Visualizing Shooting Spots using Geo-tagged Photographs from Social Media Sites

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Abstract. Hotspots, at which many photographs have been taken, might be interesting places for many people to do sightseeing. Visualization of hotspots reveals user interests, which is important for industries such as tourism and marketing research. Although several social-based techniques for extracting hotspots independently have been proposed, a hotspot has a relation to other hotspots in some cases. To organize those hotspots, we propose a method to detect and visualize relations among hotspots. Our proposed method detects and assesses relations of shooting spots and photographic subjects. Our approach extracts the relations using sub-hotspots, which are split from a hotspot that includes photographs of different types. We demonstrate our approach by discovering relations using photographic metadata such as tags, photograph orientation, and photograph locations from Flickr.

1 Introduction

According to the increasing popularity of mobile devices such as digital cameras and smart phones, numerous photographs taken by photographers have been uploaded to photo-sharing web services such as Flickr [1] and Panoramio [2]. Recently those devices have included embedded global positioning systems (GPSs). Using them, photographers can readily take photographs with photographic metadata such as location and photograph orientation information. Particularly, photographs with a photograph-orientation feature have become numerous recently (Zheng et al., 2011). In addition, many photographs on social media sites have metadata that are annotated by users through social tagging.

Many people might take photographs of subjects such as landscapes based on their own interests. Then they might upload those photographs to social media sites. As locations at which many photographs have been taken, these places might also be interesting places for many people to sightsee or visit. As described in this paper, we define such places as **hotspots**. Figure

1. http://www.flickr.com/
2. http://www.panoramio.com/

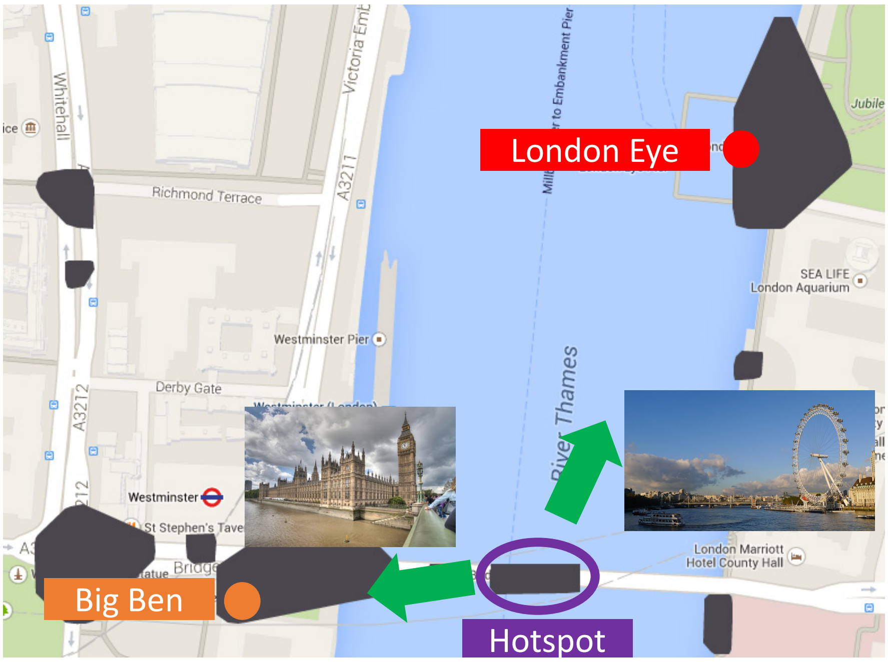

FIG. 1 – *Examples of hotspots.*

1 presents examples of hotspots extracted using our proposed method from photographs taken around Big Ben. In this figure, black polygons represent the areas of extracted hotspots. Some methods have been proposed to extract hotspots from data from photographs at photo-sharing sites (Crandall et al., 2009; Kisilevich et al., 2010; Shirai et al., 2013; Hirota et al., 2014). The extracted hotspots might reflect people's interests, or be useful for marketing research, spatial analysis, and so on. Analyzing such places is important for industries such as those related to tourism (Sengstock and Gertz, 2012; Kisilevich et al., 2010). Furthermore, tourist attraction recommendation systems such as (Lu et al., 2010; Popescu and Grefenstette, 2011) can use this approach. By presenting hotspots to people who visit a city for the first time, our approach assists tourism.

Although many methods to extract and visualize hotspots from social media sites have been proposed, those studies visualize the user interests but they do not specifically examine those relationships (Crandall et al., 2009; Kisilevich et al., 2010; Shirai et al., 2013). Therefore, we extract relations among hotspots. Hotspots in past studies are extracted independently, but some hotspots are related. However, extracting and visualizing the relations among hotspots is important to organize hotspots, and to find the nature of hotspots. For example, in Figure 1, around Big Ben in London, hotspots were extracted from inside of Big Ben and around Big Ben. Photographs taken around Big Ben have been taken in the direction of Big Ben. Therefore, those hotspots have some relation to the shooting spot and the photographic subject. As described in this paper, we extract such relations of shooting spots and photographic subjects.

We define a shooting spot as one type of hotspot in an area where photographs have been taken in the direction of interesting places such as a landmark at a place that is distant from there. Extracting shooting spots from social sites reveals attractive places for tourists, based on user activity. In addition, the range within which people are able to take photographs of a landmark is important for tourist attractions and routing recommendation systems. Therefore, in this paper, we specifically examine extraction and visualization of relations between shooting spots and photographic subjects of hotspots from social media sites.

Additionally, we extract the relations using sub-hotspots. A sub-hotspot is a hotspot that includes photographs of different types. It is split to separate types of hotspot. For example, in Figure 1, around Big Ben, several areas are apparent where photographs have been taken to famous landmarks: Big Ben and the London Eye (a famous giant Ferris wheel near the Thames River). Hotspots are extracted from this area. The hotspot marked by a violet circle in this figure is associated with photographs taken of both Big Ben and the London Eye. Therefore, the hotspots are shooting spots for both landmarks. To extract relations from the shooting spot to each landmark, we must split a hotspot to sub-hotspots based on the landmarks. Therefore, we split a hotspot into sub-hotspots using social tagging, and extract relations.

The remainder of the paper is organized as follows. Section 2 presents works related to this topic. Section 3 presents a description of our proposed method to calculate relations of photographic subject and shooting spot using photograph orientations, photograph locations, and social tagging. Additionally, we describe sub-hotspots from extracted hotspots using social tagging. Section 4 explains several examples of our proposed system and presents a discussion of the results. Section 5 concludes the paper with a discussion of results and future works.

2 Related Works

2.1 Extraction of hotspots from photo-sharing sites

Some methods have been proposed to extract hotspots from the many photographs that are available on photo-sharing sites. Those methods use density-based clustering algorithms such as DBSCAN (Ester et al., 1996) to extract hotspots from a huge photograph dataset. Crandall et al. presented a method to extract landmarks and hotspots using a clustering technique based on many geo-tagged photographs available from the internet (Crandall et al., 2009). In addition, Kisilevich et al. proposed a method to extract a hotspot using the density of photograph locations based on clustering results (Kisilevich et al., 2010). These methods treat each hotspot as independent. However, some hotspots are related to other hotspots such as photographic subjects and shooting spots. Shirai et al. proposed a method to extract a hotspot and to calculate the relation of hotspots (Shirai et al., 2013). To discover a wide area of interest, this approach infers the relation among hotspots based on the photograph location and orientation. However, other relations among hotspots might exist such as shooting spots and photographic subjects. Additionally, although those studies extract hotspots from social media sites, they do not consider contents of the hotspots.

As described in this paper, we detect sub-hotspots based on social tagging from a hotspot for extracting relations of the photographic subject and shooting spot among sub-hotspots to consider photograph orientation.

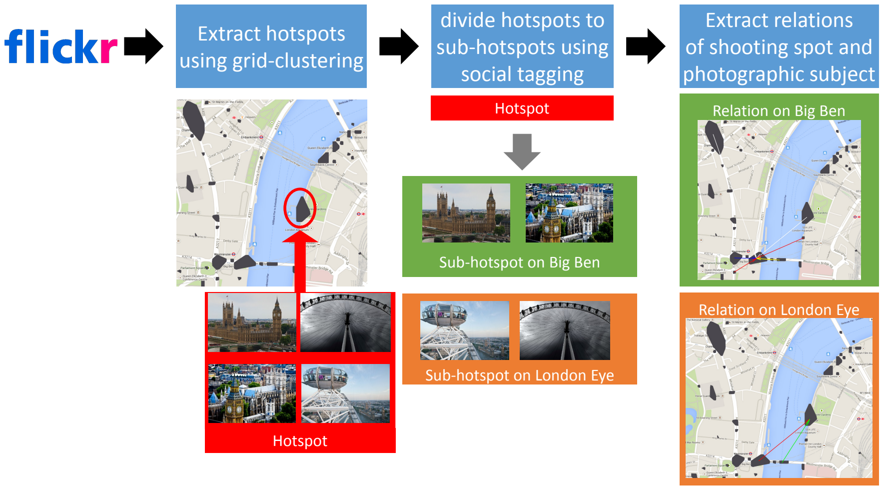

FIG. 2 – *Overview of our proposed method.*

2.2 Visualization based on photograph orientation

According to photographs with a photograph orientation have become more commonly available, photograph orientation is used for extracting hotspots. Lacerda et al. proposed a method for extracting hotspots using photograph orientations (Lacerda et al., 2012). This method calculates the intersections between lines of photographic orientation of many photographs. The intersections are clustered using DBSCAN. In addition, Thomee et al. proposed a method for consideration of inaccuracies affecting GPS location measurements (Thomee, 2013). We regard this approach as effective for extracting photographic subjects, but this approach has a limitation of extracting areas in which photographs have been taken as hotspots. In addition, current GPS data merely identify the location at which the picture was taken. Most cameras are not equipped with sensors to measure the orientation. As a result, to extract hotspots, the approach of using photograph orientation is not applicable for the area where huge photographs have been taken. Therefore, we apply a clustering algorithm based on photograph locations to extract hotspots.

In the related literature, some methods to estimate the photograph orientation have been presented, even for photographs that appear to have no photograph orientation (Park et al., 2010; Huang et al., 2012). Our method uses the photographs with photograph orientation to extract relations. Therefore, we expect to use the estimated photograph orientation to increase the accuracy of our method.

3 Proposed Method

We propose a method to detect the relations of photographic subjects and shooting spots using photograph orientation, location, and social tagging. Therefore, we use photographs for which the obtained result includes information related to the photograph orientation, location, and tags. We present an overview of our approach in Figure 2. To detect the relations of shooting spot and photographic subject, our approach includes the following steps.

1. For a particular area, we obtain vast numbers of photographs from Flickr.
2. We apply a grid-based clustering algorithm to the obtained photographs based on photograph locations to extract the places at which many photographs have been taken as hotspots.
3. Using extracted hotspots, we cluster tags of photographs based on their geometric distribution. we use extracted clustered tags to divide the extracted hotspots to different sub-hotspots.
4. Calculation of the relevance of sub-hotspots using hotspot location and orientation, to extract the relation between the shooting spot and the photographic subject.

We describe details related to the respective steps below.

3.1 Extraction of hotspots

To identify hotspot places at which many photographs have been taken, we specifically examined the number of photograph locations to find those locations where photographs are taken by many people. To achieve this, we map photographs that have a photograph location to a two-dimensional grid. Those photographs are mapped to the coordinates as follows.

$$y = M_{height} - \frac{(Lat - Lat_{min}) * M_{height}}{Lat_{max} - Lat_{min}} \tag{1}$$

$$x = M_{width} - \frac{(Lng - Lng_{min}) * M_{width}}{Lng_{max} - Lng_{min}} \tag{2}$$

Here, Lat represents the latitude of the photograph (GPSLatitude in Exif). Lng is the longitude of the photograph (GPSLongitude in Exif). Lat_{max}, Lat_{min}, Lng_{max}, and Lng_{min} respectively denote the maximum and minimum values of Lat and Lng. Additionally, M_{height} and M_{width} are the height and width of the grid (This is decided using a parameter d for adjustment that how many cells we want to make in this procedure.). Consequently, each cell in the obtained grid includes a photograph taken in the range.

Using the obtained grid, we extract the cells for which the number of photographs including its cell is greater than threshold $minP$. The nearby extracted cells, which are mutually connected cells, are joined. Each group of joined cells is defined as a cluster.

To extract hotspots from the obtained grid, we apply the Axis-Shifted Grid-Clustering algorithm (Chang et al., 2009) to the obtained grid. This clustering method is density-grid based clustering with an axis-shifted partitioning strategy to identify areas of high density. An important benefit of this method is the dynamic adjustment of the size of the original cells in the grid and reduction of the weakness of borders of cells, by shifting the original grid in each dimension of the data space after the clusters generated from this original grid are obtained.

The procedure of Axis-Shifted Grid-Clustering includes the following steps

1. Extraction of clusters by the method using the procedure described above. This clustering is denoted as C_1.

ben, big ben, clock	eye, london eye, wheel	shard, skyscraper	bridge
railway, station, train	stone, ceiling, museum	river, Thames	tower

TAB. 1 – *Examples of clustered tags.*

2. The grid used for extracting C_1 is transformed. The grid is shifted by half of the distance $d/2$ in each dimension. To obtain new clustering results, the procedure for extracting clusters is applied again to the shifted grid. This new shifted clustering result is denoted as C_2.
3. Clustering result C_1 is revised using C_2. We find each overlapped cluster in both clustering results, where $C_{1a} \cap C_{2b} \neq \emptyset, C_{2b} \in C_2$, and $C_{1a} \in C_1$. C_1 is modified, by joining the extracted overlapped clusters. Consequently, the final clustering result includes $C_1 \cup C_2$. Finally, each extracted cluster is defined as a hotspot. Each hotspot includes photographs of the cluster.

3.2 Clustering tags to make sub-hotspots

After extracting hotspots from photographs, we split each hotspot into sub-hotspots because a hotspot often has several photographs taken in the direction of the photographic subject. Therefore, for this study, we infer sub-hotspots for each subject from such a hotspot based on tags that photographs have. When we make sub-hotspots, we organize similar tags that represent the same meanings into clusters such as “big ben” and “ben”. Photographs with each clustered tag in a hotspot might reveal one aspect of the meanings associated with the hotspot.

To organize similar tags, we cluster social tagging using hotspot feature vectors based on geo-spatial feature vectors (Zhang et al., 2012). The different types of tags of photographs have different geographical distributions. The geo-spatial feature vector of a tag is represented by a geo-bin, which includes cells in a grid having the number of photographs with the tag. As a result, the dimension of the vector is extremely large. However, the grid obtained from photographs with tags is sparse. Therefore, to decrease the computational cost, we calculate the feature vectors using extracted hotspots instead of geo-bins.

To compute a geo feature vector for tag_i, we count the photographs with tag, which were taken in an area of hotspot h as $U(g,t)$. We count the users who applied a tag within a hotspot instead of the photographs. Thereby, we prevent high-activity users from biasing the distribution (Ahern et al., 2007). Then we apply L2-normalization to the vector to calculate the geo-bin $v_i(t)$ of tag t as follows.

$$v_i(t) = \frac{U(g,t)}{\sqrt{\sum_{j=1}^{|H|} U^2(j,t)}} \tag{3}$$

Here, $|H|$ is the number of hotspots extracted in Section 3.1. It was described in an earlier report (Zhang et al., 2012) that this L2-normalization functions better. Therefore we use the same method.

After geo-feature vectors of each tag are calculated, we cluster tags based on the similarity of geographical distributions using hierarchical agglomerative clustering. Then, we use a method for calculating the distance between clusters. Furthermore, for stopping agglomerative steps, we use a criterion parameter: the minimal cluster distance is greater than the criterion. Examples of clustered tags are presented in Table 1.

Finally, we define a subset of photographs with tags of a cluster in i-th hotspot h_i as a sub-hotspot h_i^s of h_i. h_i^s includes photographs that have one tag of the s-th cluster or more.

3.3 Extraction of relations of shooting spot and photographic subject

To extract relations of shooting spots and photographic subjects, we calculate the relevance of extracted sub-hotspots based on geometric location. If photographs in sub-hotspot h_i^s were taken to photographic subjects included in h_j^s, then h_i^s is a shooting spot of h_j^s. Those sub-hotspots have a relation between h_i^s and h_j^s. To confirm the orientation of h_i^s to h_j^s, features of three types are used: distance, orientation, and ratio of photographs.

First, we calculate the Hubeny distance between h_i^s and h_j^s because photographs related to the shooting spot might have been taken near a hotspot that includes a photographic subject. The Hubeny distance $d_s(i,j)$ is calculated as

$$d_s(i,j) = \sqrt{(M * dP)^2 + (N * cos(P) * dR)^2}. \tag{4}$$

Therein, P signifies the average latitude of centroids of h_i^s and h_j^s. Also, dP and dR respectively represent the differences of latitude and longitude of centroids of h_i^s and h_j^s . M stands for the radius of curvature for a meridian. N is a radius of curvature for a prime vertical.

Next, we ascertain whether the orientation of photographs in sub-hotspot h_i^s to h_j^s. h_i^s might be a shooting spot for taking photographs of subject in h_j^s if many photographs of h_i^s face the direction of h_j^s. Therefore, we calculate the degree of orientation of h_i^s to h_j^s. First, we calculate the main orientation of h_i^s. We split the values of photograph orientation of h_i^s by 20 deg and counted the photographs of each class. We use metadata (GPSImgDirectionRef or GPSImgDirection in Exif) as the photograph orientation. The max class md_i^s is the main orientation of h_i^s . We calculate the average of those classes if the number of max classes is greater than one. Next, we calculate the orientation of ld_{ij}^s from centroid (x_1, y_1) of h_i^s to centroid (x_2, y_2) of h_j^s as

$$ld_{ij}^s = tan^{-1} \frac{cosy_2 * sin(x_2 - x_1)}{cosx_1 * siny_2 - siny_1 * cosy_2 * cos(x_2 - x_1)}. \tag{5}$$

The degree $o(i,j)_s$ of orientation of h_i^s to h_j^s is calculated as

$$o_s(i,j) = |md_i^s - ld_{ij}^s|. \tag{6}$$

We calculate the ratio of photographs of h_i^s and h_j^s. This feature is used to avoid the case in which another shooting spot is located at the middle of shooting spot h_i^s and the photographic subject in h_j^s. Avoiding this case is difficult based on previously described features. In the area of photographic subjects such as a landmark, people have taken many photographs inside or nearby. The number of photographs in the shooting spot for the subject is roughly the same or less than the extracted sub-hotspot from the area. The ratio $r_s(i,j)$ of photographs of h_i^s and h_j^s is calculated as

$$r_s(i,j) = \frac{|h_j^s|}{|h_i^s|}. \tag{7}$$

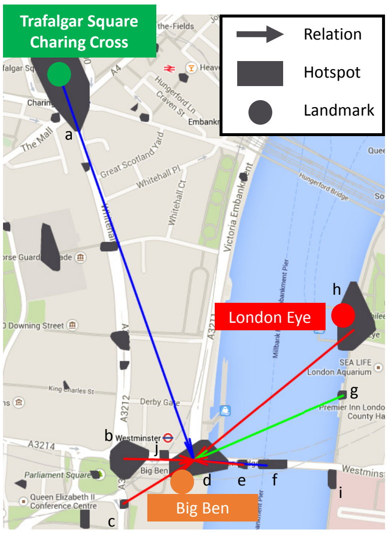

FIG. 3 – *Relation for Big Ben (London dataset).*

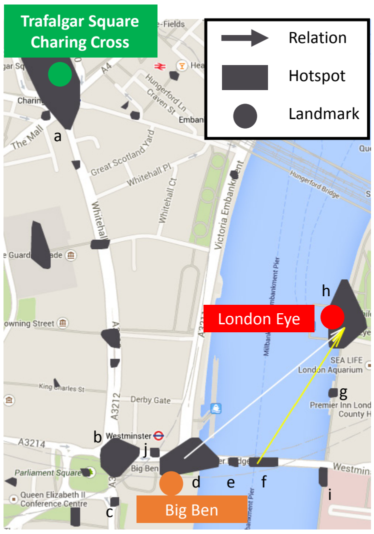

FIG. 4 – *Relation for London Eye (London dataset).*

Therein, $|h_i^s|$ and $|h_j^s|$ is the number of photographs of h_i^s and h_j^s.

Finally, we calculate the relevance from $rel_s(i,j)$ to h_i^s and h_j^s as

$$rel_s(i,j) = \sqrt{d_s(i,j)} * o_s(i,j) * \frac{1}{r_s(i,j)}. \quad (8)$$

The smaller value of $rel_s(i,j)$ is the strong relevance from h_i^s to h_j^s. Here, we eliminate the relation from the hotspot of photographic subject to another hotspot. Therefore, we detect the hotspot that includes photographic subjects from extracted hotspots on s-th clustered tags. As described herein, we define the hotspot collected relation from many other hotspots as a hotspot that includes a photographic subject. The hotspot of a photographic subject is more than $|rel_s| * 0.5$, where $||rel_s|$ is the number of relations on s-th clustered tags. We visualize relation $rel_s(i,j)$ as less than the adjustable threshold on Google Maps[3].

4 Experiments

This section presents a description of experiments conducted using our proposed method. We present and discuss several examples of detection of relations of shooting spots and photographic subjects. Photographs for experiments are obtained from photographic search results of Flickr. Those photographs have Exif metadata of latitude (GPSLatitudeRef, GPSLatitude), longitude (GPSLongitudeRef, GPSLongitude), tags, and timestamps.

Figures 3 and 4 present results of relations of shooting spots and photographic subjects in the area of Big Ben and the London Eye. We used 1,123,550 photographs taken during

3. https://www.google.co.jp/maps/

1 January 2010 - 31 June 2014 and taken in London (latitude: -0.450439 - 0.148315 and longitude: 51.301643 - 51.669361). The clustering parameters are set as $d = 200$ and $minP = 20$. In those figures, the black polygon shows the place extracted as a hotspot. The arrowed line shows the relation. The arrow points to a hotspot of the shooting spot to another hotspot of a photographic subject. Here, no difference exists between colors of those lines. This is only an easy-to-view representation. In addition, in those figures, several famous places and landmarks exist in this area: Big Ben (orange point), the London Eye (red point), Trafalgar Square, and Charing Cross (green point).

Figure 3 shows the many hotspots with arrowed lines to the hotspot that includes Big Ben. In hotspots connected by lines, the hotspot that includes Big Ben (d in Figure 3) has photographs taken around Big Ben. Others ($a - c$, $e - g$ in Figure 3) have photographs taken in the direction of Big Ben. For example, hotspots of b include the seven photographs taken to 60-120 deg, where 0 deg is north, increasing with clockwise rotation. Here, lines between some hotspots (such as i and j) and hotspot d were not drawn. Those hotspots include photographs of Big Ben, but few photographs among those have no orientation metadata. Therefore, we can not calculate the relations between those hotspots. In addition, using the features of distance, orientation, and ratio, the relation from hotspot f to d is extracted appropriately. For example, if we extract relations among those hotspots based on the distance between hotspots or orientation, the relation of hotspot f is extracted as facing hotspot e. Our method extracted the relations between the shooting spot and photographic subject using three features. Additionally, in Figure 4, the two hotspots (d and f) have arrowed lines to hotspot h. Why some hotspots have no relation to hotspot h is the same reason as that of the number of photographs with orientation metadata, as described previously. Hotspot f has two types of photographs taken to Big Ben and the London Eye. The place of hotspot f is a shooting spot to take those landmarks. Furthermore, for comparison to Figures 3 and 4, in shooting spots and photographic subjects, hotspots h and d are interchanged based on what relation on a subject we extract. Therefore, splitting hotspots to sub-hotspots based on social tagging and then extracting the relations of each type of photographic subject is important.

Next, we emphasize the effectiveness of combining three features: distance, orientation, and the ratio of the number of photographs. Here, we show the results of relations of shooting spots and photographic subjects obtained from another dataset of photographs taken in New York. We used 1,300,315 photographs taken during 1 January 2010 - 31 June 2014 and taken in New York (latitude: 40.700422 - 40.804324 and Longitude: -74.028454 - -73.929577). The clustering parameters are set as $d = 500$ and $minP = 50$. Figures 5, 6, 7, and 8 show extracted hotspots and relations around the Brooklyn Bridge as orange and Manhattan Bridge as white in those figures. The relations in Figure 5 were extracted based on three features of Equation 8. In addition, the relation in Figures 6, 7, and 8 were extracted based on each feature.

Figure 5 shows many hotspots related to hotspot b, in which the center of the Brooklyn Bridge exists. These results show that those places are shooting spots for taking photographs of the Brooklyn Bridge. In Figure 6 based on photographic orientations, it is apparent that some hotspots have a relation to different hotspots such as hotspots a and g, compared to Figure 5. However, indeed, many photographs taken in those hotspots are taken in the direction of the center of the Brooklyn Bridge. The one reason why relations extracted based on the orientation are taken in the direction of a hotspot might be the error of orientation metadata measured using GPS. Additionally, if any metadata are measured inaccurately, in terms of

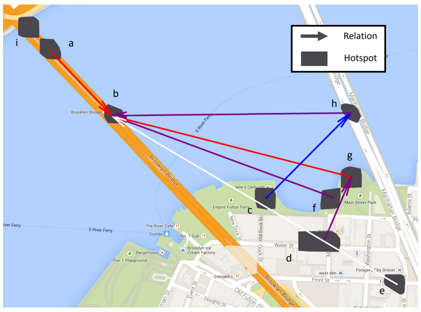

FIG. 5 – *Extracted relations based on three combined features (New York dataset).*

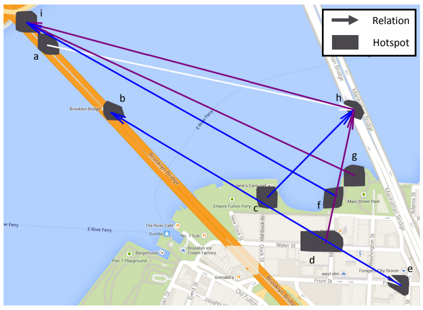

FIG. 6 – *Extracted relations based on orientations (New York dataset).*

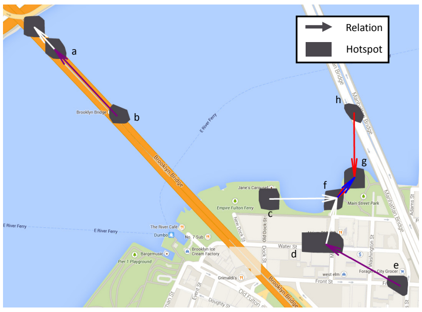

FIG. 7 – *Extracted relations based on distance separating hotspots (New York dataset).*

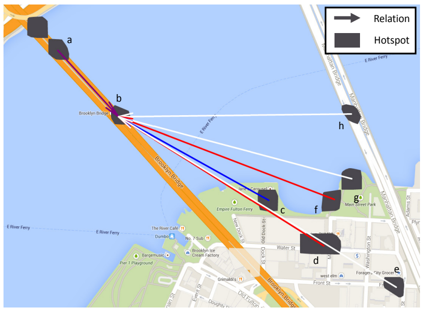

FIG. 8 – *Extracted relations based on the ratio of the number of photographs (New York dataset).*

photographic composition, then the photographic subject is not positioned at the center of the photograph. A gap separating the center of photographs and measurements might occur. Because of those gaps and because of the inaccuracy of measurement, we think that extracting relations based only on orientation is inadequate. Furthermore, in Figure 7, hotspots show a relation to a closer hotspot. As a result, a relation by which photographs were taken to the Brooklyn Bridge or Manhattan Bridge is not extracted. In Figure 8, all hotspots have relations to hotspot b. However, hotspot c in Figure 5 has a relation to hotspot h because hotspot c includes photographs of the Brooklyn Bridge, but more photographs of Manhattan Bridge. Therefore, to extract relations of the shooting spot and photographic subject, those features which are applied to hotspots are not feasible. Results show that our method based on the combined features extracts relations effectively.

5 Conclusions

We proposed a method to extract and visualize the relation of a shooting spot and a photographic subject using photographs with location information related to photo-sharing sites.

We extract hotspots of places where many photographs have been taken. Then we split the extracted hotspots into sub-hotspots based on geometric distributions of social tagging. To calculate the relations, our approach uses photographic orientation, positional relations of hotspots, and the ratio of the number of hotspots. We presented some examples of results obtained from Flickr using our method. In several cases, our methods were sufficient to detect and visualize the relations of shooting spots and photographic subjects. Additionally, we discussed the availability of using three features to extract relations.

Future studies will be conducted to estimate metadata such as photographic orientation and social tagging to increase the number of photographs with metadata. The applicability of our approach depends on the number of photographs that have metadata and their accuracy. Therefore, we will estimate the metadata to photographs without metadata, using other photographs with metadata. Additionally, we will recommend travel routes considering shooting spots because we think that places from which people can take photographs of famous landmarks are important for tourism.

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Résumé

Hotspots, à laquelle de nombreuses photographies ont été prises, pourraient être des lieux intéressants pour beaucoup de gens faire du tourisme. Visualisation des hotspots révèle les intérêts des utilisateurs, ce qui est important pour les industries telles que la recherche et du marketing touristiques. Bien que plusieurs techniques basées sociaux-pour hotspots extraction indépendamment ont été proposés, un hotspot a une relation à d'autres hotspots dans certains cas. Pour organiser ces hotspots, nous proposons une méthode pour détecter et de visualiser les relations entre les hotspots. Notre méthode proposée détecte et évalue les relations de taches de tir et sujets photographiques. Notre approche extrait les relations à l'aide de sous-hotspots, qui sont fendus d'un hotspot qui comprend des photographies de différents types.