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Information Visualization published online 27 January 2013
DOI: 10.1177/1473871612472177

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Article

Information Visualization
0(0) 1–11

DOI: 10.1177/1473871612472177
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Automatic tourist attraction and representative icon determination for tourist map generation

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Abstract

Tourist maps are designed to direct tourists to tourist attractions in unfamiliar areas. A well-designed tourist map can provide tourists with sufficient and intuitive information about places of interest. Thus, providing up-to-date information on places of interest and selecting their representative icons are fundamental and important in automatic generation of tourist maps. In this article, approaches for determining places of interest and for determining their representative icons are introduced. In contrast to general digital tourist maps that use text, simple shapes, or three-dimensional models, we use photos that offer abundant visual features of places of interest as icons in tourist maps. The photos are automatically extracted from a repository of photos downloaded from photo-sharing communities. Tourist attractions and their corresponding image icons are determined by means of photo voting and photo quality assessment. Qualitative analyses, including a user study and experiments in several areas with numerous tourist attractions, indicated that the proposed method can generate visually pleasant and elaborate tourist maps. In addition, the analyses indicated that the map produced by our method is better than maps generated by related methods and is comparable to hand-designed tourist maps.

Keywords

Information visualization, digital tourist map, clustering

Introduction

Cartography is the process of compiling and formatting a collection of data into a virtual image. The primary function of this technology is to produce maps that contain accurate map elements such as detailed roads and general information on a specific area. Existing maps can be classified into two categories: *general map* and *thematic map*. General maps are constructed for general users, and thus, the maps contain a variety of map elements and information to indicate locations in a specific area. In contrast, thematic maps are designed to highlight a particular activity or theme in a specific area and tell a story about that place. The past decade has witnessed a substantial increase in the volume of geographic data. As a result, thematic maps have become increasingly useful for combining specific activities with maps. Recently, some promising systems for thematic map generation have been proposed.[1–3] By utilizing cartographic generalization techniques, these systems automatically generate route, tourist, and destination maps to ensure easy navigation in an unfamiliar area. They focus on emphasizing the most important roads and landmarks, and on de-emphasizing less important elements in a map. However, the visual features of places of interest are not fully presented in maps. This

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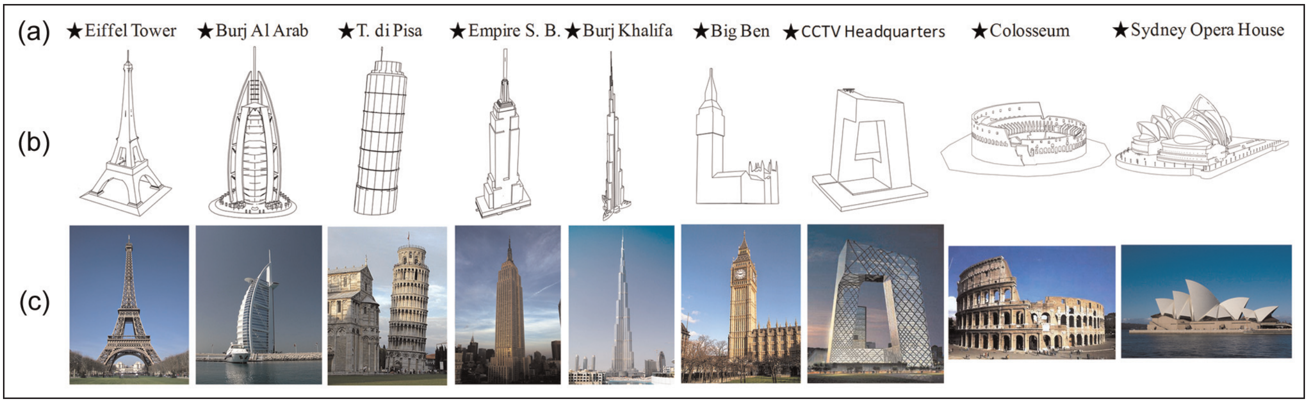

Figure 1. Comparison between various icons that represent landmarks in a map: (a) star shape with text label, (b) nonphotorealistic rendering of 3D models,[2] and (c) photos (used in the proposed method).
3D: three-dimensional.

study aims to generate a tourist map that presents not only the important map elements but also emphasizes the visual features of tourist attractions.

Unlike hand-designed static maps, digital maps that use continually updated data can provide up-to-date information. However, existing digital maps are not suitable to serve as tourist maps due to poor recognizability of tourist attractions and unsuitable map generalization (too much information are visualized in a map, resulting in tourists having difficulty in filtering the information they need).[2] In this article, we propose approaches to automatically determine places of interest and select their representative icons for digital tourist map generation. In contrast to general digital tourist maps that use text, simple shapes, or three-dimensional (3D) models[2] to represent places of interest, our approach uses photos that offer abundant visual features as image icons (see Figure 1). For each place of interest, a representative photo is extracted from a repository of photos downloaded from photo-sharing applications such as Panoramio[4] and Flickr.[5] The representative photo is selected through voting and photo quality assessment. These photo-sharing applications are constructed based on the concept of Web 2.0, enabling users to upload and share their geotagged photos. This makes the automatic determination of places of interest and image icon selection feasible. The basic idea behind the proposed method is to consider user-uploaded photos as votes for the places of interest and their representative shots. A location having many user-uploaded photos is considered a place of interest. Thus, a simple unsupervised clustering approach is used to select places of interest according to the locations where user-uploaded photos were taken. A representative photo is then extracted from the photos of each place of interest based on photo quality. The remainder of this article is organized as follows. Section "Related work" reviews the related studies. The system overview is described in Section "System overview." The proposed approaches are introduced in section "Methodology." The experimental results are shown in section "Experimental results and discussion," and the conclusions and recommendations for future studies are given in section "Conclusions and future work."

Related work

Many methods for map generation were proposed in the last decade. This study reviews only related studies on thematic map generation.[1–3,6–9] A detailed survey of previous studies on general and conception map generation can be found in Refs. 10 and 11. Avelar and Muller[6] proposed an approach for generating a topologically correct schematic route map. Based on the fact that routes in a map are usually drawn as straight lines, roads are straightened under the constraints of preserving topological structures. Agrawala et al.[1] proposed a cartographic generalization technique to improve the usability of route maps. This approach is based on cognitive psychology[12,13] and analysis of map generalization that are commonly found in hand-drawn route maps. Similarly, Kopf et al.[3] proposed a system for creating destination maps based on map design principles, cognitive psychology,[10] and cartographic generalization.[14,15] This system includes techniques for selecting important roads based on mental representations of road networks and for laying out the roads by using a nonlinear optimization procedure. The final layouts are labeled and rendered in a variety of styles ranging from informal to more formal. Hilton et al.[9] proposed a system for presenting accident frequencies and characteristics based on geographic location. This system uses heat maps as a visual representation of the spatial density of traffic fatalities.

In most research, map generation uses simple shapes, such as circle, triangle, and star, as well as text

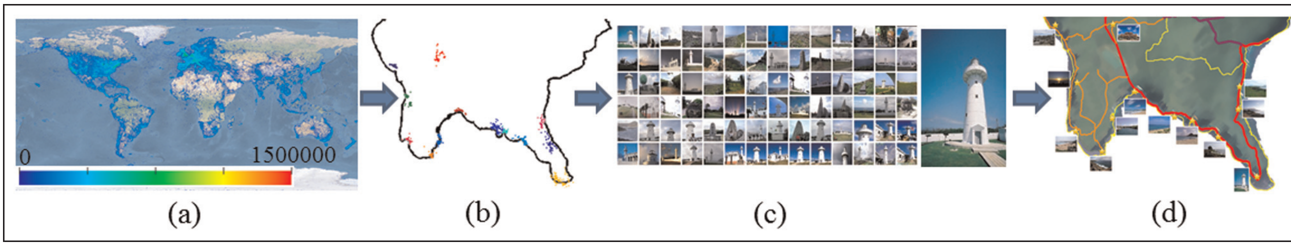

Figure 2. System workflow: (a) Locations of user-uploaded geotagged photos: the numbers of photos are displayed by colors ranging from blue to red (0.15 million photos), (b) place of interest determination: the determined places of interest are visualized by colors, (c) image icon selection, and (d) image icon placement.

labels,[16,17] to mark a particular place in a map. This representation is not intuitive for tourists who are unfamiliar to a place. Recently, Grabler et al.[2] presented an excellent map generation system that uses nonphotorealistic renderings of 3D models (see Figure 1) as icons to visually emphasize landmarks and places of interest while de-emphasizing or eliminating irrelevant elements. This system uses information on the Web to automatically extract important features such as landmarks, paths, and districts, and this system evaluates the importance of features according to three factors: semantic, visual, and structural.[18] The semantic features are computed by using web-based information extraction techniques, while visual and structural features are extracted based on the analysis of object geometries and textures. Therefore, a complex geometrical and textured 3D city model is required in this system. Simon et al.,[7] Chen et al.,[8] Kennedy and Naaman,[19] and Quack et al.[20] presented novel icon generation approaches to represent landmarks in a map. Inspired by the concept of photo tourism presented by Snavely et al.,[21] the authors utilized the obtained viewpoints of photos to synthesize an icon for a landmark from a set of geotagged photos. However, icon generation requires the nontrivial processes of image matching and warping. In addition, these approaches focus on extracting in-focus objects from a photoset, which makes generating an icon for a scenic place difficult. In our study, those nontrivial processes and the requirement of complex 3D city models are excluded. The places of interest are determined by using a simple voting strategy, and the image icon to represent each place of interest is chosen by selecting a high-quality photo from a set of user-shared photos of landmarks and scenic places.

System overview

Figure 2 schematically illustrates the workflow of the proposed system, which consists of three main steps: *tourist attraction determination*, *representative icon selection*, and *icon placement*. In the first step, geotagged photos are collected from photo-sharing communities. In general, tourists take photos of places and sights that interest them. Through photo voting, a location having many user-uploaded photos is selected as a place of interest. An unsupervised clustering approach is used to group the user-uploaded photos; the locations that are the subject of grouped photos are selected as places of interest. In the next step, a representative photo is selected from each photoset. Based on the fact that tourists take photos of landmarks or scenes that interest them, the grouped photos are further clustered into several subsets; each photo subset may contain a popular view of the location. The popular view is referred to the most commonly photographed angle or aspect of the location. The largest subset contains photos of the most popular view in that location. Therefore, a photo quality assessment approach is adopted to select a high-quality photo from this subset. The selected photo then represents the place of interest in the map. In the last step, the selected photos are viewed as icons and placed in the map by using point-feature label placement technique.[16]

Methodology

The approach of place of interest determination is described in section "Place of interest determination," followed by the approach of representative image icon selection, which is described in section "Representative icon selection."

Place of interest determination

With the rapid development of Internet technologies and smartphones (cell phones with cameras and global positioning system receivers), many photo-sharing applications are developed based on the Web 2.0. In photo-sharing communities, such as Panoramio and Flickr, users can upload and share their photos with geographical identification metadata, which contain latitude and longitude photo-acquisition coordinates. These communities have a huge number of user-uploaded photos; for instance, there are over 100 million photos in Flickr. The acquisition locations of these

Figure 3. Photo clustering for the photo data set captured in Kenting National Park (located in the south of Taiwan): (a) photo clustering result—each group is represented by a color and (b) photos within the place marked by red circle—the landmark in this location is a lighthouse called Eluanbi Lighthouse.

photos are shown in Figure 2; locations marked as blue indicate that fewer than 1000 photos were taken there, and locations marked as red indicate that more than 0.15 million photos were taken there. To determine places of interest, each user-uploaded photo is counted as a vote for tourist attraction selection. Based on this idea, the places of interest are automatically determined from the collected photos by using photo clustering. Any robust clustering approach can be adopted at this stage. For simplicity, the commonly used mean shift algorithm[22] is adopted to cluster these photos according to their geographical identification metadata, that is, longitude and latitude coordinates. The mean shift algorithm is a nonparametric clustering technique, which does not require prior knowledge of the number of clusters. An example of photo clustering is shown in Figure 3(a). A location having numerous user-uploaded photos indicates that this location may be a tourist attraction.

Representative icon selection

A tourist attraction may contain several popular views and landmarks. The most popular view or landmark is selected to represent the primary visual feature of a tourist attraction in a map. We use an unsupervised image clustering algorithm based on the idea that each user-uploaded photo is a vote for the popular view or landmark selection. To cluster photos taken of a scene or a landmark by various cameras and in various lighting conditions, a photo is represented by both color descriptor, which is suitable for scenic view clustering, and shape descriptor, which is suitable for object clustering. The idea on shape descriptor is to represent object shapes according to the distribution of directions of feature edges, that is, the boundaries of objects. Hence, an edge detection technique is first applied to a photo, and then the histogram of the gradient directions of feature edge pixels is calculated. The histogram of gradient directions, denoted as HoG, is divided into k bins, and the shape descriptor $S(I)$ for photo I is represented as

$$S(I) = \{HoG_1(I), \ldots, HoG_k(I)\} \quad (1)$$

Color histograms are commonly used to calculate image similarity in a color space. This approach is efficient and easy to implement. However, this descriptor lacks spatial information, resulting in ambiguity for images that have different appearances but have similar histograms. To avoid this ambiguity, we adopt the approach proposed by Pass et al.[23] in which spatial information is incorporated into the color histogram. In this approach, each pixel in a given color bin is identified as either coherent or incoherent based on whether this pixel is a part of a large similarly colored region. Then, a color coherence vector, denoted as CCV, recording the number of coherent and incoherent pixels for each color in an image is calculated. The CCV can prevent coherent pixels in one image from matching incoherent pixels in another. By separating coherent pixels from incoherent pixels, CCV can provide better distinguishability than the color histogram.

Once the shape and color features of photos are extracted, the photos are clustered by using the graph-cut-based clustering method.[24] The following is a brief introduction to this clustering method. In Chen et al.'s study,[24] image clustering is formulated as a graph partition problem. An image set is represented by a weighted graph $G = (\mathbf{V}, \mathbf{E})$, where $\mathbf{V} = \{I_1, \ldots, I_n\}$ is the set of graph nodes that represent images (n represents the number of nodes) and $\mathbf{E} = \{(I_i, I_j), I_i, I_j \in \mathbf{V}\}$ is the set of weighted edges that connect the nodes. Here, the weight of edge w_{ij} is defined as the similarity between the connecting nodes/images I_i and I_j. By using the feature vectors of images, the similarity is formulated as

Figure 4. Photo quality: (a) overexposed photo, (b) underexposed photo, and (c) photo with high QA value.

$$w_{ij} = \|S(I_i) - S(I_j)\| + \|CCV(I_i) - CCV(I_j)\| \quad (2)$$

The graph is organized into a similarity matrix, with the *ij*th entry given by the weight w_{ij}. The normalized graph cut algorithm[25] is then used to search for cuts that optimally partition the nodes into several groups so that the within-group similarity is high, and the between-group similarity is low. In other words, the graph cut can be considered as a measure of the between-groups similarity. The goal here is to find the optimal cuts. A simple way to measure the cost of cut that divides graph nodes into two disjoint sets is to calculate the total weights of the edges that connect these two sets. Thus, the cost of a graph cut is defined as

$$cut(\mathbf{A}, \mathbf{B}) = \sum_{i \in \mathbf{A}, j \in \mathbf{B}} w_{ij} \quad (3)$$

where **A** and **B** are the disjoint node sets partitioned by the cut *cut*(**A**,**B**). This graph cut approach favors grouping small sets of nodes because the cost of cut defined in equation (3) does not contain any within-group information. Therefore, overgrouping will occur when the cutting is recursively applied. To solve this problem, the cutting cost shown in equation (3) is reformulated as

$$Ncut(\mathbf{A}, \mathbf{B}) = \frac{cut(\mathbf{A}, \mathbf{B})}{cut(\mathbf{A}, \mathbf{V})} + \frac{cut(\mathbf{A}, \mathbf{B})}{cut(\mathbf{B}, \mathbf{V})} \quad (4)$$

where $cut(\mathbf{A},\mathbf{V}) = cut(\mathbf{A},\mathbf{B}) + cut(\mathbf{A},\mathbf{A})$ and $cut(\mathbf{A},\mathbf{B}) = cut(\mathbf{A},\mathbf{B}) + cut(\mathbf{B},\mathbf{B})$. By using equation (4), the photos can be clustered into several groups. Based on the concept of photo voting, the group that contains the maximum number of photos is the most popular group that may contain the most popular view or landmark. In the example in Figure 3(b), the photoset is partitioned into six groups. The object in the photos that belongs to the largest group is the Eluanbi Lighthouse, which is a landmark in that location.

Next, a high-quality photo is extracted from the largest photo group to represent the place of interest. Two image indexes, namely, *entropy* and *mean*, are used for quality assessment. In information theory, given a photo I with statistically independent random events $\{z_0, \ldots, z_{L-1}\}$ (where L represents the number of gray levels) and associated probabilities $\{p(z_0), \ldots, p(z_{L-1})\}$, the average information of this photo (i.e. entropy) is formulated as follows

$$e(I) = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i) \quad (5)$$

To avoid selecting an overexposed or underexposed photo in cases where all photos have similar entropy values (see Figure 4), the quality index *mean* is included in the assessment. This index is formulated as follows

$$m(I) = \sum_{i=0}^{L-1} \frac{p(z_i)}{(z_i - \mu) + \delta} \quad (6)$$

where $\delta = 0.001$ is used to avoid the error of division by zero, and μ is the intensity mean value of all photos in an extracted group. μ is not set to 128, that is, the median gray value, because unfavorable results may be produced when all photos in a group have high or low intensities. By integrating these two indexes, the quality assessment is formulated as

$$QA(I) = Norm_e(e(I)) + Norm_m(m(I)) \quad (7)$$

where $Norm_e()$ and $Norm_m()$ are the normalization functions that normalize the indexes $e(I)$ and $m(I)$ to the range [0, 1], respectively. The photo with the highest QA value is selected as the representative icon. An example of representative icon extraction is shown in Figure 5. A high-quality photo is selected from a photoset to represent a place of interest. Note that the goal is not to select the best photo. The selection of best photo is subjective. Even though some photo esthetic rules such as horizon balance and locations of region of interests are utilized, it is difficult or impossible to select the best photo.

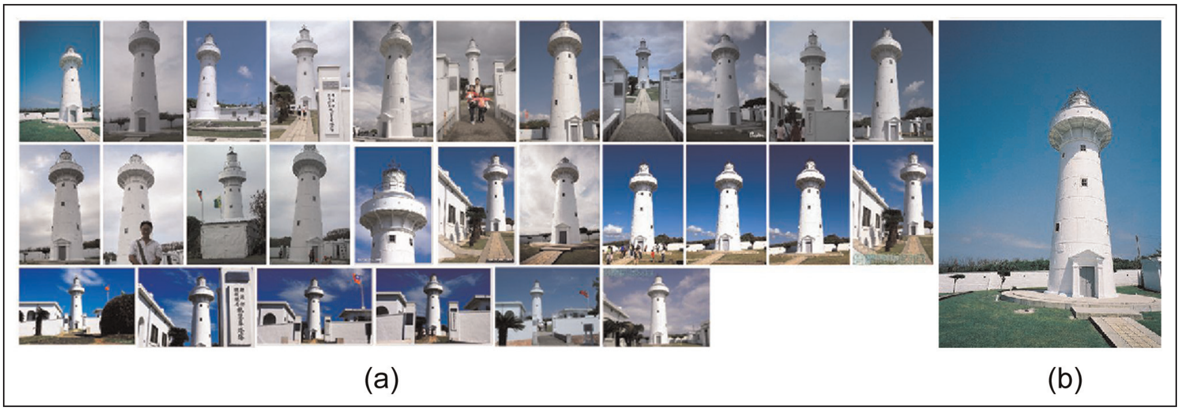

Figure 5. Example of photo quality assessment: (a) from a set of photos using the proposed quality assessment approach, (b) a representative photo is selected.

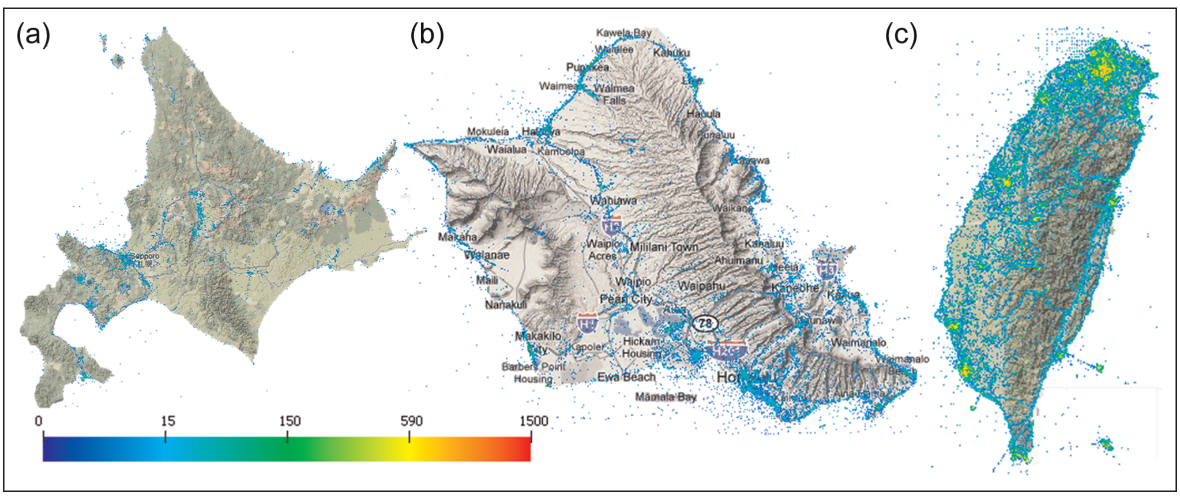

Figure 6. Locations of user-uploaded photos: (a) Hokkaido, (b) Honolulu, and (c) Taiwan.
The color that ranges from blue to red (1500 photos) represents the number of photos.

Experimental results and discussion

The proposed method was applied to several popular tourist attractions such as Taiwan, Hokkaido, and Hawaii for evaluation. The photo data set contained approximately 0.8 million photos in Taiwan; 0.08 million photos in Hokkaido, Japan; and 0.1 million photos in Honolulu, Hawaii, which were downloaded from Panoramio[4] and Flickr.[5] Parts of these photos were shown in Figures 1 to 5 and 8 to 12, and the acquisition locations were shown in Figure 6. The proposed approaches are based on the concept of counting a user-uploaded photo as a vote. Thus, this section details the experiments in which photo voting is used to determine places of interest and to select the representative image icon; the results are shown in Figure 7. The number of photo groups, that is, places of interest, extracted from the Hokkaido, Hawaii, and Taroko National Park (located in the east of Taiwan) data sets is 15, 13, and 15, respectively. The extracted places of interest are displayed by colors. Upon comparing with the tourist attractions given in the official sites of the places of interest, most of the tourist attractions are extracted because these regions contain numerous user-uploaded photos. However, some tourist attractions were not extracted by our method because those places have been closed for a long time. For instance, Wunshan Hot Spring located in Taroko National Park was closed several years ago; thus, only a few photos of this location are uploaded, and this location is not extracted by our method. This experiment demonstrates that our method can provide continually updated information on tourist attractions and can potentially be applied to digital map applications.

In Figure 8, several results of photo clustering and representative image icon selection are shown.

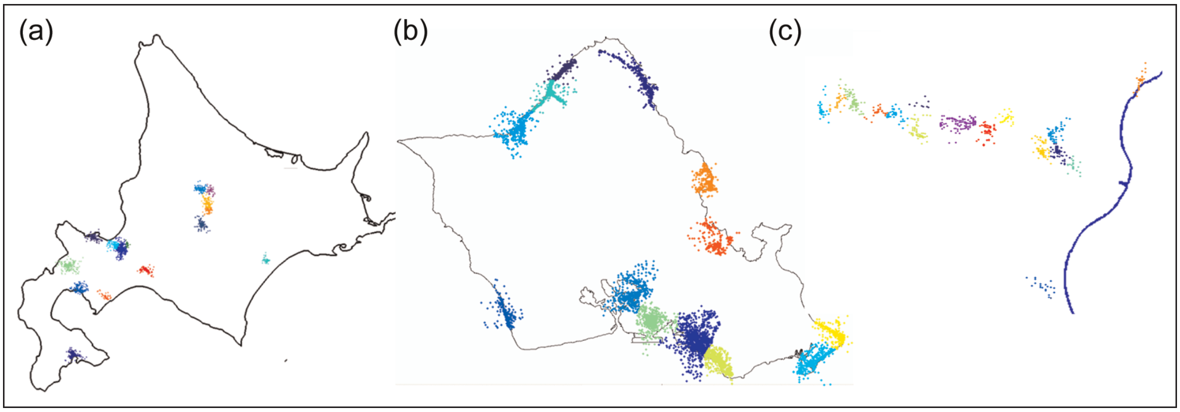

Figure 7. Results of place of interest determination: (a) Hokkaido, (b) Honolulu, and (c) Taroko National Park (located in the east of Taiwan).
Each group (or extracted place of interest) is represented by a color.

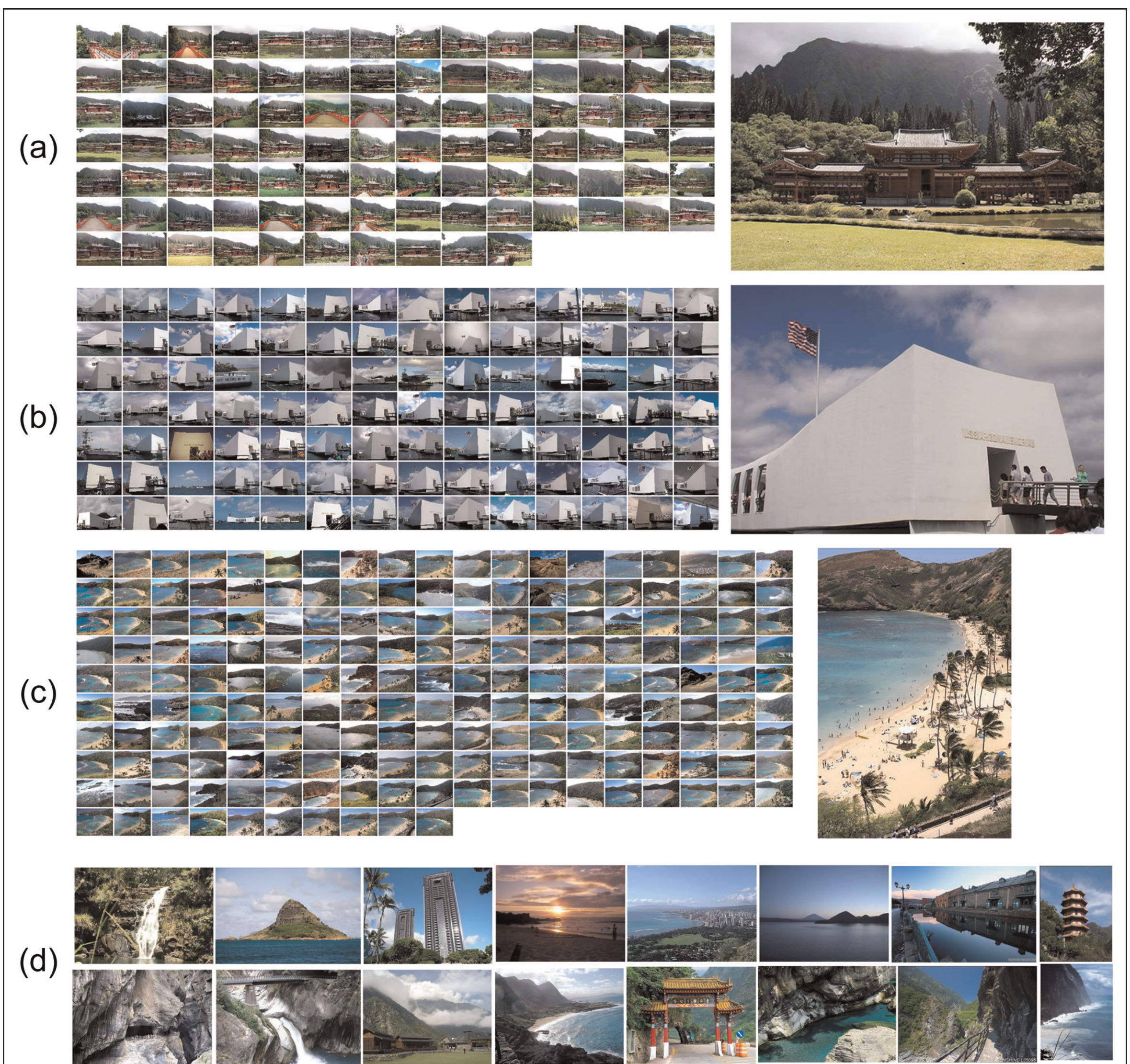

Figure 8. Results of representative image icon selection: (a) first case: Byodo-In Temple in Honolulu—photos in the largest group (left) and selection results (right), (b) second case: Pearl Harbor in Honolulu—photos in the largest group (left) and selection results (right), and (c) third case: Hanauma Bay in Honolulu—photos in the largest group (left) and selection results (right), and (d) additional icon selection results..

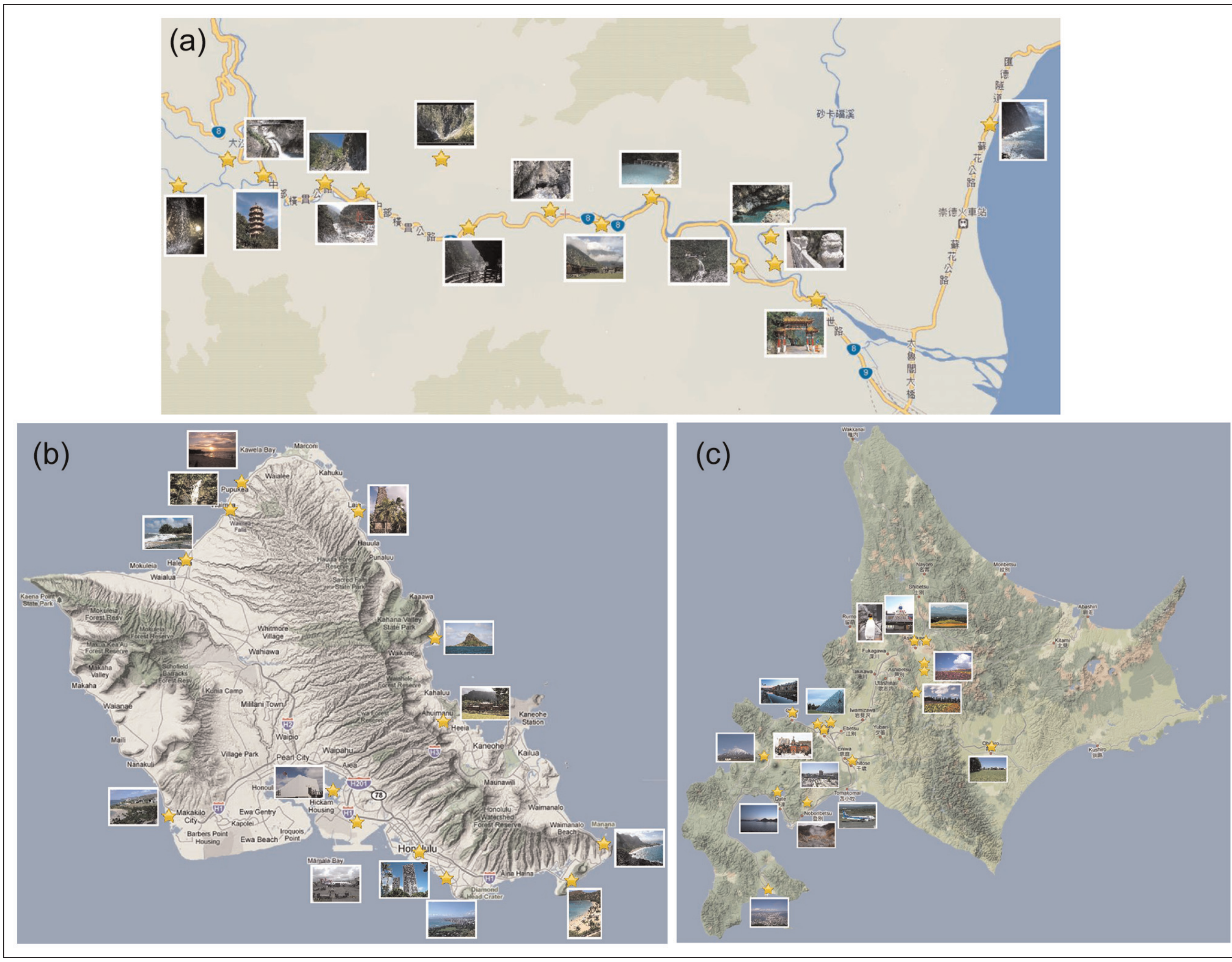

Figure 9. Results of tourist maps: (a) generated tourist maps for Taroko National Park, Taiwan (15 places of interest); (b) Honolulu (13 places of interest); and (c) Hokkaido (15 places of interest).

Similarly, the most popular view is extracted through photo voting. Then the representative image icons are selected according to image content and quality. From the tourist attractions provided in official web sites, the extracted photos contain famous views or landmarks in those places. Therefore, the photos that contain visual features of these places are suitable to serve as image icons for a tourist map, and the proposed method based on photo voting strategy is feasible for tourist map generation. With the aid of feature-point-feature label placement technique, the determined places of interest and their representative image icons can be placed in a map. The results are shown in Figure 9.

To evaluate the proposed approaches, our result is compared with official web-based tourist map, maps used in Panoramio and Flickr, and hand-designed tourist map. The comparisons are shown in Figure 10. Unlike the official web-based tourist maps, which generally use a simple shape with a text label to represent the tourist attractions, the proposed approach uses photos as an image icon that contain visual features of the selected places. Tourists can easily determine the visual features of the tourist attractions and their locations using the proposed map. Unlike the tourist maps generated by Grabler et al.,[2] which use nonphotorealistic rendering results of 3D models to represent landmarks (see Figure 1 or refer to figures shown in Grabler et al.'s study[2]), the proposed approach can represent both landmarks and scenic spots by using image icons. In addition, taking photos is much easier than building 3D models for landmarks.

User study

We conducted a user study that involved 103 participants with ages ranging from 20 to 40 years to evaluate the proposed method and compare the results with the related maps. In this user study, participants were

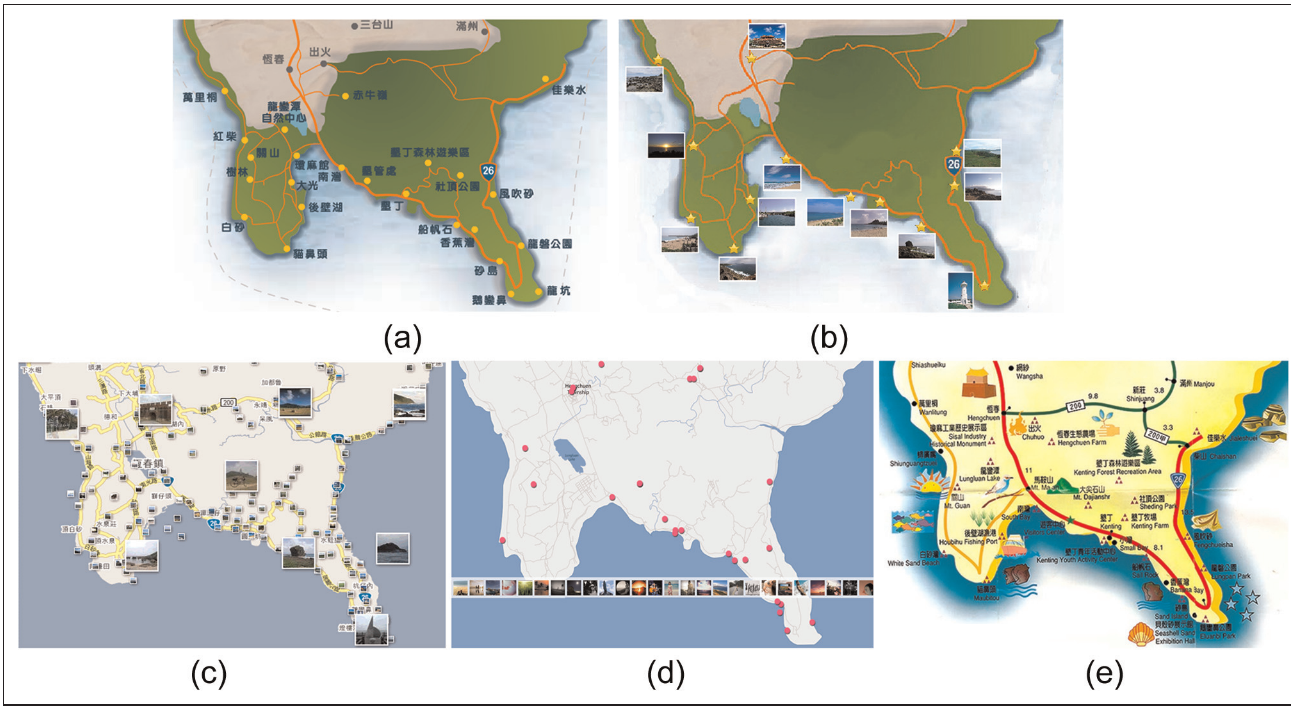

Figure 10. Map comparison: (a) official web-based tourist map, (b) the map generated by using our approach, (c) Panoramio, (d) Flickr, and (e) the hand-designed tourist map.

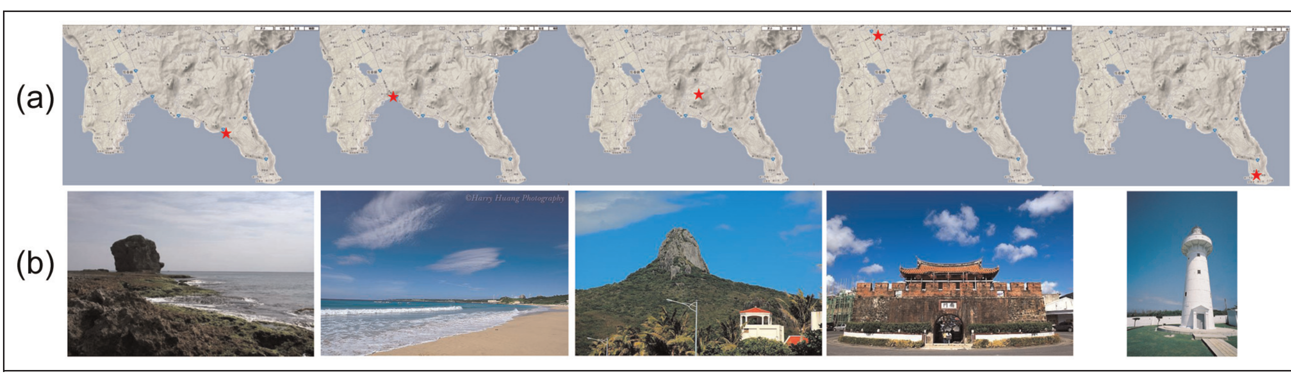

Figure 11. Results of representative image icon selection. The photos were captured in Kenting National Park located in the south of Taiwan. The tourist attractions are (from left to right): Nanwan Bay, Dotzing Mountain, Chuanfanshin, Hengchun Township, and Eluanbi Lighthouse. (a) The locations of tourist attractions are shown at the top and (b) the selected image icons are shown at the bottom.

shown various types of icons that represent tourist attractions in a map, including a shape pattern, a non-photorealistic rendering of 3D model, and the proposed icon, and various maps that contain tourist attractions that the participants are familiar with. This survey aimed to determine which type of icon presents the tourist attraction well and whether the generated image icons can appropriately represent the visual features of tourist attractions. Some of the data sets used in the survey are shown in Figures 1 and 10 to 12, and the other data set and materials are available as supplementary documents. The user response shown in Figure 13(a) indicates that the icons generated by our method are better (66% of votes) than the simple shape (11% of votes) and 3D models (23% of votes) used in the related method.[2] In the survey on image icon representation (see Figure 13(b)), the user response shows that 78% (i.e. score: 5 and 4) of the selected image icons can well represent the visual features of tourist attractions and that 20% of the selected

Figure 12. Results of representative image icon selection. The photos are captured in Taroko National Park located in the east of Taiwan. The tourist attractions are (from left to right): Cingshui Cliff, Buluowan, Yanzihkou, Jiucyudong Tunnel, and Baiyang Track. (a) The locations of tourist attractions are shown at the top and (b) the selected image icons are shown at the bottom.

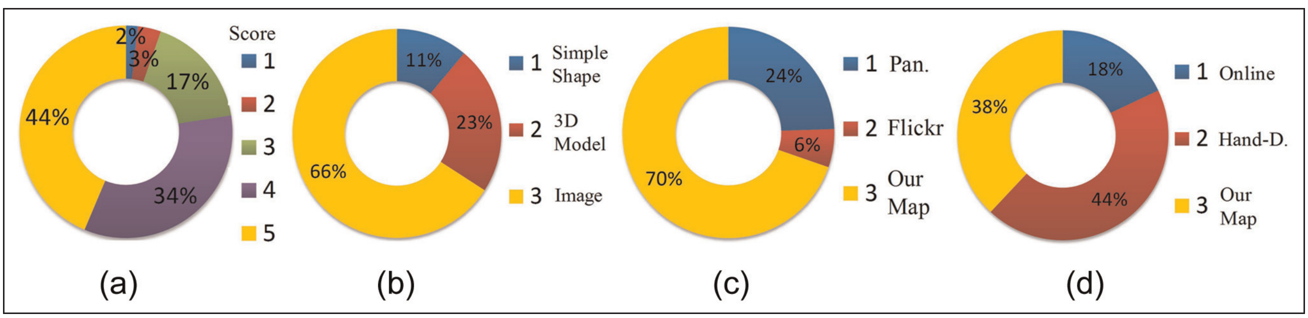

Figure 13. User study. (a) Result of the survey for image icon representation. A score of 5 indicates very good icon quality and that it can fully represent the visual features of the tourist attraction, a score of 4 indicates good icon quality and that it can partially represent the visual features of the tourist attraction, a score of 3 indicates fair icon quality and that it can partially represent the visual features of the tourist attraction, a score of 2 indicates that the icon can barely represent the visual features of the tourist attraction, and a score of 1 means that the icon cannot represent the tourist attraction; (b) comparison between the tourist attraction representations, including simple shape (blue), 3D model (red), and photo (yellow); (c) comparison among tourist maps including Panoramio (denoted by Pan.), Flickr, and our map; and (d) comparison among tourist maps, including the official tourist map, hand-designed tourist map (Hand-D.), and our map.
3D: three-dimensional.

image icons present partial features of tourist attractions (i.e. score: 3 and 2). We find that using only a photo cannot substantially represent all the visual features of tourist attractions that have several good views. For the tourist map comparison, the user response (see Figure 13(c) and (d)) indicates that the generated tourist maps (33% of the votes) are better than the official web-based tourist maps (18% of the votes) and are comparable to the hand-designed tourist maps (44% of the votes).

Conclusion and future work

Approaches for automatic determination of places of interest and representative icon selection for tourist map generation were introduced in this study. When selecting a place of interest and a representative icon, each user-shared photo is regarded as a vote, the mean shift clustering technique is applied to extract the places of interest featured in numerous user-uploaded photos based on the photo-acquisition locations, and the normalized graph cut algorithm is used along with photo quality assessment to extract a high-quality photo that can represent the visual features of the selected place of interest. The experimental results and the user study showed that using image icons is better, in terms of visual feature representation, than using 3D models or simple shapes, and tourist maps with the selected places of interest and representative icons are comparable to the hand-designed tourist maps. In the near future, we plan to utilize more tourist information on the Web to refine photo grouping and selection. In addition, we plan to develop a hierarchical icon placement approach to place icons consistently at different scales on a map, which could be useful in map zooming.

Funding

This paper was supported in part by the National Science Council, Taiwan (contracts NSC 101-2221-E-006-257-MY2 and 101-2119-M-006-005), and was supported in part by the Central Geological Survey, Ministry of Economic Affairs, Taiwan.

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