SMEs within destinations (e.g. restaurants, accommodations) (OECD, 2010); tourists incline to customized and flexible travel products and services (Stamboulis and Skayannis, 2003). In the end, SMEs as service providers co-create service experiences with their customers during the journey. Then tourists gain the value through evaluating the customized service experiences (Sandström et al., 2008).

The destination recommendation system (DRS) or the travel recommendation system is one of the information technologies having impacts on value creation chains of tourism (OECD, 2010). Its functions include not only the travel information provision, but also suggesting end consumers destinations and arouse their desires to visit the places (Skadberg et al., 2005). Therefore, DRS is supposedly an appropriate tool to increase the destinations' competence level by establishing a mutual relationship between destinations and tourists, and satisfy tourists all over the world via recommending favorable destinations (Yuksel and Bilim, 2009).

DRS provide an object situation for tourists to review existing destinations. These destinations are dynamic ranked by DRS according to individual customers for alleviating their burden of searching through thousands and hundreds of tourism products and services on the Internet. Nevertheless, it has been widely recognized that a gap exists between customers' expected services and their perceived services provided by information systems as shown in Figure 1 (Pitt et al., 1995). Being an information system, it is vital for DRS to understand what tourists want, i.e. the customers' expectations, in order to close this gap. Actually, capturing the personal needs (as shown in Figure 1) of tourists is an essential step to derive the tourist satisfaction of recommenders that aim at providing information of desirable destinations and SMEs within tourism destinations.

Further, tourism is an experience based industry. These experiences are individually unique and emotion attached. It was claimed that insufficient attention has been paid to the service experiences, including the emotional dimensions (Sandström et al., 2008). Therefore, a DSR should have capabilities of capturing tourists' needs, especially the emotional needs, and producing recommendation according to the psychological or emotional properties of tourism products and services.

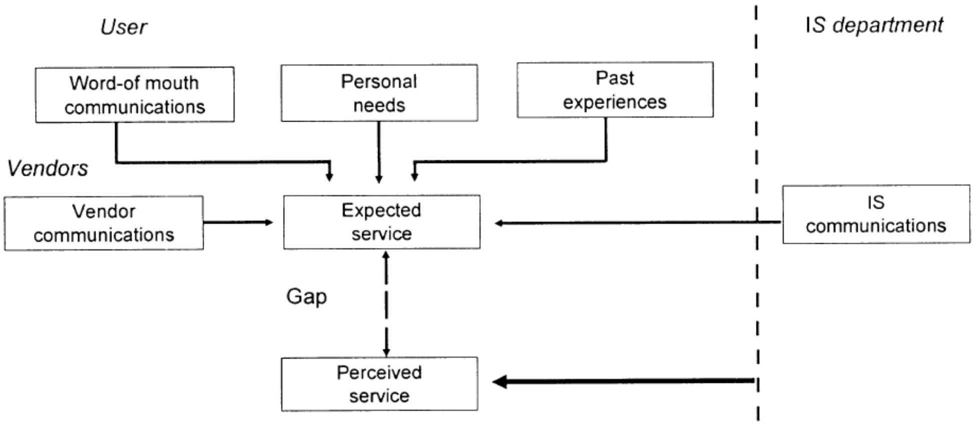


Figure 1. Determinants of Users' Expectations (Pitt et al., 1995)

1.2 Research Question

Since the emotional information and experiences of tours occur and are confined to only individuals, we argued that a DRS have to capture both tourists' minds, i.e. the emotional needs, and the psychological elements of destinations, in order to suggest customers the best fit results. Without capturing tourists' minds in recommendations, the DRS would find itself only satisfied restricted market segments that people favor popular attractions.

Reviewing recommendation systems or platforms nowadays, the technologies they used are generally categorized into content-based, collaborative filtering, knowledge-based, and hybrid methods. However, we found all of these technologies are function oriented, such as content-based recommendation deals with the product descriptions (Zhang et al., 2009); collaborative filtering stresses on the rating data (Wang et al., 2006); and knowledge-based infers recommendation results from functional knowledge about customers, items, and the mapping relations between them (Burke, 2002).

Besides, in the previous research, customer expectations and needs were only represented with questionnaires (Quader, 2009; Robledo, 2001) or a query input describing item information and constraints. But for an efficient travel recommendation system, there have to be a uniform representation which can stand for tourist expectations (emphasizing the emotional needs), destinations, and SMEs so that we can manipulate them to do the matching through a uniform comparison of their similarities. In this way, the flexibility of questionnaires appears to be insufficient to reflect these three stakeholder roles' real-time images, because the result data is static and limited by the question designers.

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 and 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.

We believe that images can serve as the uniform representation for destinations, SMEs, and tourists in our DRS. The reasons include: (1) image is an output of the mental picturing process which people will execute before starting a trip; and (2) images have been commonly used in the marketing of tourism destinations (Robledo, 2001); (3) images can be expressed in languages, so that the material for images can be obtained from Web resources and is dynamic and open-ended.

In this research, 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 research proposes a resolution method and system in response to two questions and the method has two main components—Image Modeling and Image Mixing—that will be illustrated later.

1.3 Research Method

In our system, each tourist, destination, and SME has their own image, which consists of psychological adjectives. We utilize color as a tool to model all the images of these stakeholder roles.

Color impacts our everyday life. We can treat it as a source of information to make decisions based on the aroused emotions. It is widely accepted that color can be mapped onto emotions (Xin et al., 1998; Kobayashi, 1981, 1992, 2001; Nijdam, 2005; Ou et al., 2004; Suk and Irtel, 2010). To name a few, the red color can stand for festive and hot feelings; green can be associated with a peaceful or health image. Although the reaction to colors varies person by person, researchers have clarified that there exist universal color factors, including warm–cool, heavy–light, active–passive, and hard–soft (Ou et al., 2004).

Kobayashi and the Nippon Color & Design Research Institute developed Color Image Scale (Kobayashi, 1981, 1992, 2001), which specified the meaning of 130 basic colors according to the two factors: warm–cool and hard–soft. These meanings were assigned with 180 image words (adjectives). On the scale, the similarity and dissimilarity of the emotional word meanings are indicated with the distances between the corresponding colors.

With these color-emotion mapping knowledge, we can obtain more information dimensions about our image models than word meanings, such as their inter relations with precise distances on a color space, the possible matching pairs among them according to the color harmony theory. For example, a man with an image model mainly colored red which means festive and dazzling, and hot. He will be pleased with our recommendation—Taichung and Pingxi Sky Lantern, in all likelihood.

Sometimes, things with different images or emotions will be put together to obtain a fresh new image. For example, SMEs will forge an alliance to build distinguishing features for attractiveness and uniqueness. Besides, the images carried by tourists, SMEs, and destinations will influence each other during their interactions. To understand the consequences of these alliances and interactions to the images, the image mixture should be functioned in our system.

Since images can be represented by colors, the image mixture may have a strong connection to the color mixture. We propose that the additive color mixing method (normally used to do the light mixture) can serve as the tool for image mixing, for the reason that image or impression is virtual. That means there is no need to concern about its spectral composition, which is a consideration when mixing pigment or printed colors which use subtractive color mixing (Broackes, 1992). With this color mixing method, we can not only shrink the distance between the images and the real status of the stakeholder roles by reflecting the real-time interactions between these stakeholder roles, but also foreseen the results of potential SME alliances.

1.4 Purpose and Contribution

The aim of this research is to demonstrate a destination recommendation system that uses images to capture tourists' needs or intrinsic motives, and recommends destinations and SMEs which can meet tourists' 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 3 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.

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 fulfill 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 needs or intrinsic motives of destinations and to be involved in the image modeling process, e.g. attendance of trips and feedbacks, which correspond to the concept of value in-use.

1.5 Content Organization

This research is organized as follow brief introductions:

- Chapter 2 – Literature Review

  This chapter compares different recommendation technologies in the mainstream. Each of them has their own merits and shortcomings. By introducing the between them and ours, our system can be positioned as a model-based recommendation system.

- Chapter 3 – Motivation Application

  This chapter depicts the whole picture of our research project that this research is one of its underlying components.

- Chapter 4 – Color Imagery for Destination Recommendation

  In this chapter we introduce the conceptual framework and the system architecture of the color imagery destination recommendation system. The detailed design and methodology will be described, including the explanation of Image Modeling and Image Mixing components.

- Chapter 5 – Application Scenario

- Chapter 6 – Evaluation

  Hypotheses and six experiments for evaluation are depicted in this chapter.

- Chapter 7 – Conclusion

  Contributions, implications, limitations, and future works of our research are provided in this chapter.

CHAPTER 2 LITERATURE REVIEW

This section reviews three topics. First, we briefly introduce and discuss popular recommendation technologies used in recommendation systems today, and position our research work through identifying their similarities and differences and examining the characteristics of tourism environment. Second, we overview the tourism expectation formation and define our target customers by clarifying their needs. Last, we introduce the relationship between color and emotion, color mixture, and their related works. From the literature review about colors and their relations to psychology and mathematics, we believe colors can serve as a modeling tool for representing and computing the images of the tourist expressive needs (psychologically dominant) and the images of destinations. In this research, we propose a model-based DRS that is based on color modeling and computing and emphasizes the emotional tourist service experience

2.1 Travel recommendation system

Recommendation systems (RS) are designed for comforting people searching for objects they want/need including but not limiting to products and services, or for navigating them with information in a complex environment where a large number of options exist. With characteristics actively or passively provided by users, recommendation systems can facilitate their decision making process in an individualized way (Burke, 2002; Göksedef and Gündüz-Ö güdücü, 2010; Zhang et al., 2009).

In practice, recommendation systems are widely applied in e-commerce, for example, Amazon.com successfully utilizes recommendation technology upon the principle “people who bought X also bought Y” to suggest customers’ favorable merchandises (Burke, 2002; Towle and Quinn, 2000; Wang et al., 2006). As one of e-commerce instances, the travel information service has additional features including wide-data, diverse types, and highly experience-related (OECD, 2010; Zhang et al., 2009). Before discussing travel recommendation systems, we reviewed several recommendation technologies commonly used today in the following paragraphs.

Technologies used in recommendation systems can be generally categorized into content-based recommendation, memory-based (includes user-based and item-based) and model-based methods of collaborative filtering technology, knowledge-based recommendation, and hybrid recommendation systems composed by some of above technologies and other technologies as extensions (e.g. grid technology and semantic ontology) (Burke, 2002; Ricci, 2002; Towle and Quinn, 2000; Wang et al., 2006; Weng et al., 2009; Zhang et al., 2009).

Content-based recommendation utilizes item descriptions whose format can be either text-based or attribute-value based. Basically, it retrieves items to match user needs, preferences, and constraints represented in provided languages (e.g. attributes) (Bridge et al., 2005; Ricci, 2002). In advance, similar to item-based approach emphasizing on rating data, Burke (2002) and Huang (2008) declare that content-based approach performs the recommendation based on the similarities between the content of a particular object and the contents of those objects in the current user’s selection history. The most significant shortcoming of content-based method is the difficulty to analyze the multimedia content of items (Huang, 2008; Zhang et al., 2009). Another issue may arise owing to the necessity of constructing categories with a set of feature variables for each kind of item. This is also the reason why many travel recommendation systems only focus on the suggestion of destinations, which are comparatively stable and reusable concepts (Ricci, 2002).

Instead of dealing with item contents, collaborative filtering approaches usually concentrate on rating data enabling the ability to represent complex objects such as music and movies. They are often divided into two categories: memory-based (which includes user-based and item-based method) and model-based (Burke, 2002; Wang et al., 2006). In memory-based approach, a user-item matrix will form in the recommendation system through collecting scoring information explicitly or implicitly from users. With this matrix, user-based collaborative filtering predicts the scores of the current user's unrated items according to the historical rating data of his "nearest neighbors", a team of users having similar preferences with the current user; while pure item-based collaborative filtering predicts the score of a particular item by averaging the current user's rating data of similar items in the past. However, there often exists sparsity problem due to that only rated items can be recommended, or a user must have rating records to be a candidate of "nearest neighbors" (Bridge et al., 2005; Burke, 2002; Göksedef and Gündüz-Ö güdücü, 2010; Wang et al., 2006; Zhang et al., 2009). In certain cases, item-based approach is a better choice because the item quantity is comparatively stable. Generally, there is an option to pursue efficiency — unifying user-based and item-based approaches brings the expansibility against the limited accuracy caused by a small portion usage of the user-item matrix (Wang et al., 2006; Zhang et al., 2009).

Model-based recommendation uses training examples (often historical rating data) with various learning technique (e.g. neural networks (Jennings and Higuchi, 1993), latent semantic indexing (Foltz, 1990), and Bayesian networks (Condliff et al., 1999)) to derive a model or to find patterns to predict item ratings for the current user. It can dynamically reflect user interests, and soothe the sparsity problem to a certain degree (while knowledge-based approach is considered as a better solution to this problem but more difficult to realize). Although numerous parameters are needed to be tuned and the model construction is time-consuming (which can be implemented off-line), it is still worthwhile to adopt this approach because the quality of the recommendation results are usually found satisfying (Burke, 2002; Wang et al., 2006; Zhang et al., 2009).

Knowledge-based recommendation infers the prediction with pre-existing functional knowledge describing how favorable items can meet user needs. While being one of solutions to the challenges of memory-based collaborative filtering there is still a tough point of this approach, the acquisition of knowledge. It requires knowledge about objects, knowledge about mappings between user needs and objects, and user knowledge. Google search engine is a good example using knowledge about the relations between Web pages to infer the desired query results (Burke, 2002). Furthermore, once the development of semantic ontology is mature, the vision of the accurate, automatic, and intelligent recommendation systems will come true (Burke, 2002; Hatala and Wakkary, 2005; Towle and Quinn, 2000; Zhang et al., 2009).

Hybrid recommendation systems combine two or more recommendation techniques to construct a module for better performance (Burke, 2002; Göksedef and Gündüz-Ögüdücü, 2010). Hybridization methods are various including Weighted, Mixed, Switching, Feature Combination, Cascade, Feature augmentation, and Meta-level. To adapt the dynamic e-commerce environment and various user needs, hybrid recommendation technologies are suitable solutions if adequate research work is conducted to define the tradeoffs (Burke, 2002).

Overall, recommendation technologies we have discussed are all function-oriented which can be demonstrated in the following facts: 1) Content-based recommendation retrieves items from their descriptions. All the elements in this process including the queries from users, the matching method, and the item contents mainly manipulate functional item features such as a title and an author name of a book. 2) Collaborative filtering accounts on rating information from users. 3) Knowledge-based approach grounds functional knowledge related to items, users, and the relationship between the items and the user needs (Burke, 2002). However, since tourism is an industry which is highly experience-related, it is beneficial for travel recommendation systems to take emotional elements of travel products and psychological emotional needs of tourists into account.

According to the review of tourism executed by OECD (2010), experience economy is a trend and innovating product development and service delivery in tourism. SMEs within a travel destination provide services as value propositions and co-create service experiences with their customers, where a service experience is defined by B. Edvardsson (2005) as “a service process that creates the customer’s cognitive, emotional, and behavioral responses, resulting in a mental mark, a memory.” Finally, tourists evaluate the consumed service experiences according to the individual and situational filter, which results in the so-called value-in-use (Sandström et al., 2008).

Service experience creates value. However, Sandström et al. (2008) claimed that “insufficient attention has been paid to the total service experience, including the emotional dimensions.” Besides, experiences are memorable, revealed, sensed by individual (Pine and Gilmore, 1998). That is, we cannot conclude that any two travelers' trips are the same even though they went together (Ricci, 2002).

The comparison among different kinds of recommendation technology including ours is shown as the table 1.

Table 1. The Comparison among Recommendation Technologies

Technique	**Content-based**	**Collaborative Filtering**		**Knowledge-based**	**Color Imagery**
		User-based / Item-based	**Association Rules** (Zhang et al., 2009)		
Input	Item Descriptions	Rating Data from Users, Item Information	Transaction Data	Information about Items, Users, and Mappings between Items and User Needs.	Content, Transaction Data
Representation	Text or Attribute-value	User-item Matrix	Features	Knowledge	Word / Color Vector
Mechanism Type	Content-based	Memory-based (User Model and Item Model)	Model-based (Rules)	Knowledge-based, Case-based	Model-based (Color Image)
Algorithm	Retrieving	Nearest Neighbors, Item Similarity	Apriori Algorithm, Frequency	Case Similarity	Color Matching , Color Mixing
Output	Articles (*PRES*) (van Meteren and van Someren, 2000)	Books, Music (*Amazon.com*)	Websites (*SurfLen*) (Zhang et al., 2009)	Operational Amplifiers (Analog Devices) Television Programs (PTVPlus) (Bridge et al., 2005)	Destinations, Service Providers

2.2 Tourist Expectation Formation

In the previous section, we learned that most of recommendation systems do not catch users' expectations of suggested objects (preference-driven systems) or merely via inputting item descriptions and constraints (data-driven systems). However, customer expectations play an important role in IS service quality equaling the gap between the perception and the expectation of a service (Pitt et al., 1995). Capturing tourist expectations (emphasizing emotional needs) is thus essential to increase customer satisfactions of travel recommendation systems, which is highly experience related.

Understanding tourist expectations is beneficial to tourism management and product development. According to Gnoth (1997), tourism expectation is defined as "… positively or negatively inclined and contain measures of cognitions, affect, and conations, whereby the conational element expresses itself in two aspects: the intensity and persistence with which the confirmation or falsification is desired or longed for, and the extent to which the tourist evaluates levels of possible satisfaction the targeted experiences might procure. In other words, expectations are tentative (mental or neural) representations of future events or unfinished learning processes." On the other hand, Truong and Foster (2006) considered destination attractiveness or images perceived to examine the ability of satisfying tourists' vacation needs as part of expectations.

The tourism expectation formation process was well illustrated in Gnoth (1997)'s work shown as Figure 2. Initially, needs are established as an urge, which is emotional and can be deemed as an action tendency (pull factors). This action tendency leads to a person's perception reviewing an objective situation where objects such as destinations can satisfy tourists' motives. Motives here are distinct from motivations. The former can be regarded as latent needs and implies a direction and a target, while the latter actually includes the targets and becomes the results of the interaction between motives and situations with a person's perception and value (or an individual filter, can be either cognition-dominant or emotion-dominant). Once motivations formed, people then stand in a subject situation existing stimuli of tourism objects (pull factors). Thus attitudes and expectations of travel products or services are shaped while the latter takes emotions into account.

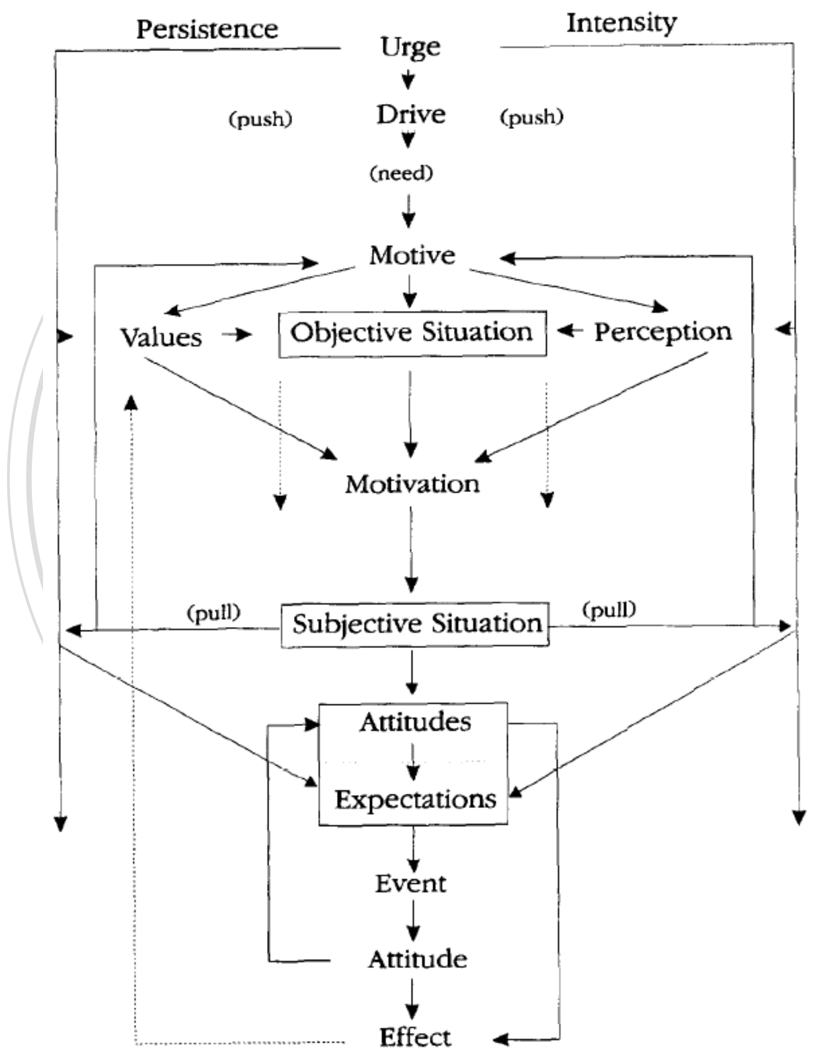


Figure 2. The Process of Motivation and Expectation Formation (Gnoth, 1997)

In our destination recommendation system, things we capture from tourist are the intrinsic needs or the motives in Figure 2 (push factors), which are psychologically dominant and formed before the perception of value propositions provided by SMEs in regional tourism (pull factors) (Gibson and Yiannakis, 2002).

To adapt the rising demand for customized and flexible products and services in experience-based tourism (Stamboulis and Skayannis, 2003), we further narrowed our tourists' needs down to expressive needs (the other category is utilitarian needs), "requirements for products/services that provide social or aesthetic utility", defined by MacInnis and Jaworski (as cited in Yuksel and Bilim, 2009). Expressive needs are composed of "socially expressive needs (i.e., the desire to express one's actual self or ideal self-image) and experiential needs (i.e., the desire to consume products/service for their cognitive or sensory stimulation) (Yuksel and Bilim, 2009)"

During the tourism expectation formation process, questionnaires like the SERVQUAL and the HOLSAT instrument are the most common tools to represent or model needs, motivations, and expectations (Pitt et al., 1995; Robledo, 2001; Truong and Foster, 2006). For the purpose of modeling psychological needs in a recommendation system, however, the flexibility of questionnaires is insufficient to reflect roles' real-time images, i.e. the result data is static and limited by the question designers. Instead, a uniform, dynamic, and open-ended modeling tool has to be developed.

Yuksel and Bilim (2009) declared that the more a brand personality of a destination is similar to a tourist's needs and the self-image, the more likely this destination is to satisfy him/her. The tourist decision process is shown as Figure 3, indicating that the destination branding starts from the evaluation of destination image with a strong emotion attached. The destination branding succeeds when a mutual relationship is established between destinations and tourists by satisfying their needs or motives.

The brand personality here can be treated as the destination image, a component authorities used to position the destination (Echtner and Ritchie, 2003). Tourists make decisions based on these images that will be interpreted by their motives and later become the attitudes and expectations toward the corresponding destinations (Yuksel and Bilim, 2009).

On the other hand, the self-image is defined as “the totality of the individual’s thoughts and feelings having reference to himself/herself as an object or how individuals perceive themselves to be (Chon and Olsen; Litvin and Kar (as cited in Yuksel and Bilim, 2009)) and as a mental picture of themselves (Chon and Olsen; Morrison (as cited in Yuksel and Bilim, 2009)).” Tourists preserve or enhance their self-images via visiting favorable destinations and service providers whose images are regarded as matching with their own images (Yuksel and Bilim, 2009).

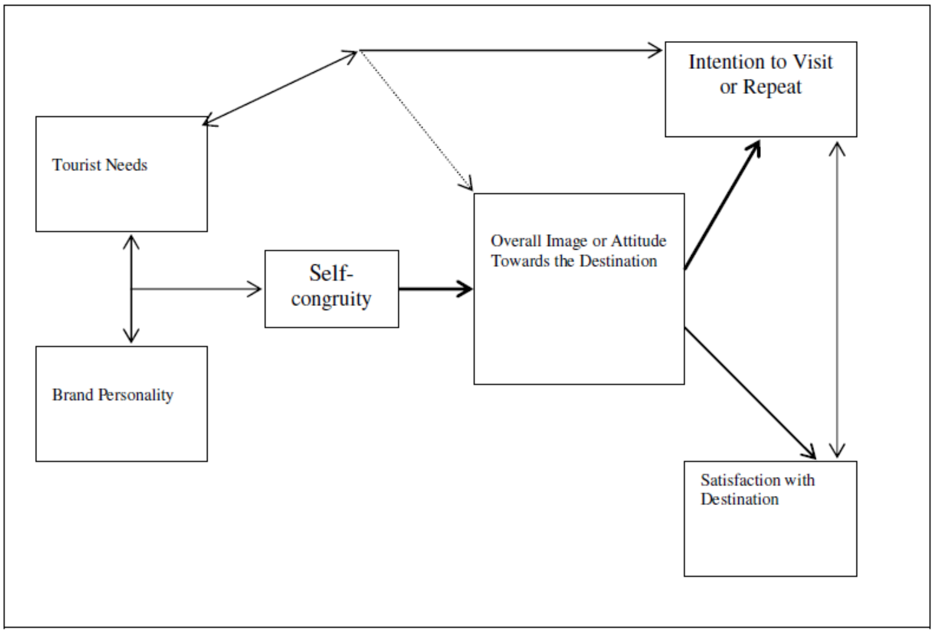


Figure 3. The destination branding and tourist decision-making process (Yuksel and Bilim, 2009)

2.3 Color Emotion and Color Mixture

Color can evoke human's emotional feelings (Xin et al., 1998; Kobayashi, 1981; Nijdam, 2005; Ou et al., 2004; Suk and Irtel, 2010). Kobayashi (1981) stated that every color has its own meaning, which can be mapped onto one or more words. For example, "red is regarded as adventurous, sociable, and powerful; yellow is thought to be cheerful, jovial, and exciting (Xin et al., 1998)" These emotional feelings, impressions, or images are called color emotions (Ou et al. 2004).

Researchers contributed efforts to quantify the relationship between color and emotion for the advantages brought by the integration of color's physical property of the spectrum of light and its psychological nature. One of these advantages is that color selection can be more objective if the emotions every color conveys are specified. Another is that using numerical value or standard colorimetric systems such as RGB or CIE to represent color emotions facilitates the communication between different parties (e.g. Web designers and programmers) (Xin et al., 1998).

To achieve the goal of quantifying the color emotions, four color-emotion factors are claimed to cross-culturally exist, including warm–cool, heavy–light, active–passive, and hard–soft (Ou et al., 2004). These factors can be considered as color semantics or high-level properties which are color-induced sensations, whereas low-level properties are the syntactic characteristics such as hue, luminance and saturation (Corridoni et al., 1999). In the content based image retrieval field, researchers often combine the syntactic level and the semantic level to devise formulas for transforming colors into emotions (Corridoni et al., 1999; Solli and Lenz, 2009). However, the number results calculated by these formulas are convenient for machine computation but have a lack of human readability.

Kobayashi intensified the combination of color science, color emotion and word semantics. He and his team at the Nippon Color & Design Research Institute have developed Color Image Scale (Kobayashi, 1981, 1992, 2001), which explicitly defined the meanings of 130 basic colors (Figure 4) and over 1000 color combinations. Each of them is assigned one or more image words (an adjective) (Figure 5) through investigation and factor analysis. These colors are categorized with Hue and Tone System (Kobayashi, 1981, 1992, 2001), consisting of 40 hues and 12 tones (value-chroma) and based on the ISCC-NBS color naming method and the Munsell color System.

Three psychological axes including warm-cool, soft-hard, and clear-greyish correspond to the hue, value, and chroma in the Munsell system (Kobayashi, 1981). The closer the distance between colors on the scale, the greater the similarity between their images. On the Single Color Image Scale, colors belonging to the same tone are arranged in order of hue, whose images vary but have common characteristics the tone conveys. Take vivid tone for example, it means vivid, bold, clear, full of life, and attract attention (Kobayashi, 1992).

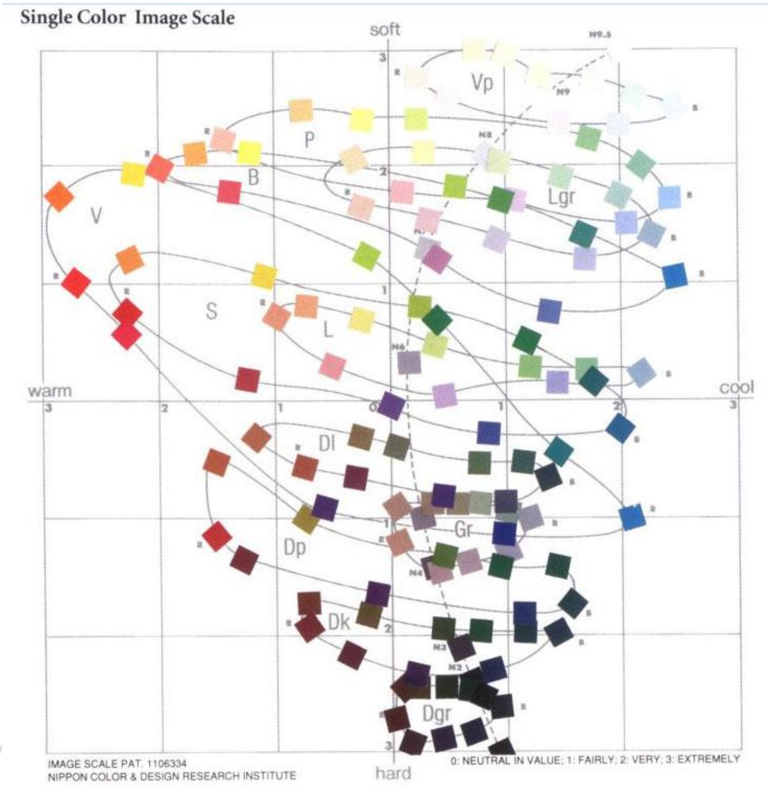


Figure 4. Single Color Image Scale (Kobayashi, 1992)

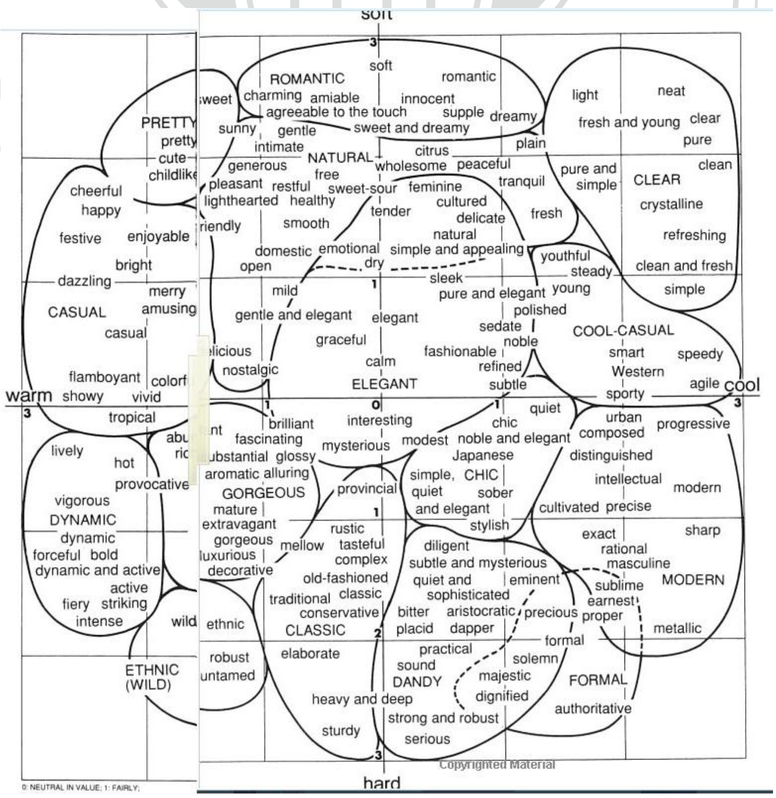


Figure 5. Key Word Image Scale (Kobayashi, 1992)

Newton's "centre of gravity" law of additive color mixing is "a method to predict the colour of a mixture of lights from the colours of its component lights, using a diagram in which the colours of the spectrum are arranged on the circumference of a circle, and white (the colour of the mixture of all of these kinds of light) lies at the centre. If you consider the points on the colour circle that represent the component spectral lights in the mixture, and assign to each of them a weight proportional to the intensity of light of that kind, then the centre of gravity of the resultant figure will represent the colour of the mixture of lights (Broackes, 1992)."

The additive color mixing has been applied to many fields such as painting restoration (Pei et al., 2004), OLED display (Wu et al., 2006), and colored visual cryptography (Yang and Chen, 2008) for its natures of saturation and de-saturation concept, preventing the introduction of unnatural colors, and the capability of brightness manipulation (Lucchese et al., 2001; Pei et al., 2004).

The equation (1) (Lucchese et al., 2001) illustrates the Center of Gravity Law of color mixing, where C_2 (x_2, y_2, Y_2) results from the mixture of C_w (x_w,y_w,Y_w) and C_s (x_s, y_s, Y_s). These coordinates use CIE xyY color space representations, which can be converted from RGB values and then be obtained from the normalization of CIE XYZ system as equation (2) and (3).

$$x_2 = \frac{x_s \frac{Y_s}{y_s} + x_w \frac{Y_w}{y_w}}{\frac{Y_s}{y_s} + \frac{Y_w}{y_w}}, \quad y_2 = \frac{Y_s + Y_w}{\frac{Y_s}{y_s} + \frac{Y_w}{y_w}}, \quad Y_2 = Y_w + Y_s \qquad (1)$$

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.49000 & 0.31000 & 0.20000 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00000 & 0.01000 & 0.99000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (2)$$

$$x = \frac{X}{X+Y+Z} \quad \text{and} \quad y = \frac{Y}{X+Y+Z} \qquad (3)$$

CHAPTER 3 MOTIVATING APPLICATIONS

This chapter depicted the whole picture of our research project – "uVoyage". The proposed mechanism in this research, including image model creation, evolvement, and matching, is one of its underlying components.

3.1 Conceptual Framework of uVoyage Service Platform

The uVoyage conceptual framework is composed of four tiers as shown in Figure 6. The first tier includes (1) a destination which is the target environment where SMEs reside; (2) entry level technology embedded in the environment; and (3) relationships among businesses and consumers enables different B2B and B2C business models.

To encourage the business development of SMEs, the second tier of the conceptual model consists of image modeling and sheltering operations which are mechanisms for the frontline service provision of the centric platform. As described in Chapter 4, image modeling is an automatic mechanism for gathering and analyzing the feedback, customer behavior, and other data resources, in order to model the images of destinations, tourists, and businesses. On the other hand, sheltering operations energize marketing and managerial operations and increase the productivity for the businesses.

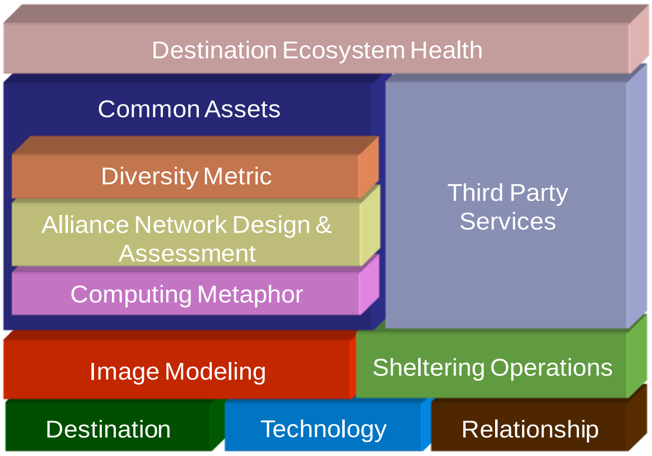


Figure 6. Conceptual framework of uVoyage service platform

Diversity metric, alliance network design and assessment and computing metaphor are the common assets of uVoyage conceptual framework in the left side of the third tier. These common assets aim to create incentives for business cooperation, including partner recommendation and selection for business cooperation to achieve given goals, evaluate possible alliance value network formation and compute the selected alliance value network's feasibility, and measure the service diversities of the ecosystem.

Third party service providers, such as transportation or other independent software vendors, act as auxiliary enablers built on top of the common assets in order to supply their services for value network operation.

On the top of the conceptual model, the destination ecosystem health measures the growth and diversity of service development through the prosperity of business and their cooperation. The unique properties of the uVoyage conceptual framework are protective, proactive and prosperous:

- Proactive implies that businesses can keep being alert to the changes of the environment and the customers based on the image modeled. After the changes are discovered, the common assets of the technology can then facilitate businesses to create niches and complementary partners for growth.

- Prosperity shows the outcome of value co-creation in an ecosystem. Our framework aims to encourage businesses proposing better value propositions in terms of different value networks. Therefore, the ecosystem which contains many value networks would also receive benefits from business development.
- Productiveness highlights the features of industrial cooperation for customers to enhance overall productivity of a regional industry.

The implementation of first two tiers which discover and understand customers' needs and business relationships in the environment on the basis of the destination image theory is to assist the value creation process in the tourism ecosystem.

3.2 uVoyage System Architecture

There are mainly six modules uVoyage as shown in Figure 7. The modules of image modeling and image mixing are related to the first two tiers of the uVoyage conceptual framework which are responsible for sensing the dynamics environment and customers according to their image models. The sheltering service management module is designed for realizing the sheltering operations for SMEs mentioned in the technology. The other two modules named SME alliance service formation and alliance feasibility management module aim for assisting business cooperation and value sharing. The keystone strategy can be achieved through the six modules through facilitating business value creation to value sharing in the ecosystem.

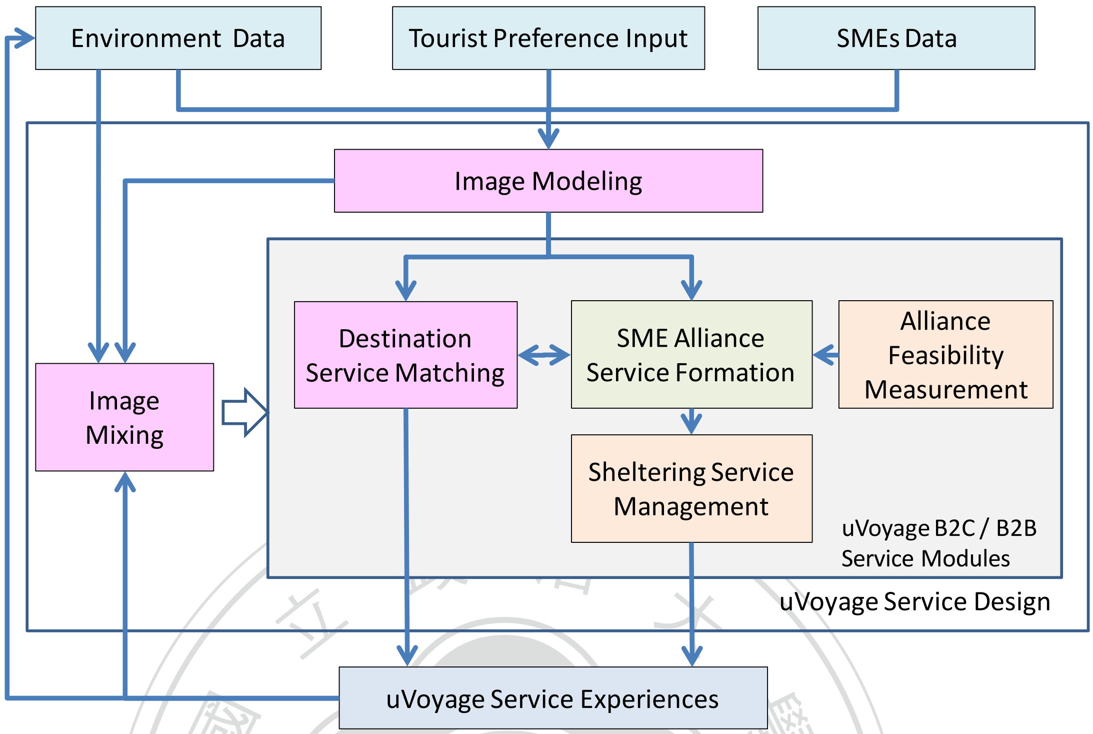


Figure 7. uVoyage Service System Platform Architecture

Both tourists and regional tourism SMEs are the target users in uVoyage, that is, tourists search for desired services through evaluating their images, whereas SMEs cooperate to achieve the specific images. Tourist preferences and the personality, SME related data, and environment data are used as the primary input for the image modeling module that constructs images for destinations, businesses and tourists.

SMEs within the region can search cooperation and combine their services to meet tourists' changing needs or create new services facilitated by the alliance service formation modules. When cooperative intention occurs, images from collaborated services with different SMEs or destinations will be calculated by the image mixing module. Meanwhile, every cooperation suggestion resulted from the alliance service formation module will be evaluated by the alliance feasibility measurement module for assessing the possibility of cooperation success.

Afterward, the destination service matching module recommends services to tourists by matching images of tourists (aggregated with their emotional needs) and SMEs' services. With the sheltering service management module fulfills related electronic cooperation management and marketing functions, tourism SMEs can deliver their services more effectively. In the end, both tourists' and SMEs' service experiences as feedbacks will affect both environment data (i.e., discussion on web or blog) and all involved role images.

CHAPTER 4 COLOR IMAGERY FOR DESTINATION RECOMMENDATION

4.1 The Conceptual Framework

The underlying conceptual framework (i.e., the main ideas) of our method is shown in Figure 8 prescribing the interrelationships (arrow (1)~(4)) of the basic concepts (tourist emotional needs, destination images, image modeling, image mixing and destination alternatives).

In Figure 8, we assume tourist images and destination images are the targets to be processed to attain the matching, that is, pairs of tourist images and destination images being the outputs of the recommendation process.

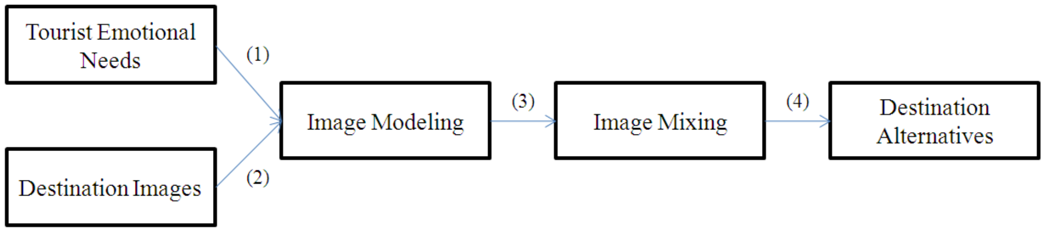


Figure 8. Conceptual framework of the destination recommendation system

Tourist Emotional Needs: People often do traveling to fulfill their emotional needs. In the planning stage of the journey, they have some motives for the destinations and SMEs (i.e. local stores, like restaurants or hostels) before reviewing existing tourism products and services. 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 Chapter 1 and 2, 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 tourist emotional needs and destination images, customer emotional needs or motives are regarded as demands and destinations are the candidates for these demands. Image as a medium is capable to express both emotional needs 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 emotional needs, 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. 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 and Ritchie, 2003; Mackay and 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 comprehensiveness, all of the actors’ opinions, behaviors and transactions could be 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). In this research, we used transaction data for the analysis.

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 (Xin 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 building distinguishing features for attractiveness and uniqueness 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 punk."

Besides, 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.

For the sake of revealing the facts mentioned above, the image mixture have to be functioned in our system.

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 and Mitra, 2000; Lucchese et al., 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 tourist emotional needs and destination images can then be realized and the recommendation can be accomplished in different levels with destination alternatives as system outputs.

4.2 System Architecture

In order to fit into the tourism environment featuring individuality, emotional dimensions, wide data, and diverse product types (i.e. various services provided by hotels, restaurants, and entertainment stores), we position our system as a model-based recommendation system. Since memory-based approach is unable to distinguish personal travel experiences relying on "nearest neighbors"; content-based lacks the ability to highlight the emotional dimensions, we engage psychological/emotional features of tourism products through explicitly modeling both destination images expected by users (emotional needs) and images of tourism products (popular mental impressions) as profiles of each stakeholder role.

With the uniform representation of images, we can also avoid the costly construction of categories for each kind of tourism product. Additionally, based on the causal relations and interactions between these roles, their image models (profiles) mature over time. This learning mechanism alleviates the wide data management contributing the recommendation quality. In the end, we gain suggestions through a mapping between the image models belonging to users and tourism products.

In this research, there are three assumptions adopted for our destination recommendation system as listed below.

- Assumption 1: We do not consider possible combinations of destinations and activities (Ricci, 2002).

  All the activities recommended are within a previously chosen destination by the current user. Tour packages or complete travel plans will be suggested based on other users' travel logs.

- Assumption 2: Our customers seek deep tours which are able to meet their spiritual/emotional demands. Thus their expectations are narrowed down to the individually emotional needs.

- Assumption 3: Function-oriented selection can be done with a filtering option provided by our system.

  Ricci argued (2002) "an effective travel recommendation system should not only notice the user's main needs or constraints in a top-down way but also allow the exploration of the option space and support the active construction of user preferences (in a bottom-up way)." Thus, we keep the chances to explore destinations for users which may meet their potential demands by leaving the filter function (functional constraints) after the initial query results based on their destination image expectations and preferences derived from log files.

The architecture of our destination recommendation system is presented in Figure 9 that is based on the underlying conceptual framework as mentioned in the previous section. 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.

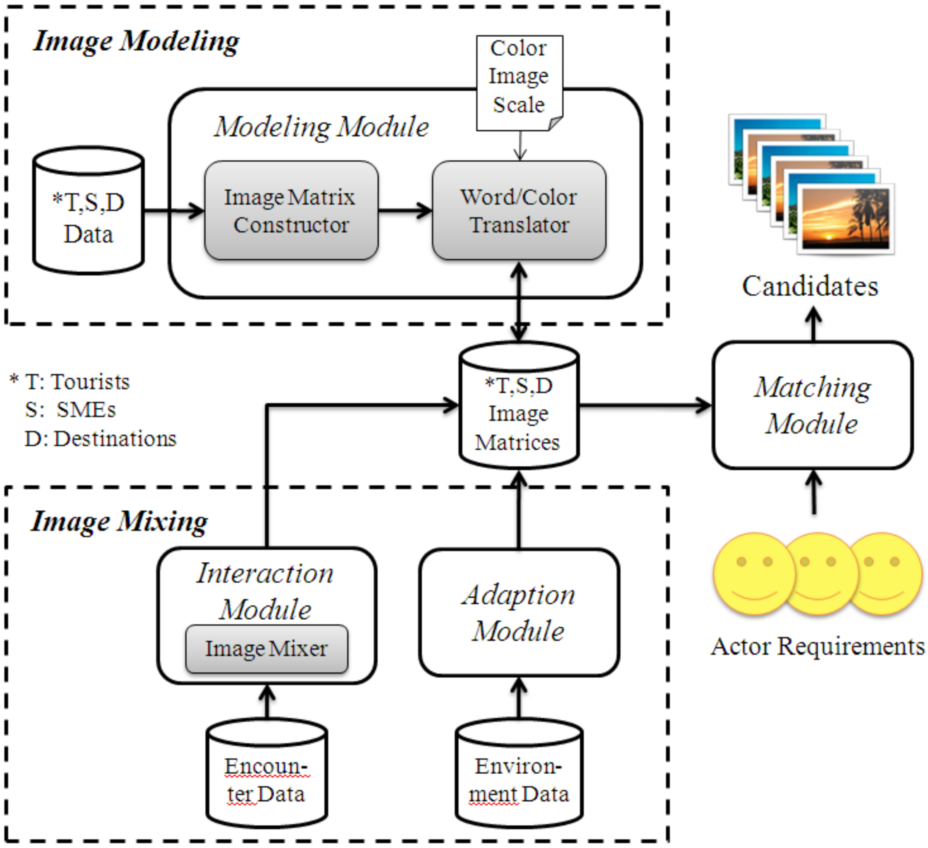


Figure 9. Architecture of the destination recommendation system

In the system, all data from tourists, 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. tourists' 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 directly adjusts their images, because every kind of image interactions will influence with each other. It can be explained 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 occasional 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 shot, and this makes destination image change.

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

4.3 Modeling Module

This module is designed for modeling 3 kinds of images as profiles for each stakeholder, including tourists, destinations, and SMEs (service providers). Every image model is composed of psychological characteristic attributes. Corresponding to the concepts introduced in the previous section, the origin and the purpose of the three image model types are described below:

- Tourist Image model: It reflects a tourist's self-image representing his/her personality and preference derived from a machine-learning process. When a tourist inputs an imagery-based query (considered as a short-term image representing the tourist instant emotional needs translated from a query when planning a trip), the query would be used as a filter to build a candidate list from the database, followed by the list being sorted based on the tourist's long-term image model for personalization.

- Destination Image model: It reflects the real-time mental vision or the impression of a destination from the population including tourists and resident SMEs.
- SME Image model: It reflects the real-time mental vision or the impression of a SME from the population. Meanwhile, SME owners can utilize it as an examination tool to diagnose their operation strategies and processes, and also as a marketing / positioning tool by partially modifying their images.

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

- Data Sources for building Tourist Image

(1) Classification: We assume tourists are categorized into three tourist types—Independent Mass Tourist, Explorer, and Drifter (Lepp and Gibson, 2003). Images of each type are predefined based on their characteristics correspondingly and a tourist's classification can be attained from a simple questionnaire.

(2) Learning from Tourist Behavior: As the initial images for every tourist are established, they can start to grow based on four main tracks of tourists' behavior. First, those on our recommendation system platform e.g. searching and browsing history. Second, information about the journeys they attended, including

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 tourists' preference; and service index scores they gave can show their emphases. Forth, expecting destination images that we gain from tourists' inputs every time when they are planning a trip. This one is distinct from others because it has the immediacy. In the beginning of the matching process, we will prepare an additional short term image for a tourist, which stands for his/her instant emotional need to a destination or a trip, while the existing image is long term and has been growing.

- Data Sources for building 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 tourists' feedback. Besides, the image of the destination where they reside will also influence their own images (Interaction Module's responsibility).

- Data Sources for building Destination Image

(1) It is constructed by the emotional words given by SMEs and tourists, 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 (i.e., a representation of image attributes).

These words come from Color Image Scale (Kobayashi, 1992) and all of them are adjectives. With Color Image Scale, converting the feelings about products, services, and experiences into mathematical notations becomes easier, because on the Internet, they are usually accompanied with text information which can be analyzed with text mining techniques.

Table 2 presents part of image attributes taken to construct an image model within our system. In total, we choose 122 image attributes from Color Image Scale, and they can be categorized into 14 groups (casual, chic, classic, clear, cool-casual, dandy, dynamic, elegant, formal, gorgeous, modern, natural, pretty, and romantic) according to their meanings. The original Color Image Scale has 130 colors and 180 emotional words. However, their positions on the scale are not exactly and directly mapped, and some of colors are too close to be distinguished, so only 122 relations among them could be clearly identified and used in our research.

Each image attribute in our system is represented by a psychological word and has several properties: color notations, including Munsell and RGB value, and adjective factor (evaluative, sensitive, dynamic, emotional, scale (Kobayashi, 1981)), which will be used in the image matching and mixing process.

Because our raw data for building image models are gathered either by text mining from Internet or through open questions from tourists and SMEs, we will use DISCO, a JAVA tool (http://www.linguatools.de/disco/disco_en.html), to retrieve the semantic similarity between external words and psychological words in Color Image Scale. In consequence, all the external text contents could be translated into words within the boundary of our modified Color Image Scale.

Table 2. Exemplars of Image Attributes/Elements in Modified Color Image Scale

Image Attribute	Chinese	R	G	B	Munsell	Adjective Factor	Category
amusing	好玩的	184	28	16	R/S	evaluative	CASUAL
bright	多采多姿的	216	128	0	YR/S	sensitive	CASUAL
casual	休閒的	192	0	112	RP/V	dynamic	CASUAL
cheerful	開朗的	255	217	0	Y/V	emotional	CASUAL
dazzling	耀眼眩目的	208	0	32	R/V	evaluative	CASUAL
delicious	美妙的	186	69	131	RP/S	sensitive	CASUAL
enjoyable	享樂的	216	128	0	YR/S	emotional	CASUAL
friendly	友善的	239	143	184	RP/B	evaluative	CASUAL
chic	雅緻的	54	96	141	PB/S	evaluative	CHIC
modest	簡樸的	129	145	66	GY/Dl	evaluative	CHIC
noble and elegant	高貴典雅的	82	131	124	BG/Dl	evaluative	CHIC
quiet	清靜的	133	153	186	PB/L	scale	CHIC
simple, quiet and elegant	簡單、安靜和優雅的	171	157	109	Y/Gr	evaluative	CHIC
sober	穩重的	102	120	149	PB/Dl	scale	CHIC
stylish	新潮的	0	33	152	PB/V	evaluative	CHIC
classic	經典的	102	0	117	P/Dp	evaluative	CLASSIC
complex	複雜的	184	147	143	R/Gr	scale	CLASSIC
conservative	保守的	112	92	0	Y/Dk	evaluative	CLASSIC
elaborate	精緻的	104	0	31	R/Dk	evaluative	CLASSIC

Since image elements can be represented either by words or by colors, every image model in the system has three matrices as shown in Figure 10, which contains 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.

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 11) 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 many to one (it is many to many in the original version), that is, every image attribute has its own meaning, and it can be presented either by multiple words or one single color.

$$\begin{bmatrix} W_{0\,0} & \cdots & W_{0\,36} \\ \vdots & \ddots & \vdots \\ W_{4\,0} & \cdots & W_{4\,36} \end{bmatrix} \quad \begin{bmatrix} C_{0\,0} & \cdots & C_{0\,36} \\ \vdots & \ddots & \vdots \\ C_{4\,0} & \cdots & C_{4\,36} \end{bmatrix} \quad \begin{bmatrix} I_{0\,0} & \cdots & I_{0\,36} \\ \vdots & \ddots & \vdots \\ I_{4\,0} & \cdots & I_{4\,36} \end{bmatrix}$$

Figure 10. Image Matrices in three formats

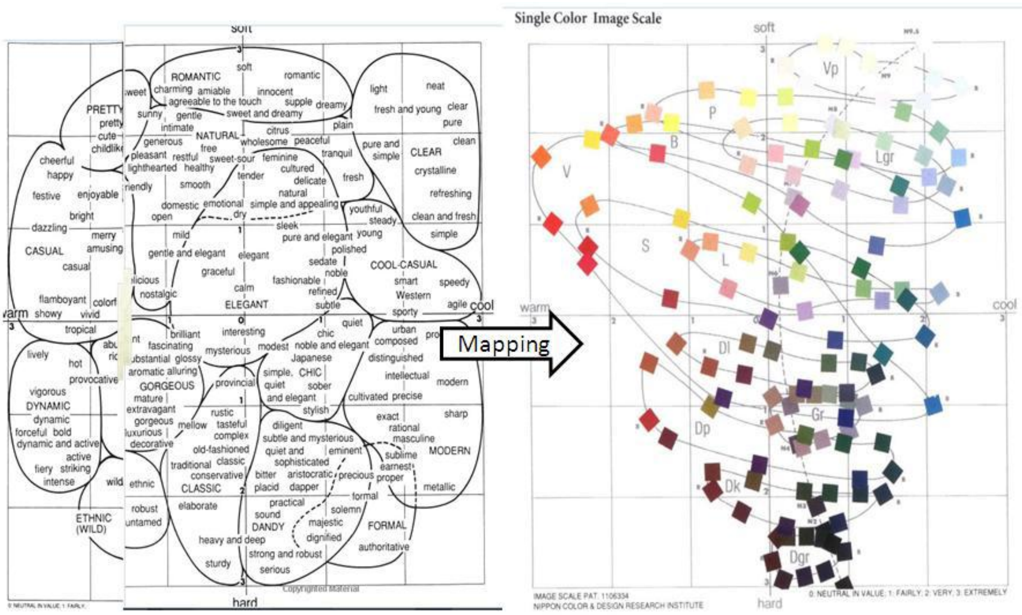


Figure 11. Concept of mapping emotional words onto colors (Kobayashi, 1992, 2001)

4.4 Interaction Module

Since each kind of stakeholder role's image has influences on others to a certain extent, Figure 12 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.

Tourists are less powerful on the influences than the other two because choices convey humans' preferences. We believe destinations have more significant attraction to tourists 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 tourist images than that from SMEs to tourists. But why does the 3 points is given to the one from tourist to SME images and 1 point from tourists to destination images? For the 3 points, it's quite common that the types of tourists 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 tourists, 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 tourist images are considered to have similar influences to SME images.

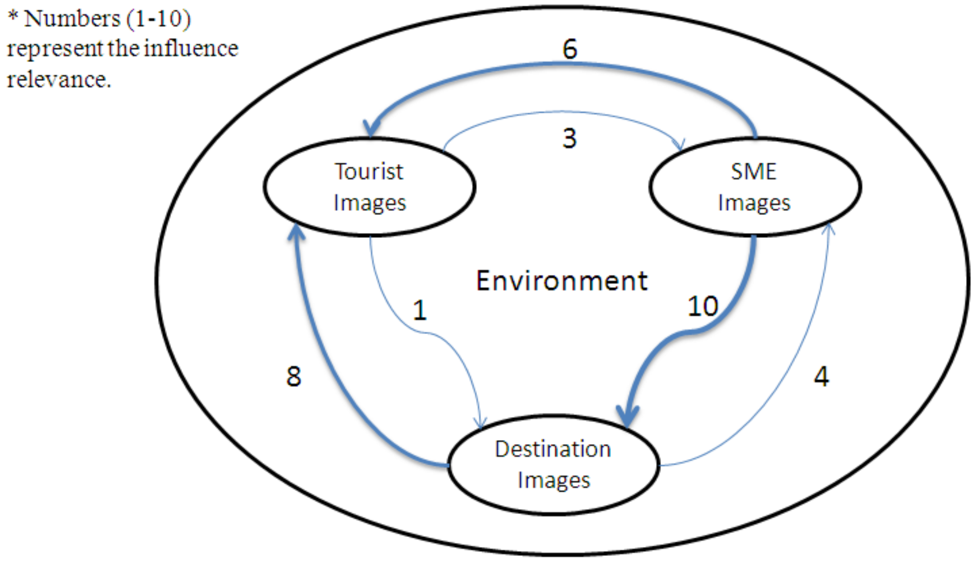


Figure 12. Influences of the interactions among stakeholders' roles

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 13 is given as an example):

Step 1. Select image elements in each stakeholder's image model whose intensities are higher than a threshold (say 10% here).

Step 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 to the sum of the percentage values of the referred same word, e.g. in Figure 13, 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	
healthy	**10.00%**
traditional	**36.00%**
nostalgic	**20.00%**
aromatic	**10.00%**
convience	2.00%
cool	6.00%
classic	2.00%
amusing	**10.00%**
mild	4.00%

\+

Bull Cart	
simple	4.00%
natural	8.00%
nostalgic	**32.00%**
rustic	8.00%
deligent	**12.00%**
hot	4.00%
traditional	**24.00%**
sound	4.00%
casual	4.00%

\+

Kiln BBQ	
nostalgic	**20.00%**
earnest	4.00%
sweet	4.00%
mild	**20.00%**
traditional	4.00%
amusing	**40.00%**
happy	4.00%
intellectual	4.00%

=

Alliance		
healthy	10	4.27%
traditional	60	25.64%
nostalgic	72	30.77%
aromatic	10	4.27%
amusing	50	21.37%
diligent	12	5.13%
mild	20	8.55%
Total	234	100%

Figure 13. The image mixing process for an alliance comprising the images of 3 SMEs (Pounded Tea, Bull Cart, And Kiln BBQ)

- Level 2 –Most Comprehensive:

  Assuming there are two stakeholders interacting with each other. Their image models are IM1 and IM2. In the following steps, we are going to find what image elements IM1 will be attained as the results of its interaction with IM2.

Step 1. Categorize all images elements in IM1 and IM2 into five groups according to their adjective factors: Evaluative, Sensitive, Emotional, Dynamic, and Scale (Kobayashi, 1981).

Step 2. For both IM1 and IM2, use the additive color mixing method to find five centers of gravity according to the group types. This method requires the percentage of each image element (its amount / weight in the mass) as parameters for the percentage of luminance used in the additive color mixture method. Use a squash function to adjust their intensity values as the inputs (i.e. percentage = squash(element.intensity), the squash function we use is f(x) = x*2.5, for more details please refer to section 6.3), because the intensities might be so small after the categorization in step 1 that the produced center of gravity would become a bias.

Step 3. Now we have five new color points of IM1 and IM2 respectively. Use the additive color mixing method again to find the center of gravity in each pair[1] of these color points (each pair is in the same adjective category). This time, use the influence weight values corresponding to the IM1's and IM2's stakeholder roles (e.g. (1-0.6) and 0.6 if IM1 is a tourist's image model and IM2 is a SME's) as the required percentage parameters.

Step 4. Find image elements in Color Image Scale whose colors have shortest distances in RGB space with the five centers of gravity gained from step 3.

Step 5. The image elements we get from step 4 are the image mixing results IM1 will be given after interaction. That is, they are treated as additional ones which will be added into IM1 as influenced by the other stakeholders.

Since we have intensity values, image elements which have less influences will be like 'filtered' during the mixing process. In addition, image mixing *increases the possibility* with which we find image elements that differ from anyone within all participants' 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 images or impressions are virtual. We don't have to worry about their 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 (whereas CMYK color model is for printing) and CIE XYZ color space whose value are convenient to be extracted and converted (Fairman et al., 1997; Lucchese et al., 2001; Pei et al., 2004) from NCD's Hue and Tone system

[1] There could be more than two image models participating in the mixing process. It is not necessary to be 'a pair', which is for a simple explanation.

(Kobayashi, 1992, 2001). Here we introduce the 4 steps of the additive color mixture method we adopted in the image mixing process:

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

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

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

Step 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).

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

Step 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 2 illustrates the computing process of the image mixing by above steps. Table 3 then exemplifies some results of the image mixing experiments.

Table 3. Computing of image mixing

				CIE Color Space			CIE xyY color space			After Mixing			Mixing Result
Munsell	**R**	**G**	**B**	**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

Table 4. Experiment of image mixing

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

4.5 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 tourists 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.

4.6 Matching Module

With the fundamental element, images, being comprehensively cultivated, this module can process them to find the good destination / service provider matches to fulfill tourists' emotional needs. The recommendation procedures are shown as the following steps:

(1) Attain tourist images: Analyze the tourist (the current user)'s instant inputs on the system platform, which stands for his/her expected destination image. Now this tourist has a short-term image model and a long-term image model referring to his/her existing profile.

(2) Get a selection pool: Use the short-term image model attained from previous step to filter candidate image models in the database. Image elements' intensity value in these candidate models must exceed a certain threshold.

(3) Retrieve similarity value: First, select top three colors having the most intensity value in the tourist image model and candidate image models. Then based on the "i type[2]" of color harmony theory as depicted in Figure 14 (Cohen-Or et al., 2006), we calculate the similarity of each pair of them (colors not in the same particular zone in a color model[3] will gain zero score). There is one thing to note: The reason why we don't compare whole images is because we want to encourage SMEs and destinations to be differentiated.

---

[2] All the eight types of color harmony theory (see Figure 14) could be used in similarity calculation. In this research, similar things are intuitively considered most likely to be accepted and most potentially to satisfy users when they get recommended. Therefore, we only use the "i type" of color harmony theory in this preliminary stage of study, based on an idea that things having similar images / colors would be deemed as a pleasing arrangement of parts.

[3] In our system, we use HSL color cylinder, which is an alternative representation of RGB color model, to mark these "harmony zones" for recognition of similar colors. For example, if there are two colors c1 and c2, and we'd like to know whether they are similar colors, in our definition the first step is to confine an area in HSL cylinder with c1 centered. The edges of this area are c1's hue value +- 15 degrees, c1's saturation value +- 0.1, and c1's lightness value +- 0.1. Next and the final step, see whether c2 is located in this area. If the answer is yes, then we say c1 and c2 are harmonious colors and will have high similarity score.

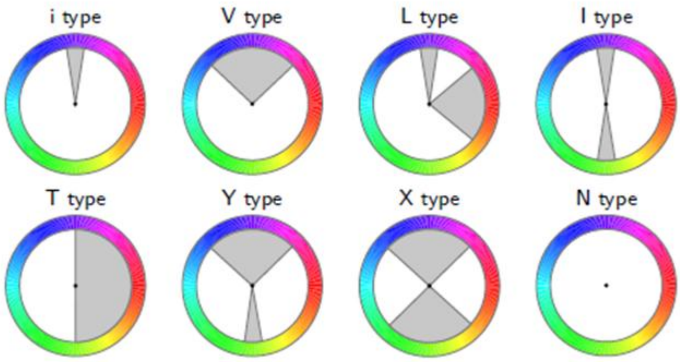


Figure 14. Harmonic templates on the hue wheel. A collection of colors that fall into the gray areas is considered to be harmonic. (Cohen-Or et al., 1999)

(4) Making personalized recommendation list: Now each one of candidate image model has a similarity score gained from step 3. We rank this candidate list with these scores, and find out destinations or service providers who own these image models. Finally, we render this name list with an appropriate format, and present it to the current user as a personalized recommendation.

(5) Filtering (optional): we provide a filtering function after recommendation. These filters can be budget, preference, region, etc. We expect more people to see lesser known destinations and resident SMEs, so we put this function in the last step.

In this chapter, we illustrated the four modules which realize the image modeling, image mixing, and image matching procedures in our destination recommendation system. In next chapter, we will provide an application scenario for a demonstration.

CHAPTER 5 APPLICATION SCENARIO

To facilitate the development of tourism industry, the color imagery recommendation system is designed to bridge lesser-known travel regions and tourists, and build positive mutual relationships between local SMEs and customers through recommending right destinations or travel services to tourists. For backpackers, we believe lesser-known destinations have as much potentials as popular attractions to meet tourists' emotional needs though they are under development. Thus, this study attempts to figure out a systematic way to help tourists find these emotional-needs-satiable destinations and travel services.

The proposed image-based mechanisms, the creation, evolvement, and matching of image models, are invent to achieve the emotion-driven recommendation, and to strengthen the experience aspect of the tourism industry in the system. Image models are not only exploited in the recommendation process, but also utilized by travel service providers to seek business partners for unique and attractive image building. The following section demonstrates the service journey of business and tourist, and the service journey of destination and tourist.

5.1 Service journey of the application

Tourist, SME, and destination are three kinds of stakeholders we consider important in regional tourism. There will be direct encounters between a tourist and a service provider, or between a tourist and a destination, when the tourist user chooses different recommendation target type respectively (shown in 錯誤！找不到參照來源。 and 錯誤！找不到參照來源。). The service journey of destination and tourist is the simple version of the service journey of business and tourist. We use Mr. Yang's story for a demonstration of the later service journey.

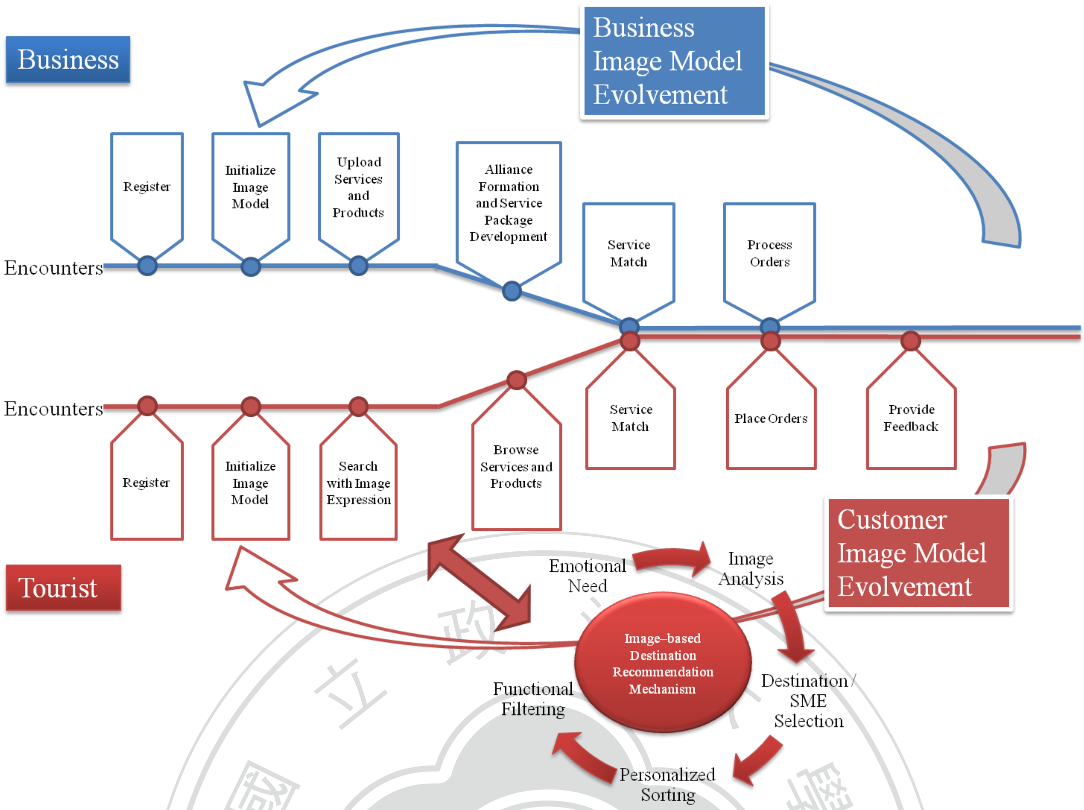


Figure 15. The Service journey of business and tourist

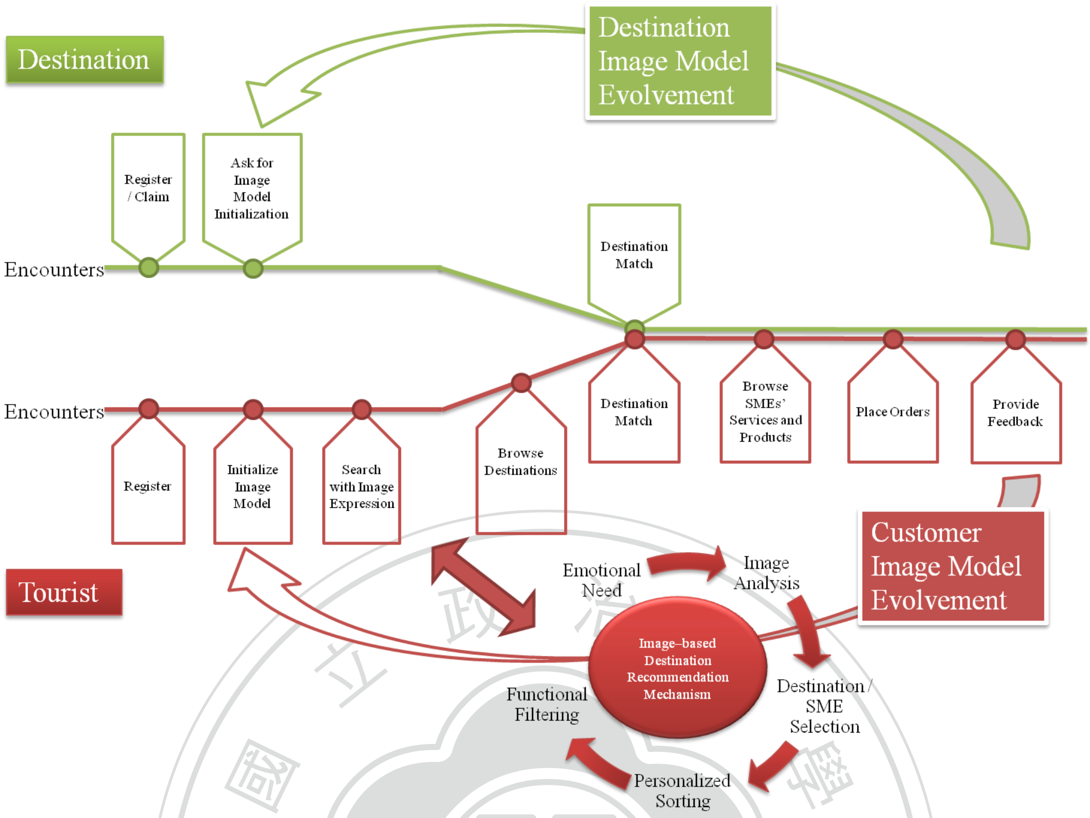


Figure 16. The Service journey of destination and tourist

Mr. Yang was always busy at work. He noticed the conversation between him and his wife became less and less. So he registered at our travel service platform named *uVoyage*, with a hope that a vacation could bring them happiness. To quickly acquaint the system with tourist user preference and characteristic, Mr. Yang answered two questions provided by uVoyage for his image model initialization (see 錯誤! 找不到參照來源。), one is "which tourist type do you belong to?" (see Table 12 for choice content), and the other is "what genres of a trip do you prefer?" (see Table 13 for choice content).

As finished the registration, he typed a word phrase "a place like paradise" into the search bar (as depicted in 錯誤! 找不到參照來源。), it appeared numerous travel services as recommendation results on the screen in seconds. Between these two actions, the query strings were first analyzed and transferred into several affective adjectives standing for image elements—“pretty, clear, sweet and dreamy, and simple”. Next, the system used these words as filters to select services whose image model contains one or more of these image elements. Third, for personalization, the system sorted the just selected candidate list through a comparison between tourist’s image model and each candidate’ image model. The more similar the main image elements of the compared image model were, the higher priority it would appear in the final recommendation list.

Through a quickly browsing, his eyes were caught by a service called “Shangri-la (世外桃源)” located in Nanpu, where he’d never been to and never heard before. But it still seemed a pleasing place after viewing its information page and other tourists’ sharing (錯誤! 找不到參照來源。). Mr. Yang couldn’t wait for this trip in Nanpu, where this couple could comfort their relationship and enjoy the peace.

Figure 17. Registration page for tourist users on uVoyage platform

Figure 18. Travel service recommendation page on uVoyage platform

Figure 19. Service information page on uVoyage platform

On the other side, Peter, a hostel host lived in Nanpu, was building the image for his business on *uVoyage*. 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 peaceful, simple, traditional, and amusing, just like a Shangri-la.

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 *uVoyage*. Most importantly, instead of a tropical island, Mr. and Mrs. Yang found their belonged paradise, a warm place close to their hearts.

The feedback Mr. Yang gave to Nanpu and Peter's alliance, and the information about the trip transaction, would become the materials for image model evolvement of just mentioned actors, Mr. Yang, Peter's alliance, and Nanpu. As stories like Mr. Yang's continuously happen in the uVoyage platform, all the actors' image models would keep updated to reflect their owners' status in the real world.

In the next chapter, the evaluation of the proposed mechanism is provided.

CHAPTER 6 EVALUATION

In this chapter, we construct several hypotheses to evaluate the system design and its attempted contributions stated in chapter 4 and chapter 1. The contributions of each system module are summarized as below:

1. With the modeling module, our recommendation system can use image models to capture tourists' emotional needs or intrinsic motives, and to reflect the population's impressions of a destination or a service provider.
2. With the matching module, our system can recommend destinations and travel services that meet tourists' emotional needs.
3. With the interaction module, our system can make stakeholders' image models evolve over time through simulating the interactions among stakeholders.
4. With the adaption module, our system can detect tourism-related events happened in the real world, and make stakeholders' image models changed as they were influenced by these events.

Before the hypotheses examination, we set a series of experiments from micro dimensions to tune system parameters for the best performance. In the end, two experiments are designed in a macro view for testing the hypotheses.

The section 6.1 describes hypotheses we proposed. In section 6.2, experimental

6.1 Hypotheses

Image models are the basic elements in our dynamic service system. We exploit them as active resources to gain better recommendation results and to provide managerial reports to regional owners and service providers. Even more, SME could utilize these image models to find business partners for creating a niche. Therefore, assuring image models' representation of their stakeholders is essential. Now we have our first hypothesis:

- Hypothesis 1: Each image model in our system is being able to represent a stakeholder's emotional needs, characteristics, and public impressions.

This hypothesis can be further broke down into two forms according to different stakeholder roles:

- Hypothesis 1a: An image model is capable of representing a tourist's self-image composed of his/her personality, preferences, and instant emotional needs to a trip or a destination.
- Hypothesis 1b: An image model is capable of representing public impressions of a destination or a service provider, as well as their characteristics.

After the image model capability examination, the matching module should be also tested for a guarantee of recommendation performance. Here is the last hypothesis:

- Hypothesis 2: Based on color harmony theory, the matching module can effectively help tourists find destinations or travel services that meet their emotional needs.

Since the world is dynamic, image models must have the ability to update themselves. Image mixing mechanism used in Interaction Module and Adaption Module are designed for reflecting the result of interactions among stakeholders, and events happened in a travel region. In this research, we mainly use "the most comprehensive" mixing method which could add "surprising" image elements to image models. Therefore, we expect the image mixing mechanism has a certain level of ability to shrink the distance between an image model and its stakeholder's image in reality, but more importantly, the ability to increase the user satisfaction level of recommendation through disclosing the so called "surprises". Here we have another hypothesis for the image mixing:

- Hypothesis 3: The image mixing mechanism (the most comprehensive level, see section 4.4) can reveal the impacts of interactions among stakeholders and the impacts of occasional tourism-related events on their image models.

Using the analogy of biodiversity, the degree of variation of service providers within a destination, i.e. *service diversity*, may influence the interaction results. We assume the higher the service diversity of a region, the lesser the influence of an event to the destination. Thus, the hypothesis 1 can be extended into:

- Hypothesis 3a: In a destination of high service diversity, an occasional tourism-related event would have a smaller impact on the region. Also, it would take longer to reach the homogeneous status after a series of interactions among stakeholders in this destination.
- Hypothesis 3b: In a destination of low service diversity, an occasional tourism-related event would have a bigger impact on the region. Also, it would take lesser time to reach the homogeneous status after a series of interactions among stakeholders in this destination.

The homogeneous status just mentioned refers to that a destination's current service diversity is low.

6.2 Assumptions

In the following sections, some experiments are carried out with simulation. To reduce the complexity caused by factors existing in the real world during simulation, we make several assumptions as below:

- Assumption 1: Instances of the same kind of stakeholders have equal influence power.

  If a service provider interacts with multiple customers at the same time, these customers will equally share the influence weight value 0.3 we set for the C2B interaction relation.

- Assumption 2: Image models we use in the experiments have enough representativeness of their stakeholders.

  Before the release of our system platform, most image models we use for testing are randomly generated by a program under certain circumstances referring to the context of Zhenshan Agricultural Leisure Area at Yilan, Taiwan. We assume the structure of every image model and the distribution of them are representative and applicable to other regions in the world.

- Assumption 3: The mapping relations between colors and image words (emotions) are reliable.

  We rely on Kobayashi's Color Image Scale to link colors or words to a meaning of image. However, there is no precise definition of their relations in the references. Eventually, we manually map their relations according to their positions on the scale.

6.3 Design Parameters

In this section, we list parameters would affect the system performance by module. If possible, their settings will be explained via simulation experiments.

- Modeling Module

(1) The mapping relations between colors and image words

As mentioned in assumption 3 in previous section, we have tried our best to define the relations between colors and emotions on Color Image Scale. As a result, we identified 122 relations listed in Appendix A while the relationship between colors and emotions is one-to-many. The 122 colors we mapped image words onto are shown in Figure 20 (some of them are duplicated).

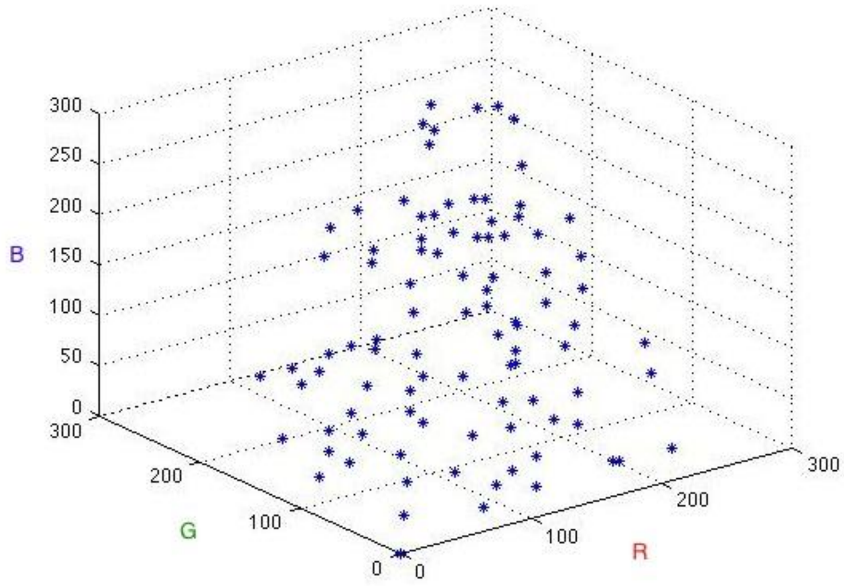


Figure 20. Image elements we use in RGB space

(2) The initial quantity setting of image elements in an image model.

According to the commission of Zhenshan Agricultural Leisure Area, we learned the average number of tourists visiting this area every month is approximately 1,500; and the number of SME residents is 25. In this sense, considering the frequencies of relevant affective words would appear in feedbacks, reviews, and transactions from customers, we set the initial quantities of image elements in each stakeholder's image model are listed in Table 5.

Table 5. Initial Quantity Setting of Image Elements in an Image Model

Stakeholder Role	**Initial Quantity Setting of Image Elements**
Service Provider / SME	• 3 kinds of main image elements, each one‘s quantity[4] is 300-350 numbers. We use a program to find a given random color’s 3 closet image elements on our revised Color Image Scale as this model’s main image elements, and set their quantity values to random numbers ranged in 300 to 350. • 10 kinds of others, each one’s quantity: 50-150 numbers 10 image elements are randomly chosen from our revised Color Image Scale, and their quantity values are set to random numbers ranged from 50 to 150. With this setting, the intensities of each element will fall in the range of 0.02-0.2[5].
Destination	Image elements whose intensities above 0.15 are selected from its SME residents’ image models as ingredients, but their quantity value are reset to 100. In our case, the intensities of each element of a high diversity destination’s image model will fall in the range of 0.07-0.14, while a low diversity’s will fall in

[4] The quantity could be viewed as a count of occurrence of a particular emotional word shows in a collection of resources including public reviews for the stakeholder and the stakeholder’s self-defined features.

[5] Each image element’s intensity value comes from its quantity value divided by the sum of quantities of every element within an image model.

	0.09-0.36.
Tourist	• 3 kinds of main image elements, each one's quantity:30-50 numbers We use a program to find a given random color's 3 closet image elements on our revised Color Image Scale as this model's main image elements, and set their quantity values to random numbers ranged in 30 to 50. • 7 kinds of others, each one's quantity:1-30 numbers 7 image elements are randomly chosen from our revised Color Image Scale, and their quantity values are set to random numbers ranged from 1 to 30. With this setting, the intensities of each element will fall in the range of 0.004-0.28.

(3) Typical tourist image models

Referring to Cohen's tourist role description (Lepp and Gibson, 2003), we define three typical tourist image models for our new registered tourist users as seen in Table 6. Based on these typical image models, tourists will further customize their own image models via preference setting and transactions on our platform.

Table 6. Typical Tourist Image Models

Typical Tourist Role	Image Elements in Image Model
Explorer	• Image Elements: "amusing, bold, casual,

	cheerful, dazzling, enjoyable, free, lighthearted, mysterious, open, refreshing, simple, tasteful, youthful” • Quantity of These Image Elements: 10-20
Drifter	• Image Elements: “bold, casual, childlike, dreamy, festive, free, lighthearted, mysterious, open, romantic, simple” • Quantity of These Image Elements: 10-20
Independent Mass	• Image Elements: “casual, enjoyable, friendly, generous, interesting, lighthearted, modest, simple, tasteful” • Quantity of These Image Elements: 10-20

- Mixing Module

In the following experiments, the image mixing method we use is the level 2, the most comprehensive one (see section 4.4). To recall, the five mixing steps can be summarized as below:

Step 1. Categorize image elements in an image model.

Step 2. Find 5 centers of gravity for each image model corresponding to image elements' categories.

Step 3. Find one center of gravity among center points got in step 2 in every category.

Step 4. Find the image elements having shortest distances in color space with the five centers of gravity got from step 3.

Step 5. Add the elements gained from last step into the image model which is going to be influenced (impact receiver).

Now we are going to demonstrate and explain the design parameters existing in the above steps.

(1) The usage of the Color Image Scale

We leverage the Color Image Scale to decrease the difficulty of translation between text and colors that carry the same emotion. However, the quantity of colors on the scale is limited. That is, the distortion is inevitable. Here we set up an experiment with simplified image mixing method to evaluate the distortion.

Experiment A – The Effectiveness of Revised Color Image Scale

Experimental Data

From our 122 image elements, we randomly chose 4 to comprise an image model A, and another 4 for an image model X. In the end, after repeating this steps 10 times, we had 10 sets of image model pairs like A and X. If not specified defined, the influence weights for each pair of image models are equal (0.5 and 0.5).

Experiment Design

We designed a simplified image mixing program here, with two image models as arguments. Every time when an interaction happens between the two models, for example X and A, X will give an influence to A, and vice versa. The influence direction indicates the model which is the impact receiver. In other words, the results of image mixing will be put back into this impact receiver's model. In the scenario illustrated in Figure 21, A is the impact receiver. The image mixing result here is the center of gravity among all of the image elements with A and X. Therefore, A’s center of gravity will continually move towards X’s center of gravity as long as the interactions don’t stop. Figure 21 shows two kinds of changing processes of A’s center of gravity after 90 times interactions with the model X. They are one case of the experiments represented in visualized way.

In this experiment, the control group and the experiment group use different setting of the simplified image mixing method—the newly mixed centers of gravity of all models’ image attributes are directly added into model A for the former, while for the latter, they are not directly added into A. Instead, we find image elements having shortest color distances in the RGB space to these center color points according to our revised Color Image Scale, and add these elements’ colors into model A.

The index we use for evaluating the effectiveness of image mixing is the shortened distance percentage between two image model A’s and B’s centers of gravity after interactions as described below:

$$\text{Shortened Distance Percentage} = \frac{d - d'}{d} \times 100\%$$

The d here is the **beginning** distance between image model A’s center of gravity and image model B's center of gravity in RGB color space; d' is the **current** distance between image model A’s and B’s centers of gravity in RGB color space. The higher the percentage, the better the performance of the image mixing method. In other words, the whole image of model A’s stakeholder and model B’ stakeholder are getting more similar.

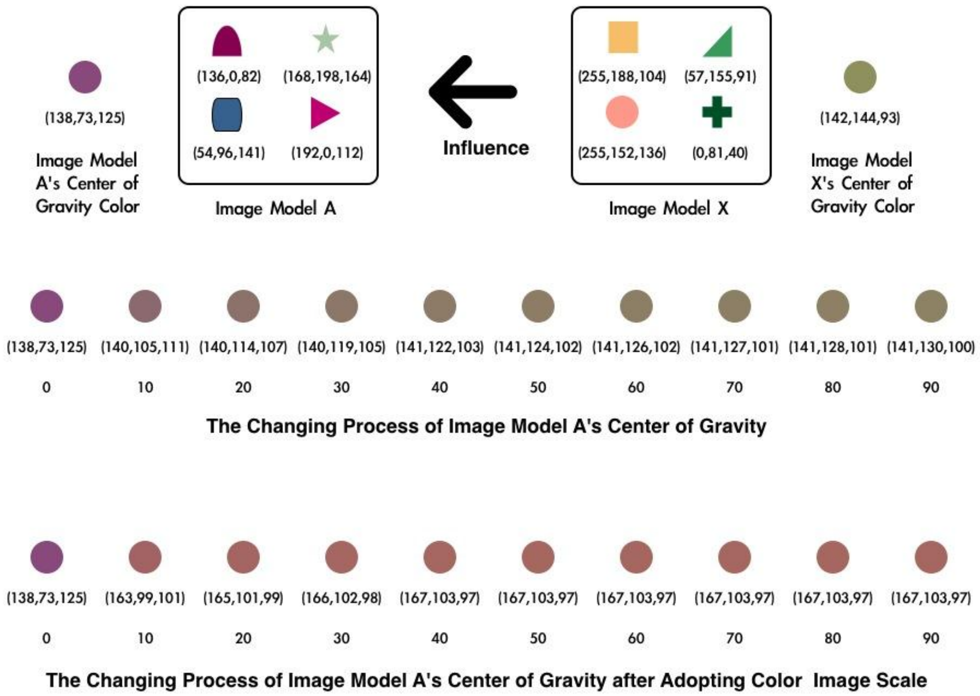


Figure 21. Basic Concept of Image Mixing

Experiment Result

Figure 22 provides the comparison between the two settings of image mixing method. The average lowered difference of shortened distance is 20% (see in Table 7) after adopting the Color Image Scale in our method. Considering the tradeoff between the benefits of the Color Image Scale and the distortion of image mixing results, we arbitrated the distortion is tolerable, and it is promising to explorer further extended applications with Color Image Scale, since there is only one case’s shortened distance under 50%.

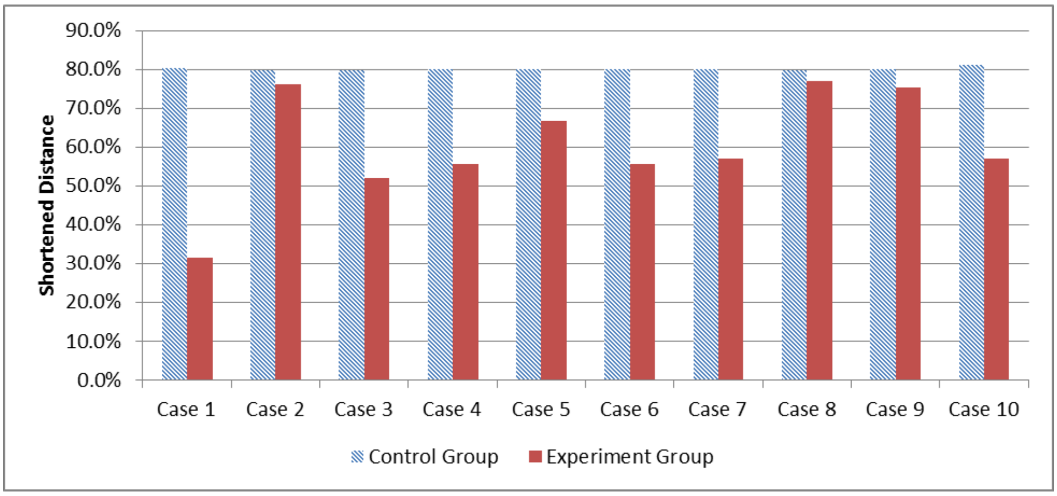


Figure 22. Shortened distance between image models' centers of gravity after several times of interactions

Table 7. Shortened distance average of two settings of the image mixing method

	Control Group Average	**Experiment Group Average**
Shortened Distance	80.0%	63.6%

(2) The classification of image elements in an image model

As mentioned in section 4.4, the introduction of image mixing method level two (most comprehensive), we categorize image elements into five groups in an image model at the first step. The purpose is to increase the number of mixing results, the new generated image elements, from 1 to 5 at least after one run of interaction process. If image attributes in an image model are not classified, the outcome of the image mixing method will be only one image element. Because the method is based on color mixture mechanism aiming at finding the center of mass/gravity, one and the only one color.

The increased quantity of generated image elements heightens the effect of the image mixing method on image models (the degree of change of the model structure) when their stakeholders have interactions with each other. So we refer to the adjective category Kobayashi used for factor analysis in his research (Kobayashi, 1981), and classify our 122 image elements by image word, as well as assign an adjective factor to each category as these elements' additional property (shown in Appendix A). The size of each adjective category is shown in Table 8.

Table 8. Adjective Category of Image Elements

Adjective Factor	**No. of Related Image Elements**
evaluative	77
emotional	15
scale	13
sensitive	12
dynamic	5

(3) The rule of removing unwanted results of image mixing

After classifying all the image elements into five groups, we will gain at least five additional image elements each time when the mixing program executed. However, the sum of image elements' intensity values in the same adjective category is almost certain to be less than 1. This will cause mixed image colors too close to the black color, because intensity value stands for the weight/amount of each participant in the mixing process (see the additive color mixture in section 4.4).

Hence, a filter/rule was added—Dirty image elements result from the mixing process will be removed, which defined as images having color distance from "black" is closer than 70 (see Table 9). We set another experiment to test the effectiveness of the filter. The effectiveness can be exhibited in Figure 23.

Table 9. Dirty Image Elements which Frequently Appear but Are Unwanted

Image Element (represented by word)	**Color Distance from the Black Color**
“bold”	0
”Intense”	0
”heavy and deep”	38.35
”strong and robust”	68.25
The maximum distance	*441.67 (white color)*

Experiment B – The Effectiveness of Dirty Image Filter

Experimental Data

We used a program to randomly produce 60 image models whose stakeholder role properties were set to SME, and image element structure settings were referred to Table 5. If not specified defined, the influence weights for each pair of image models are equal (0.5 and 0.5).

Experiment Design

Two image models from experimental data pool were randomly chosen to proceed the interaction process. We only observed one direction of the interaction though it is bidirectional. Therefore, one of the image models' center of gravity position was tracked while the other was fixed. The control experiment element here was whether the image filter was adopted in the mixing program. In the end, the mentioned process was repeated by 30 times.

Experiment Result

The dramatic effectiveness after the image filter adopted is shown in Figure 23. If the unwanted image mixing results are removed, the possibility of unexpected moves of image model's center of gravity are extremely reduced.

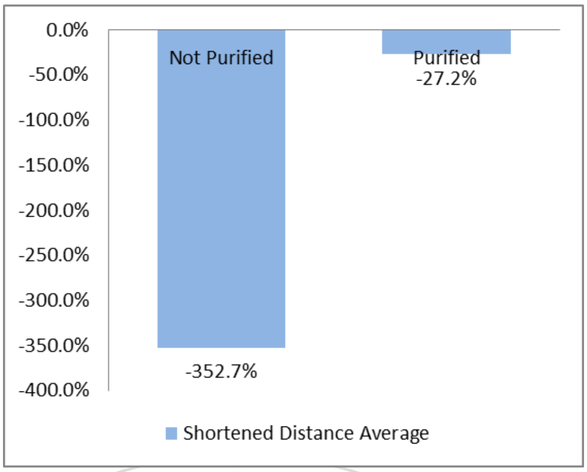


Figure 23. The comparison of image mixing performance after 'dirty image filter' adopted

(4) Intensity threshold of an image element

In order to increase the performance of the image mixing mechanism, a threshold for the image attribute selection to decide their attendances in the mixture process is suggested. However, what the portion is significant enough of an image element comparing with others in a model? To answer this question, we carried out an investigation to synchronize the sense of image attribute and the sense of number.

We used two popular travel attractions located in Taiwan, Kenting and Troko, as the investigation targets. By reviewing travel news, official sites, and blogs on the Internet, we manually selected and counted several affective adjectives for each case which we considered relevant enough to be these attractions' image attributes based on life experiences. To reduce the influence of personal perspective factor, we use these adjectives together with the name of destination as keywords to search on the Google engine, and recorded down the numbers of search results as relevance scores (Table 10 and Table 11). Finally, we ranked and marked the adjectives which we believed significant enough comparing with others (words with bold font style in the tables). 5% is the intensity threshold we decide to use in the system for image mixing.

Table 10. The Image Attributes of Kenting's Image

The Image of Kenting							
Image Attribute	English	Hand Calculation	Image Insensity	Image Attribute	English	No. of Google Search Results	Image Insensity
熱情	**Hot**	9	16.1%	**開心**	**Happy**	1150000	16.8%
悠閒	**Casual**	7	12.5%	**美麗**	**Beatiful**	1050000	15.4%
美麗	**Beatiful**	6	10.7%	**專業**	**Professional**	574000	8.4%
開心	**Happy**	5	8.9%	**陽光**	**Sunny**	504000	7.4%
豐富	**Substantial**	5	8.9%	**浪漫**	**Romantic**	485000	7.1%
陽光	**Sunny**	4	7.1%	**豐富**	**Substantial**	424000	6.2%
清涼	Cool	3	5.4%	**明亮**	**Bright**	400000	5.9%
有趣	Interesting	2	3.6%	**有趣**	**Interesting**	347000	5.1%
浪漫	Romantic	2	3.6%	**熱情**	**Hot**	345000	5.1%
舒暢	Relaxed	2	3.6%	耀眼	Sparkal	338000	5.0%
風趣	Humor	2	3.6%	悠閒	Casual	247000	3.6%
專業	Professional	2	3.6%	晶瑩	Crystaline	220000	3.2%
夢幻	Dreamy	1	1.8%	夢幻	Dreamy	206000	3.0%
如詩如畫	Picturesque	1	1.8%	舒暢	Relaxed	189000	2.8%
耀眼	Sparkal	1	1.8%	風趣	Humor	115000	1.7%
清靜優雅	Elegant	1	1.8%	壯觀	Sparkal	99700	1.5%
明亮	Bright	1	1.8%	清涼	Cool	77300	1.1%
晶瑩	Crystaline	1	1.8%	如詩如畫	Picturesque	49400	0.7%
壯觀	Majestic	1	1.8%	清靜優雅	Elegant	6820	0.1%
		56				6827220	

Table 11. The Image Attributes of Taroko's Image

The Image of Taroko (太魯閣)							
Image Attribute	English	Hand Calculation	Image Insensity	Image Attribute	English	No. of Google Search Results	Image Insensity
峻秀、壯麗	Majestic	6	16.7%	文化、歷史深度	Cultural	3,960,000	33.1%
美麗	Beautiful	4	11.1%	自然	Natrual	2,990,000	25.0%
文化、歷史深度	Cultural	4	11.1%	美麗	Beautiful	2,480,000	20.8%
自然	Natrual	3	8.3%	峻秀、壯麗	Majestic	690,000	5.8%
神秘	Mysterious	3	8.3%	神秘	Mysterious	639,000	5.3%
蓊鬱	Lush	2	5.6%	靜靜的	Serene	324,400	2.7%
靜靜的	Serene	2	5.6%	清澈	Clear	222,000	1.9%
崇敬、肅靜	Sublime	2	5.6%	溫柔	Tender	211,000	1.8%
莊嚴	Serious	2	5.6%	莊嚴	Serious	153,000	1.3%
年輕奔放	Untrammelled	2	5.6%	美妙	Wonderful	142,000	1.2%
清澈	Clear	1	2.8%	深沉	Deep	43,000	0.4%
清亮	Clear and Bright	1	2.8%	沁涼	Fresh and Cool	23,900	0.2%
沁涼	Fresh and Cool	1	2.8%	崇敬、肅靜	Sublime	19,750	0.2%
美妙	Wonderful	1	2.8%	年輕奔放	Untrammelled	19,400	0.2%
深沉	Deep	1	2.8%	蓊鬱	Lush	16,700	0.1%
溫柔	Tender	1	2.8%	清亮	Clear and Bright	13,400	0.1%
		36				11,947,550	

(5) The squash function and its arguments

In the mixing process step 2 (see section 4.4, image mixing method level 2), we have mentioned that the sum of image elements' intensity values in the same adjective category is almost certain to be less than 1. This implicates that these image elements will lose their original semantic meanings during the mixing process. Hence, we designed a simple formula as a squash function to adjust their intensity values:

New intensity = original intensity * x, where x is a parameter we had to find through simulations.

Experiment C – Find the Parameter for Squash Function

Experimental Data

We used a program to randomly produce 60 image models whose stakeholder role properties were set to SME, and image element structure settings were referred to Table 5. Previously mentioned, there is a program will find three most close image elements from the given color argument for a model as its main images. Here, the 60 models were divided into 6 groups. For their main images (the number of main colors each model has is 3), the arguments we gave were {255,0,0}, {255,255,0}, {0,255,0}, {0,255,255}, {0,0,255}, and {255,0,255}, which are color red, yellow, green, aqua, blue, and fuchsia (pink)'s RGB code. If not specified defined, the influence weights for each pair of image models are equal (0.5 and 0.5).

Experiment Design

For Figure 24: Two image models out of 60 were randomly chosen to perform the image mixing process for 3000 times with different squash function parameters, 1.5, 2.0, 2.5, 3.0. The a in the tags t:a, f (m, b) listed in Figure 24 and Figure 25 means the intensity values of image elements are set to a, while b stands for the parameters for squash functions.

For Figure 25: Basically same with above, but the chosen two image models' main colors were given by color pairs on a color ring between which have an angle of 60, 120, and 180 degrees.

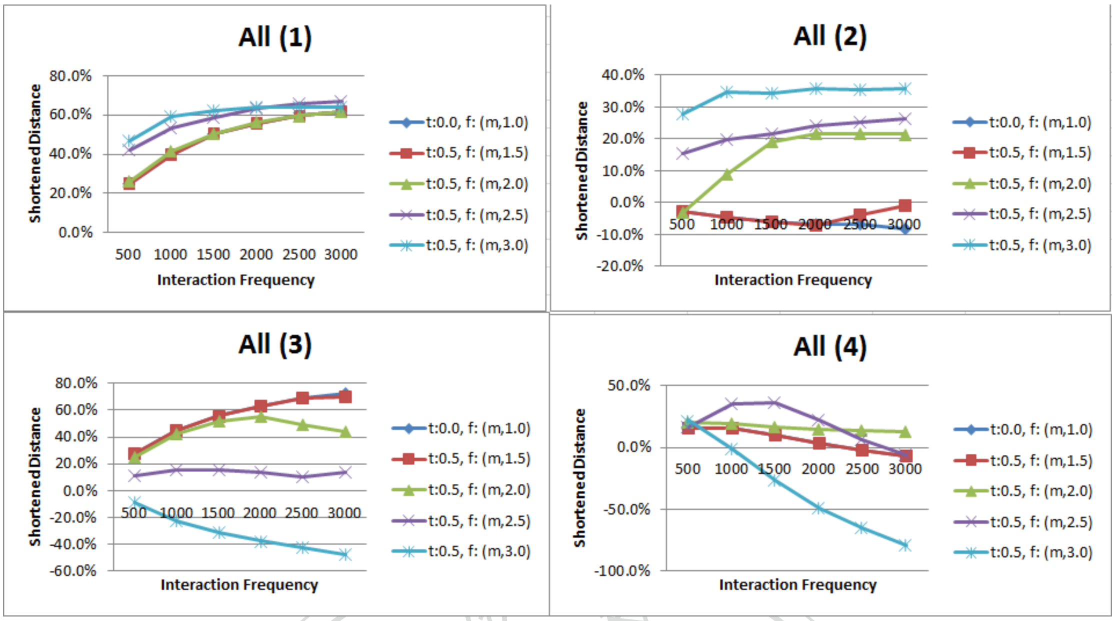


Figure 24. Image mixing with different settings

Experiment Result

The simulation results were quite different each time we executed. Figure 24 shows four kinds of typical results of image mixing. All(1) exhibits the desirable performance of the image mixing, When the sum of the intensities of image elements after the five-adjectives-classification is far less than 1, the effect of the squash function will then not be too over or too less. If the effect is too over, the curve of shortened distance will start to decline. That is the reason we have these various simulation results shown in Figure 24.

Seeing the unexpected results, we tried to figure out the reason, and found the performances of the mechanism would be various when participant models' main images had certain relationships (Figure 25). When there were an about 120 degrees of angle between the models' main image colors, the performance would be best (the shortened distance percentage could reach to 70%) compared with another two angles, 60 and 180 degrees. The discrepancy could be attributed to the revised Color Image Scale. Although there are already 122 relations between color and emotion defined, by contrast, this number is far lesser than the number of colors in RGB space, which is 255^3. In a short conclusion, it is probable that an image model having a too long or a too short distance from another will not have a high performance of image mixing.

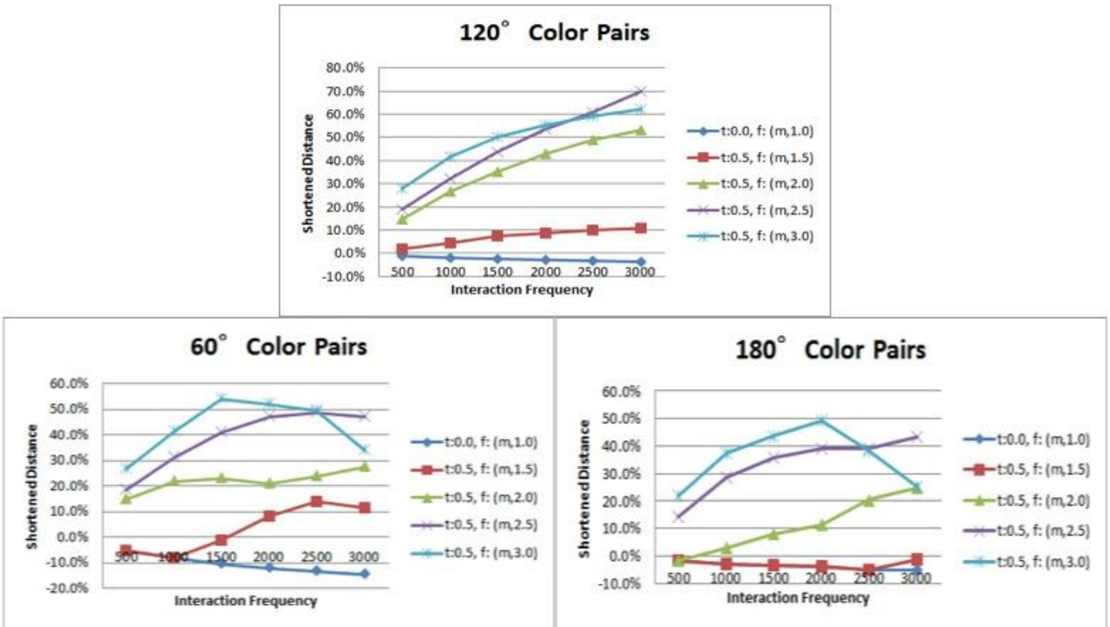


Figure 25. Image mixing of image models whose main images come from different angles of color pairs

To decide the parameter for the squash function, we reviewed each curve in Figure 24 and Figure 25, and determined 2.5 was the parameter. Unlike other parameters, its curve was most stable and had the highest capability to keep the original meanings for image elements during mixing process. Figure 26 displays the average life cycle of 10 random SME owners' image models. Because the most quantity of image elements in a SME image model is 350 (see Table 5), the high peaks usually appear after 1000-2000 times of interaction. At these moments the intensity values in the model would just have significant degree of change.

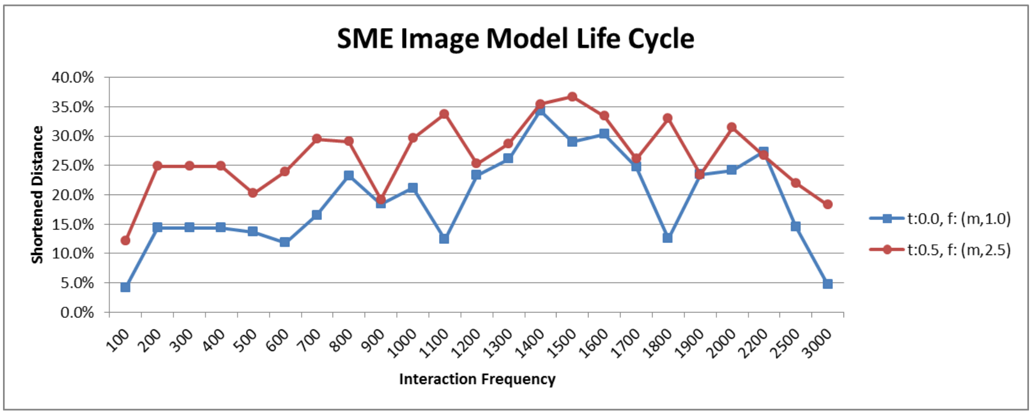


Figure 26. Life cycle of a service provider's image model

With the current setting, two scenarios of image mixing process had been visualized as demonstrated in Figure 27, which has a low performance, and Figure 28, which has a high performance. Take Figure 27 for an example, there are two image models A and B. The emotion presented for the center of gravity of A is "noble and elegant" (tagged as start°), while the emotion presented for the center of gravity of B is "simple, quite, and elegant" (tagged as end°). During the mixing process, the mixed results "simple, quite, and elegant" are continually added into A, so after 1200 times of interaction, the emotion of A's center becomes "cultivated". Further, after 2100 times of interaction, the mixed results turn into "sweet and dreamy". In the end, after 3000 times, the emotion of A's center of gravity is "refined and subtle". However, the color of this "refined and subtle" is far from B's center "simple, quite, and elegant". Hence, in this scenario, the overall shortened distance percentage is merely 30%.

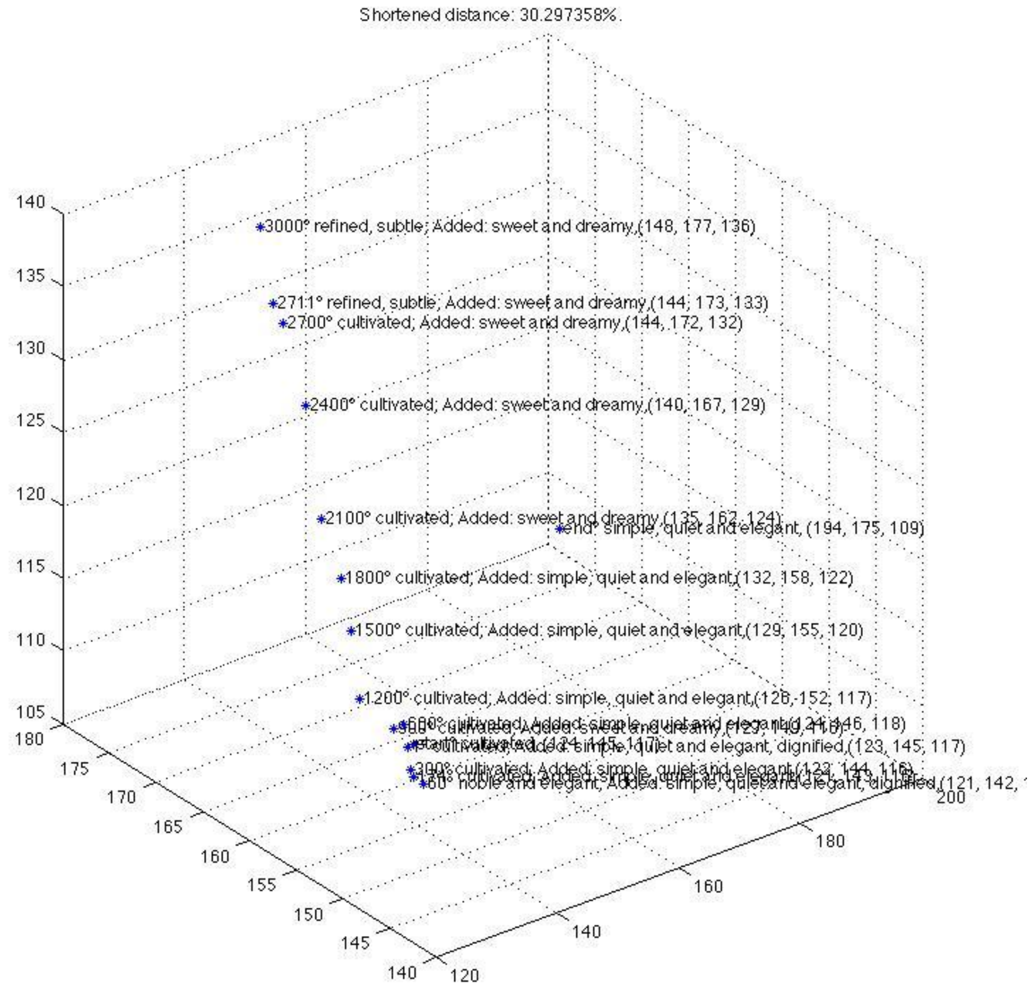


Figure 27. Visualization of image mixing process (30% shortened distance)
Note: The symbol '°' next to the points and the numbers stands for interaction frequency

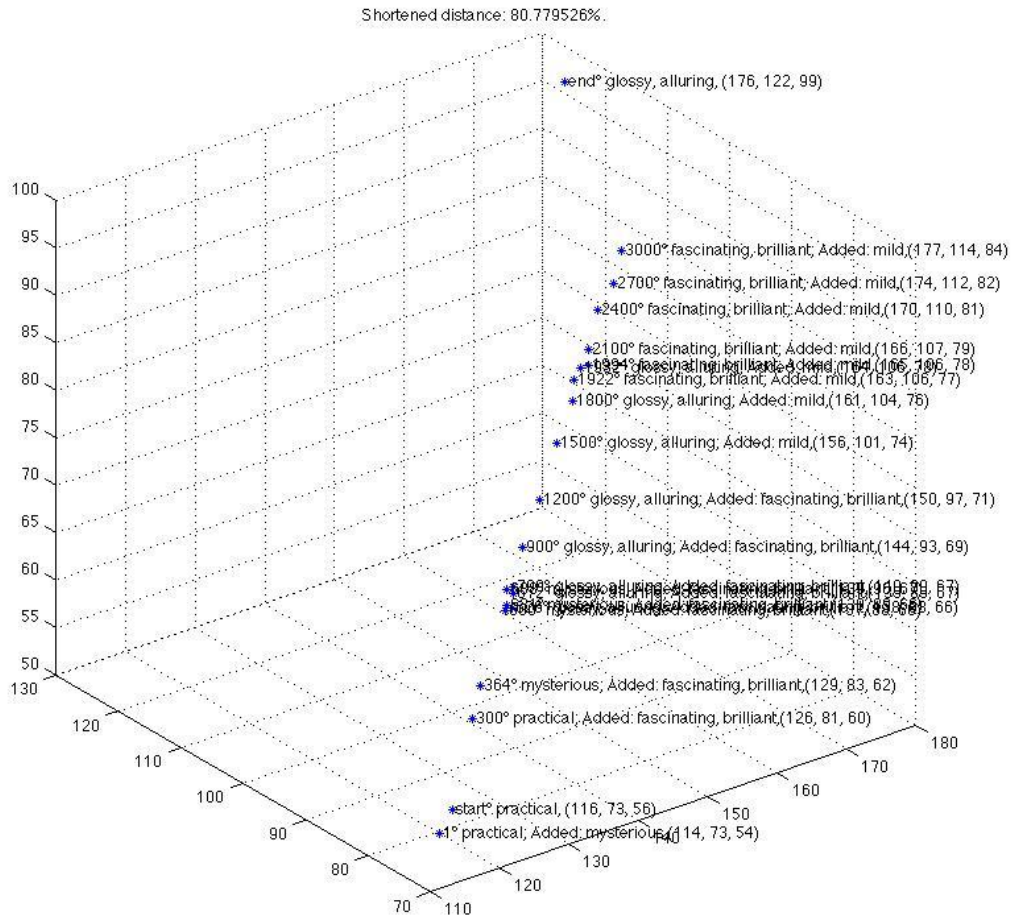


Figure 28. Visualization of image mixing process (81% shortened distance)
Note: The symbol '°' stands for interaction frequency

(6) The weight values for modeling influence power in the interaction process between each pair of stakeholder roles

We also conducted a simulation for evaluating the previously self-defined weight values (see Figure 12).

Experiment D – Validation of Influence Weights

Experimental Data

Every image model was randomly generated by a program using the structure setting as same as Table 5. We created 2 image models for a destination of high service diversity and another destination of low service diversity. The service diversity here means the variation of service providers resided in a destination.

In the context of the high diversity destination, the total number of image models for service providers we set was 30, and each 5 among them were treated as a group carrying similar main image colors (the number of main colors each model has is 3). As same as data in Experiment C, these similar main image colors were inferred from red, yellow, green, aqua, blue, and fuchsia by a program. On the contrary, the main colors of image models for the low diversity destination's SME residents were inferred from only two colors: red and yellow. So there was another 30 image models for service providers in the low diversity destination, and two groups were within, sized in 15 by each.

For tourist customers, in total we set up 300 numbers of image models, each 50 were a group having similar main image colors. Same, each group's color were inferred from red, yellow, green, aqua, blue, and fuchsia. The reason of why we gave the number 50 in each group of tourists is that, the monthly number of tourists visiting Zhenshan travel area is about 1500, and the number of SEMs there is 25-30. Thus, we simply say that every SME will have 50 customers in a month in average.

Experiment Design

Since there are two directions of interaction between two stakeholder roles, and the destination can be identified with two dimensions—high and low diversities, we tested 10 sets of simulations for validating defined influence weights. Figure 29 provides these 10 simulation results for different interaction relations, including C2B, B2C, D2B, B2D, D2C, and C2D. In each simulation, we used the previously designed weight value and two to four additional numbers near the original value to review the mixing performances.

Experiment Result

As depicted in section 4.4, we have defined a version of influence weight values. According to Figure 12, the weight for C2B interaction is 0.3, for B2C is 0.6, for D2B is 0.4, for B2D is 1.0, for C2D is 0.1, and for D2C is 0.8. Generally, the simulation results shown in Figure 29 exhibits there is no distinct difference between the effects after adopting different weights as arguments in the image mixing process, except for the C2B and B2D (high diversity) relations in the figure.

In the figure of C2B interaction simulation, we can see the higher the weight value, the lower the shortened distance is after 500 times of interactions. We argued the reason was the intensity values of participant image models are good enough (the image meaning of an image element is unlikely to change during the interaction), so there is not much room for the weight value (an intensity of an image element will be multiplied by the weight, which will possibly cause a data distortion). Even though the phenomenon we see here might be caused by the simulation data source, we still suggest changing our previous design of the weight value 0.3 into 0.2, which has the best performance in the experiment.

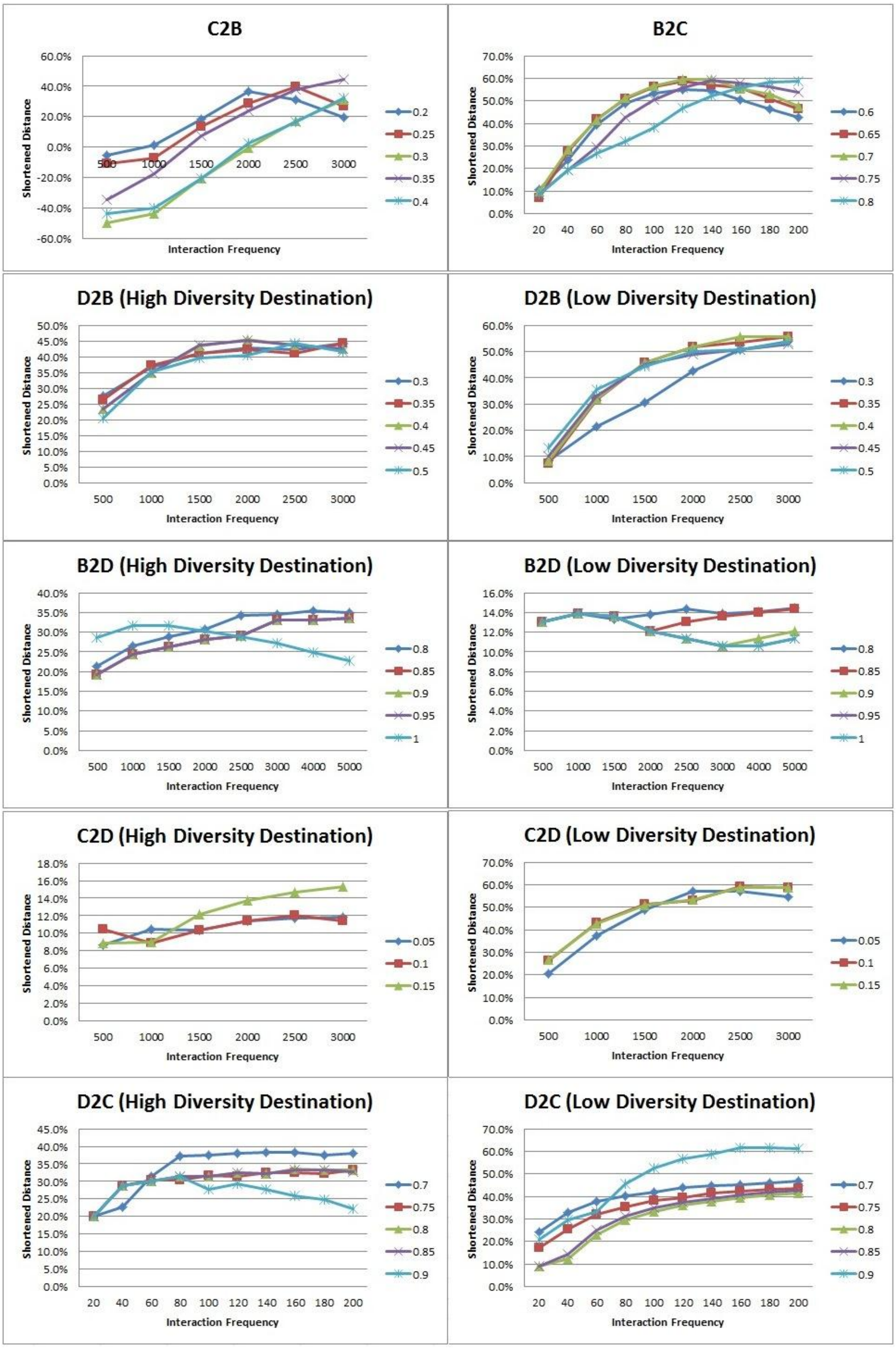


Figure 29. Validation of designed weights for interactions between different stakeholder roles

In the figure of B2D (high diversity destination), the weight value 1.0 seems to give too much influence during the interaction. Correspondingly, we changed the weigh value from 1.0 to 0.9.

In sum, the weight values we use for modeling the influence power for each kind of stakeholder role are: 0.2 for C2B, 0.6 for B2C, 0.4 for D2B, 0.9 for B2D, 0.8 for D2C, and 0.1 for C2D.

6.4 Experiments and Results

In this section, we conducted two experiments in a macro view for demonstrating the efficiency of the proposed mechanisms. One is for image matching, while the other is for image mixing.

Experiment E – Recommendation Performance Testing

Website: http://140.119.19.79:8080/uvexp/index.html

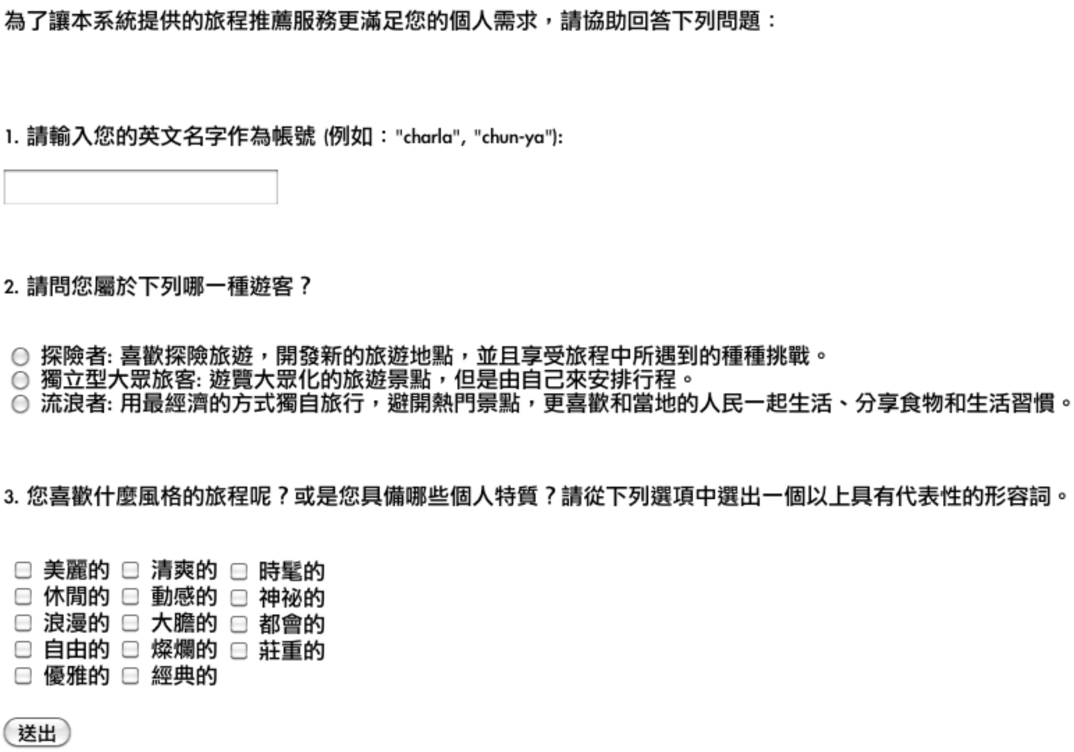
Experimental Data

We had 59 participants randomly gathered from facebook.com and school to log into our experimental travel service recommendation website. We had prepared 10 databases for every 6 users, which are all the same initially.

Before starting the travel service recommendation, these users were asked to answer a few of questions on the website (see Figure 30). In this way, we could learn what tourist types they think they are (see Table 12), and the genres of tour they prefer to initialize their image models for customization (see Table 13). These genre words were selected according to their representative for the 14 styles of groups classified in the original version of Color Image Scale.

The tourist type distribution is 14 people are explorers, 25 people are independent masses, and 20 people are drifters.

The service providers' image models we used for the recommendation pool were randomly generated via a program, and all of their image elements were randomly selected among the 122 numbers on the revised Color Image Scale. The total number of SME models was 500, and the total of the destination image models was 10. The image element quantity setting for each destination image models were the same as Table 5. Each one of them had 50 SMEs resided.


為了讓本系統提供的旅程推薦服務更滿足您的個人需求，請協助回答下列問題：

1. 請輸入您的英文名字作為帳號 (例如："charla", "chun-ya"):

2. 請問您屬於下列哪一種遊客？

- 探險者: 喜歡探險旅遊，開發新的旅遊地點，並且享受旅程中所遇到的種種挑戰。
- 獨立型大眾旅客: 遊覽大眾化的旅遊景點，但是由自己來安排行程。
- 流浪者: 用最經濟的方式獨自旅行，避開熱門景點，更喜歡和當地的人民一起生活、分享食物和生活習慣。

3. 您喜歡什麼風格的旅程呢？或是您具備哪些個人特質？請從下列選項中選出一個以上具有代表性的形容詞。

美麗的	清爽的	時髦的
休閒的	動感的	神祕的
浪漫的	大膽的	都會的
自由的	燦爛的	莊重的
優雅的	經典的	

送出

Figure 30. Questions for user registration

Table 12. Tourist Type Description (Foo 2004)

Tourist Type	Description
Explorer	Prefers adventure travel, exploring out of the way places and enjoys challenges involved in getting there.
Independent Mass	Visits regular tourist attractions but makes own travel arrangements and often "plays it by ear"
Drifter	Plans to travel wholly alone and in the most inexpensive way possible, avoids tourist attractions, and prefers to live with members of the host society, sharing food, shelter, and habits.

Table 13. Genre options for user registration

• Pretty • Casual • Romantic • Free • elegant	• clear • sporty • bold • gorgeous • classic	• chic • mysterious • urban • formal

Experiment Design

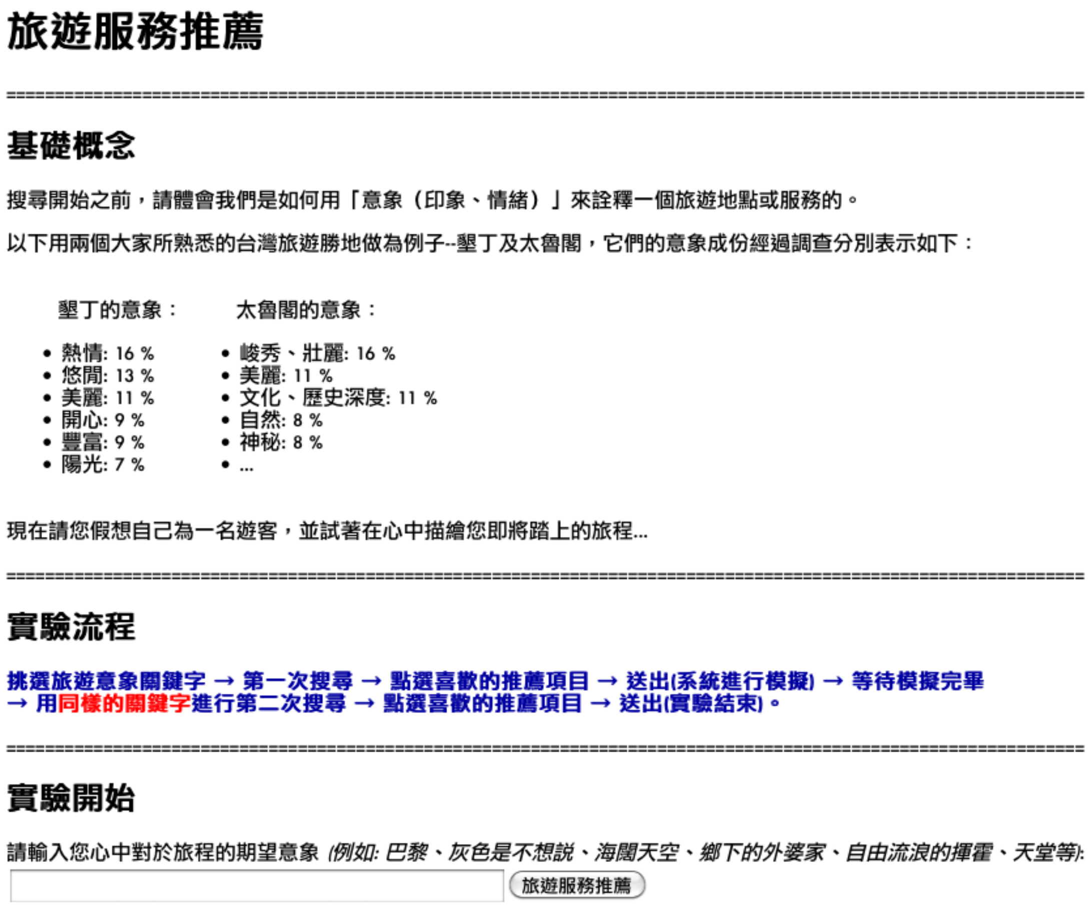
This experiment we performed for twice, 30 people for the first time, the rest for the second. The search keywords were restricted in the first experiment. This was designed for reduce the impact of a control factor on the experiment results—the efficiency of ImgComprehension module, another system module in our uVoyage platform, not involved in this research.

In the beginning, we simply explained our image definitions to the users (see Figure 31). Then they were asked to search for travel services having the capability to give emotions they desired if these services are visited or consumed.

The users also were told to input key words which could express their expected images of a trip or a destination, such as “a place like Paris” in Figure 32.

After picking up services they would like, the system would use these data as transactions to proceed interaction simulations for 30 and 14 times in the two experiments. One thing to be noted, since we used image mixing mechanism level 2, the most comprehensive method, the purpose of the interaction simulation is to increase the user satisfaction as those surprising images are added, not to increase the precision.

After the interaction simulation complete, we asked users to evaluate the recommendation list with the same standard as the first time (see Figure 33).


旅遊服務推薦

基礎概念

搜尋開始之前，請體會我們是如何用「意象（印象、情緒）」來詮釋一個旅遊地點或服務的。

以下用兩個大家所熟悉的台灣旅遊勝地做為例子--墾丁及太魯閣，它們的意象成份經過調查分別表示如下：

墾丁的意象：	太魯閣的意象：
• 熱情: 16 %	• 峻秀、壯麗: 16 %
• 悠閒: 13 %	• 美麗: 11 %
• 美麗: 11 %	• 文化、歷史深度: 11 %
• 開心: 9 %	• 自然: 8 %
• 豐富: 9 %	• 神秘: 8 %
• 陽光: 7 %	• ...

現在請您假想自己為一名遊客，並試著在心中描繪您即將踏上的旅程...

實驗流程

挑選旅遊意象關鍵字 → 第一次搜尋 → 點選喜歡的推薦項目 → 送出(系統進行模擬) → 等待模擬完畢 → 用同樣的關鍵字進行第二次搜尋 → 點選喜歡的推薦項目 → 送出(實驗結束)。

實驗開始

請輸入您心中對於旅程的期望意象 *(例如: 巴黎、灰色是不想說、海闊天空、鄉下的外婆家、自由流浪的揮霍、天堂等):*

旅遊服務推薦

Figure 31. The entry page of the experimental site

Figure 32. Recommendation page

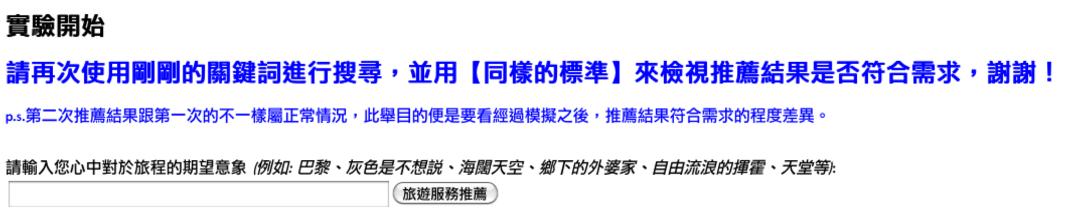


Figure 33. The second search page for a user

Experiment Result

- Hypothesis 1a: An image model is capable of representing a tourist's self-image composed of his/her personality, preferences, and instant emotional needs to a trip or a destination.
- Hypothesis 1b: An image model is capable of representing public

impressions of a destination or a service provider, as well as their characteristics.

- Hypothesis 2: Based on color harmony theory, the matching module can effectively help tourists find destinations or travel services that meet their emotional needs.

Table 14 and Table 15 show four average precision values. 60.26%, 70.65% are the precision before the interaction simulation, while 69.59%, 67.59% are after the simulation. The overall average of precision is 67.02%. Since we only listed 2/3 of the effective recommendation results to users (to keep users' patience), we claimed that this precision value could be adjusted higher.

According to the precision value, we validate our proposed mechanism for data evolvement and recommendation is efficiency. In sum, hypothesis 1a and 1b are accepted for the high enough precision and the good feedback from our testers. Hypothesis 2, consequently, is accepted for the same reasons.

Table 14. Statistics of precision value for the first experiment

			Before Image Mixing			After Image Mixing (30 Days Passed)		
No.	User	Query	NSlc	NRcmm	Precision	NSlc	NRcmm	Precision
1	susan	海闊天空	13	20	65.00%	13	20	65.00%
2	daniel	海闊天空	12	20	60.00%	15	20	75.00%
3	aarlk	心中的淨土	12	19	63.16%	12	19	63.16%
4	sharon	海闊天空	18	20	90.00%	19	20	95.00%
5	demon	金字塔	12	16	75.00%	10	16	62.50%
6	bu lee	海闊天空	15	20	75.00%	17	20	85.00%
7	mota	海闊天空	13	20	65.00%	11	20	55.00%
8	claude	海闊天空	11	20	55.00%	11	20	55.00%
9	chiao	海闊天空	14	20	70.00%	18	20	90.00%
10	lo33	巴黎	10	20	50.00%	11	20	55.00%
11	Gatsby	天堂	2	3	66.67%	14	20	70.00%
12	Ray	海闊天空	10	20	50.00%	12	20	60.00%
13	Yalin	海闊天空	17	20	85.00%	12	20	60.00%
14	DBRabit	明鏡止水	4	6	66.67%	4	6	66.67%
15	Sherry	心中的淨土	16	20	80.00%	20	20	100.00%
16	Andrew	心中的淨土	10	20	50.00%	17	20	85.00%
17	Rainyisunny	海闊天空	6	10	60.00%	14	20	70.00%
18	benbry	海闊天空	4	10	40.00%	15	20	75.00%
19	Mika	求婚的地方	8	12	66.67%	8	12	66.67%
20	Anderson	海闊天空	9	20	45.00%	18	20	90.00%
21	easonboy	海闊天空	13	20	65.00%	17	20	85.00%
22	Claire	自由流浪的	7	13	53.85%	7	13	53.85%
23	Roderick	海闊天空	13	20	65.00%	10	20	50.00%
24	fallsit	海闊天空	7	13	53.85%	6	16	37.50%
25	carol	海闊天空	7	20	35.00%	12	20	60.00%
26	marcie	海闊天空	8	20	40.00%	14	20	70.00%
27	mason	海闊天空	8	20	40.00%	12	20	60.00%
28	luzter	巴黎	10	20	50.00%	16	20	80.00%
29	Diana	天堂	7	19	36.84%	9	19	47.37%
30	rita	心中的淨土	18	20	90.00%	20	20	100.00%
				Precision:	60.26%		Precision:	69.59%

Table 15. Statistics of precision value for the second experiment (search keywords are open-answered)

			Before Image Mixing			After Image Mixing (14 Days Passed)		
No.	User	Query	NSlc	NRcmm	Precision	NSlc	NRcmm	Precision
1	brenda	自由流浪的揮霍	3	5	60.00%	11	18	61.11%
2	conmory	一望無際的天空	8	10	80.00%	9	9	100.00%
3	eve	悠閒的咖啡天堂	2	4	50.00%	2	4	50.00%
4	lily	巴黎	11	14	78.57%	6	14	42.86%
5	melissa	一望無際	9	13	69.23%	10	13	76.92%
6	Penguin	海闊天空	13	20	65.00%	13	20	65.00%
7	TUNG	巴黎	16	20	80.00%	n/a	n/a	n/a
8	Waynette	韓國 血拚天堂	2	5	40.00%	3	5	60.00%
9	a0921870111	超出常理的	15	19	78.95%	6	9	66.67%
10	audrey	浪漫的	5	14	35.71%	6	14	42.86%
11	happybicycle	海天一線	6	8	75.00%	7	8	87.50%
12	jimmyeric919	悠哉	4	6	66.67%	4	6	66.67%
13	LU	巴黎	14	20	70.00%	11	20	55.00%
14	steven	精神放鬆	4	4	100.00%	4	4	100.00%
15	young	天堂路	6	10	60.00%	6	10	60.00%
16	jack22661	日本	5	7	71.43%	4	10	40.00%
17	small fat	阿姆斯特丹	10	10	100.00%	n/a	n/a	n/a
18	ttyl	巴黎	6	12	50.00%	8	12	66.67%
19	yaya	自由流浪的揮霍	10	20	50.00%	9	20	45.00%
20	kelly pan	陽光	8	10	80.00%	10	10	100.00%
21	lucy	古典神秘 / 中古歐洲	3	3	100.00%	6	7	85.71%
22	tcy	天堂	9	20	45.00%	11	20	55.00%
23	VIOLA	海闊天空	8	20	40.00%	8	20	40.00%
24	youru	神秘國度	1	1	100.00%	3	4	75.00%
25	cerberus	慢慢的自由	4	5	80.00%	2	3	66.67%
26	judy	快樂天堂	2	3	66.67%	3	4	75.00%
27	julia	浪漫的氣氛	10	15	66.67%	10	14	71.43%
28	Rui	帥哥	4	4	100.00%	4	4	100.00%
29	tiffany	巴黎	18	20	90.00%	14	20	70.00%
				Precision:	70.65%		Precision:	67.59%

Experiment F – Interaction Simulation

Experimental Data

Similar to Experiment D, the experimental data we used for the macro interaction simulation were randomly produced by a program with given main colors. We created one high diversity destination, and one low diversity destination. There were both 15 SMEs resided in these two destinations in the beginning, but the former's residents could be divided into 3 groups according to their main image colors which were inferred from red, orange, and yellow colors, while the latter were only 1 group resided in, which inferred from red color. Although red, orange, and yellow seem to close, indeed, they are far enough from each other to comprise a high diversity destination as their saturation values are the highest in color space.

For tourists, 350 numbers of image models were created. They also could be grouped into 7 sets whose main images were inferred from colors—red, yellow, green, aqua, blue, and fuchsia.

Experiment Design

This experiment was designed for the examination of the hypothesis 3 as below:

- Hypothesis 3: The image mixing mechanism (the most comprehensive level, see section 4.4) can reveal the impacts of interactions among stakeholders and the impacts of occasional tourism-related events on their image models.
- Hypothesis 3a: In a destination of high service diversity, an occasional tourism-related event would have a smaller impact on the region. Also, it would take longer to reach the homogeneous status after a series of

interactions among stakeholders in this destination.

- Hypothesis 3b: In a destination of low service diversity, an occasional tourism-related event would have a bigger impact on the region. Also, it would take lesser time to reach the homogeneous status after a series of interactions among stakeholders in this destination.

We performed the evaluation of the impact sensitivity for a travel region via demonstrating a transformation process of a context of high service diversity destination comparing with another context of low diversity destination.

For the whole simulation process, there were 300 runs of a loop. In each run, every tourist, service provider, and destination in the context was an impact receiver in turn, which meant both directions of interaction between stakeholder roles would happen here. In order to see what an influence an occasional tourism-related event would give to a region, at the 61^{st} run and 121^{st} run of the simulation, we casted "sedate, precise" and "distinguished, stylish, dreamy" respectively into our adaption module, pretending there was an event having these images happening in the high diversity destination. In another context, we did the same actions at the same moments to the low diversity destination.

"Sedate, precise" and "distinguished, stylish, dreamy" just mentioned can be represented by color green, blue, aqua, fuchsia, and purple separately. At the 61^{st} run and 121^{st} run of the simulation, we believed SMEs having corresponding images would migrate into these two destinations, and started to have mutual influences to the region. In other words, these SMEs would make contributions to image building for destinations they resided. Mutually, local government policies and destination characteristics would sway the SMEs' operations strategies.

As mentioned in section 4.6, we assumed tourists would be attracted by those service providers owning similar major images. In this sense, we made tourists whose main colors of image models were similar to the just migrated SMEs' to visit the region and have transactions with these SMEs.

Experiment Result

To observe the impact sensitivity of the two destinations, we recorded down the shortened distance percentage between the center of gravity of all the SMEs and the center of their resided destination in each context. According to the experiment design, the impact to the region shall appear at the 70^{th} and 130^{th} runs of the simulation.

As seen in Figure 34, a steep fall shows at the 70^{th} run, and it seems nothing at the 130^{th} run, but followed by a steady rise until the end in the context of the low diversity destination. Why there is no sharp rise at the 130^{th} run of simulation? We argued that the reason was the migrated SMEs' images fell right into the moving path of the attendances' center of gravity. On the other hand, two relatively small declines appear at these moments in the context of the high diversity destination. We believe this fact responds to the biodiversity.

Service diversity in the program were calculated as the sum of all the distances between each SME image model's center of gravity and point O in the RGB color space, where O is the overall center among all the SME models' centers of gravity. Because the events happened in the two regions were the same, the two lines presented in Figure 35 錯誤！找不到參照來源。 between the 70^{th} and 120^{th} runs are very close. However, since there were interactions with tourists, the distance between these two lines are getting apart. There is a strong possibility that the speed to reach the bottom of this figure (low service diversity) of the context of the high diversity destination will be faster than the other.

In a short conclusion, based on the experiment findings, the hypothesis 3a and hypothesis 3b are accepted.

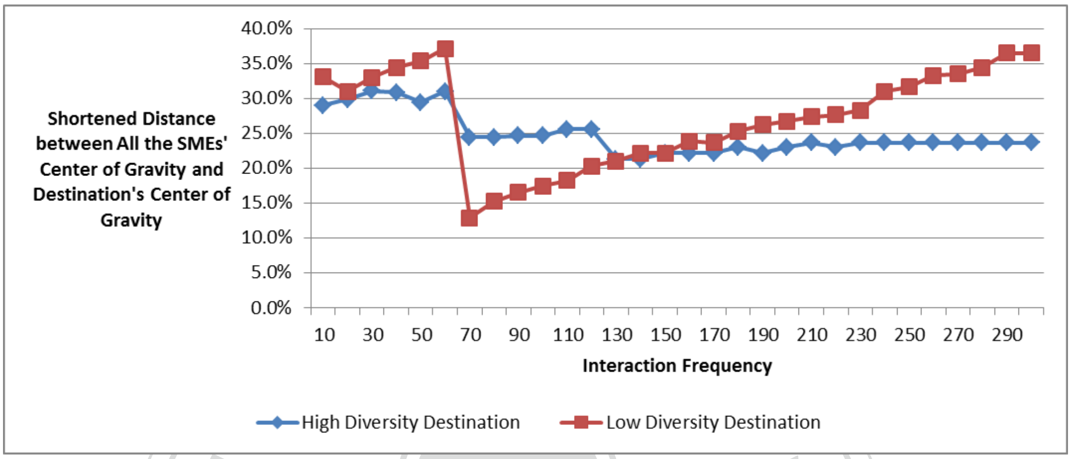


Figure 34. Transforming processes of two travel regions in different contexts

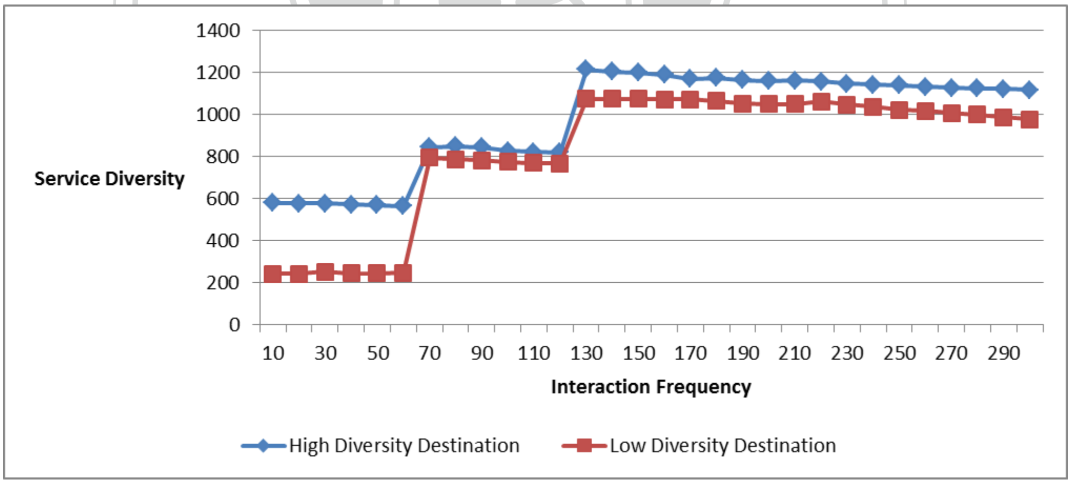


Figure 35. Changing of service diversities of two destinations in different contexts

CHAPTER 7 CONCLUSION

This research presents a recommendation service system to capture tourists' emotional needs (or intrinsic motives) 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' emotional needs, 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 tourist emotional needs 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.

7.1 Contributions

(1) The designed emotion-oriented recommendation system

Since tourism is an industry which is highly experience-related, it is beneficial for travel recommendation systems to take emotional elements of travel products and psychological emotional needs of tourists into account. In this research, the recommendation is performed based on image models, which are composed of affective feelings. We believe that bringing image into a full play would eliminate the population factor existing in traditional recommendation systems. Based on the experiment results in last chapter, we have successfully demonstrated a recommendation service system to help lesser-known travel destinations to be discovered by tourists who can be emotionally satisfied.

(2) Portability of Image

We have claimed that the design, method, and architecture of this system could be domain-independent and applicable to a wide range of services. After the precision evaluation of our recommender, the benefits of this application of image extended in the context of tourism have been confirmed. Besides, the image attributes described in Color Image Scale, that our system mechanism heavily relies on, are originally utilized in the fashion industry, and their wide-applicability was declared by Kobayashi (1992). Our faith of the portability of image has been firmly established.

(3) Emotion Computing

According to the research center, Nippon Color & Design Research Institute, where Color Image Scale was created, no one has been doing the mixture of images. They even stated that images could only be combined, but not mixed. However, after the validation of our image mixing mechanism, we quite believe that it is worthy to conduct further research on the image mixture. Not only the shortened distance between image models' centers of gravity, but also the transition of affective adjectives during the mixing process are convincing, promising, and surprising.

(4) Recommendation via the image matching based on color harmony theory

Since we have executed our experiment for an evaluation of our recommendation theory with 59 people, and the average precision value is close to 70%, the image matching mechanism we proposed is indicated as an effective and innovative design. With color harmony theory, in the future, we could further figure out other mapping rules for the recommendation.

7.2 Managerial Implications

(1) Direction of regional tourism development: high service diversity

In the Experiment F in previous chapter, it has been proved that the operation of travel regions is corresponding to the concept of biodiversity. A destination of low service diversity has a higher sensitivity to the impacts of occasional events, such as government policies. By leveraging the lesson-learned from the biodiversity, owners of destinations of lower diversity, and the service providers resided in, may have to struggle to construct a destination of high service diversity for tourism development.

(2) Image model: An evaluation tool for SME owners and destination owners

The design purpose of the image models is to reflect stakeholders' current whole image structure. Therefore, reviewing the amount and ingredients in an image model is a good way to learn whether the current popular impression is close to the one a SME owner or a destination owner intended to create for attracting customers.

7.3 Limitations and Future works

(1) The quality of image models could be further tested via deep interviews

In the Experiment E, only the image words were shown to the users, because there was a difficulty to recognize the intensity values of image elements for an untrained person. We have established an image model's capability of representativeness, but not its quality. Deep interviews with tourists, SEM owners, and destination managers are considered required for the future works.

(2) Uncovered emotions (those using three color combinations)

After the struggling of tuning the performance of image mixing, we concluded that the best way to improve the performance if to figure out as more as possible mappings between colors and emotions. After all, we greatly rely on these relations, a comprehensive revised Color Image Scale is necessary.

(3) Different settings for image element quantities in destinations of different degrees of development

As implicated from the results of Experiment C and D, the life cycle of an image model is more concerned with the quantity of its image elements. Thus, we need more practical data to learn what the best settings are for different kinds of destinations.

(4) New performance index: Factor

Now we only use the percentage of shortened distance between centers of gravity as the performance index. In the future, we could extend it to a factor, which contains the information of direction, angle, and also distance.

(5) The last one, the qualitative and quantitative field feedback will also be attained for continued improvement of our method and system.

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APPENDIX A – THE MAPPING RELATIONS BETWEEN IMAGE WORDS AND COLORS

No.	Image Attribute	Chinese	R	G	B	Munsell	Adjective Factor	Category
1	amusing	好玩的	184	28	16	R/S	evaluative	CASUAL
2	bright	多采多姿的	216	128	0	YR/S	sensitive	CASUAL
3	casual	休閒的	192	0	112	RP/V	dynamic	CASUAL
4	cheerful	開朗的	255	217	0	Y/V	emotional	CASUAL
5	dazzling	耀眼眩目的	208	0	32	R/V	evaluative	CASUAL
6	delicious	美妙的	186	69	131	RP/S	sensitive	CASUAL
7	enjoyable	享樂的	216	128	0	YR/S	emotional	CASUAL
8	friendly	友善的	239	143	184	RP/B	evaluative	CASUAL
9	chic	雅緻的	54	96	141	PB/S	evaluative	CHIC
10	modest	簡樸的	129	145	66	GY/Dl	evaluative	CHIC
11	noble and elegant	高貴典雅的	82	131	124	BG/Dl	evaluative	CHIC
12	quiet	清靜的	133	153	186	PB/L	scale	CHIC
13	simple, quiet and elegant	簡單、安靜和優雅的	171	157	109	Y/Gr	evaluative	CHIC
14	sober	穩重的	102	120	149	PB/Dl	scale	CHIC
15	stylish	新潮的	0	33	152	PB/V	evaluative	CHIC
16	classic	經典的	102	0	117	P/Dp	evaluative	CLASSIC
17	complex	複雜的	184	147	143	R/Gr	scale	CLASSIC
18	conservative	保守的	112	92	0	Y/Dk	evaluative	CLASSIC
19	elaborate	精緻的	104	0	31	R/Dk	evaluative	CLASSIC
20	heavy and deep	深沉的	64	0	24	R/Dgr	emotional	CLASSIC
21	old-fashioned	古式的	102	0	117	P/Dp	evaluative	CLASSIC
22	provincial	守舊的	166	102	126	RP/Dl	evaluative	CLASSIC
23	rustic	鄉村的	176	143	119	YR/Gr	evaluative	CLASSIC
24	tasteful	風雅的	184	147	143	R/Gr	evaluative	CLASSIC
25	traditional	傳統的	119	60	0	YR/Dk	evaluative	CLASSIC
26	clean and fresh	清新的	91	189	206	B/B	evaluative	CLEAR
27	clear	清爽的	217	253	255	B/Vp	sensitive	CLEAR
28	crystalline	晶瑩的	191	216	255	PB/P	sensitive	CLEAR
29	fresh and young	新鮮年輕的	157	247	173	G/P	evaluative	CLEAR
30	light	輕盈的	218	255	213	G/Vp	sensitive	CLEAR
31	neat	簡潔的	213	255	236	BG/Vp	sensitive	CLEAR
32	pure and simple	純粹的	166	196	188	BG/Lgr	evaluative	CLEAR
33	refreshing	別具一格的	170	188	191	B/Lgr	evaluative	CLEAR
34	simple	簡約的	91	189	206	B/B	scale	CLEAR
35	smart	聰明的	112	173	184	B/L	dynamic	COOL-CASUAL
36	sporty	動感的	52	139	118	BG/S	dynamic	COOL-CASUAL
37	steady	穩定的	179	186	200	PB/Lgr	evaluative	COOL-CASUAL
38	Western	西方的	112	173	184	B/L	evaluative	COOL-CASUAL
39	young	年輕的	179	186	200	PB/Lgr	evaluative	COOL-CASUAL
40	youthful	青春的	179	186	200	PB/Lgr	evaluative	COOL-CASUAL
41	aristocratic	貴族的	0	50	117	PB/Dp	evaluative	DANDY
42	dapper	整潔的	0	81	40	G/Dk	evaluative	DANDY
43	diligent	勤勉的	105	136	0	GY/Dp	evaluative	DANDY
44	eminent	非凡的	0	117	62	G/Dp	evaluative	DANDY
45	placid	平靜的	79	96	0	GY/Dk	scale	DANDY
46	practical	實際的	76	76	70	N3	evaluative	DANDY
47	quiet and sophisticated	低調精巧的	165	129	145	RP/Gr	evaluative	DANDY
48	serious	認真的	85	0	53	RP/Dgr	emotional	DANDY
49	sound	健全的	84	0	96	P/Dk	evaluative	DANDY
50	strong and robust	強勁的	43	53	0	GY/Dgr	evaluative	DANDY

51	subtle and mysterious	含蓄而神秘的	154	138	159	P/Gr	evaluative	DANDY
52	bold	大膽的	0	0	0	N1.5	emotional	DYNAMIC
53	intense	熱切的	0	0	0	N1.5	emotional	DYNAMIC
54	calm	平靜的	131	73	139	P/S	emotional	ELEGANT
55	delicate	細緻的	197	184	199	P/Lgr	sensitive	ELEGANT
56	elegant	優雅的	151	187	4	GY/S	evaluative	ELEGANT
57	emotional	情感的	176	220	0	GY/V	emotional	ELEGANT
58	feminine	女性化的	184	224	32	GY/B	evaluative	ELEGANT
59	festive	歡慶的	255	156	0	YR/V	evaluative	ELEGANT
60	graceful	優美的	219	149	173	RP/L	evaluative	ELEGANT
61	interesting	有趣的	131	73	139	P/S	evaluative	ELEGANT
62	mysterious	神祕的	149	132	64	Y/Dl	evaluative	ELEGANT
63	noble	崇高的	57	155	91	G/S	evaluative	ELEGANT
64	polished	高水準的	138	176	223	PB/B	evaluative	ELEGANT
65	refined	高雅的	135	205	149	G/L	evaluative	ELEGANT
66	sedate	寧靜的	57	155	91	G/S	emotional	ELEGANT
67	sleek	柔滑的	194	135	205	P/B	sensitive	ELEGANT
68	subtle	微妙的	135	205	149	G/L	evaluative	ELEGANT
69	tender	溫柔的	207	186	196	RP/Lgr	evaluative	ELEGANT
70	dignified	莊嚴的	0	51	68	B/Dgr	evaluative	FORMAL
71	formal	正式的	0	71	91	B/Dk	scale	FORMAL
72	majestic	雄偉的	0	38	102	PB/Dk	scale	FORMAL
73	precious	珍奇的	0	99	123	B/Dp	evaluative	FORMAL
74	proper	獨具的	0	99	123	B/Dp	evaluative	FORMAL
75	solemn	隆重的	0	72	69	BG/Dk	emotional	FORMAL
76	alluring	迷人的	168	104	96	R/Dl	evaluative	GORGEOUS
77	aromatic	芬芳的	168	84	0	YR/Dp	sensitive	GORGEOUS
78	brilliant	巧妙的	176	119	72	YR/Dl	evaluative	GORGEOUS
79	decorative	裝飾的	136	0	82	RP/Dp	scale	GORGEOUS
80	extravagant	豪華的	168	0	34	R/Dp	scale	GORGEOUS
81	fascinating	醉人的	176	119	72	YR/Dl	evaluative	GORGEOUS
82	glossy	光彩奪目的	168	104	96	R/Dl	sensitive	GORGEOUS
83	gorgeous	燦爛的	168	0	34	R/Dp	evaluative	GORGEOUS
84	luxurious	奢華的	136	0	82	RP/Dp	scale	GORGEOUS
85	mature	成熟的	168	0	34	R/Dp	evaluative	GORGEOUS
86	mellow	歡快的	160	136	0	Y/Dp	evaluative	GORGEOUS
87	substantial	豐富的	168	84	0	YR/Dp	scale	GORGEOUS
88	composed	沉著的	54	119	133	B/S	evaluative	MODERN
89	cultivated	文雅的	124	152	156	B/Gr	evaluative	MODERN
90	distinguished	尊貴的	0	140	113	BG/V	evaluative	MODERN
91	precise	精確的	0	108	136	B/V	evaluative	MODERN
92	urban	都會的	54	119	133	B/S	evaluative	MODERN
93	domestic	和睦的	209	171	0	Y/S	evaluative	NATURAL
94	free	自由的	206	181	159	YR/Lgr	dynamic	NATURAL
95	fresh	新鮮的	96	202	170	BG/B	sensitive	NATURAL
96	generous	大方的	255	216	40	Y/B	evaluative	NATURAL
97	gentle	溫柔的	255	188	104	YR/P	evaluative	NATURAL
98	gentle and elegant	溫柔優雅的	237	128	122	R/L	evaluative	NATURAL
99	intimate	溫馨的	255	216	40	Y/B	evaluative	NATURAL
100	lighthearted	無憂無慮的	239	143	184	RP/B	emotional	NATURAL

101	mild	溫和的	232	157	96	YR/L	evaluative	NATURAL
102	nostalgic	懷舊的	186	69	131	RP/S	emotional	NATURAL
103	open	開放的	209	171	0	Y/S	scale	NATURAL
104	peaceful	和平的	198	205	156	GY/Lgr	emotional	NATURAL
105	plain	樸素的	168	198	164	G/Lgr	evaluative	NATURAL
106	pleasant	宜人的	239	143	184	RP/B	evaluative	NATURAL
107	simple and appealing	簡單吸引人的	194	135	205	P/B	evaluative	NATURAL
108	sunny	陽光的	255	216	40	Y/B	sensitive	NATURAL
109	sweet-sour	初戀般的	208	180	176	R/Lgr	emotional	NATURAL
110	tranquil	安寧的	242	202	255	P/P	emotional	NATURAL
111	wholesome	健康的	205	191	156	Y/Lgr	scale	NATURAL
112	childlike	童趣的	255	88	80	R/B	dynamic	PRETTY
113	cute	可愛的	255	88	80	R/B	evaluative	PRETTY
114	pretty	美麗的	255	168	40	YR/B	evaluative	PRETTY
115	sweet	甜蜜的	255	152	136	R/P	evaluative	PRETTY
116	amiable	親切的	255	229	122	Y/P	evaluative	ROMANTIC
117	charming	有魅力的	255	188	104	YR/P	evaluative	ROMANTIC
118	dreamy	如夢似幻的	247	225	255	P/Vp	evaluative	ROMANTIC
119	innocent	純真的	255	255	237	RP/Vp	evaluative	ROMANTIC
120	romantic	浪漫的	255	213	159	YR/Vp	evaluative	ROMANTIC
121	soft	柔和的	255	212	200	R/Vp	evaluative	ROMANTIC
122	sweet and dreamy	甜蜜夢幻的	218	248	109	GY/P	evaluative	ROMANTIC