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Discovering Hotspots Using Photographic Orientation and Angle of View from Social Media Site

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Abstract - Hotspot is 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. Hotspot is classifiable to two types: area of interests and shooting spot. This paper introduces a new method using clustering algorithm for extracting the area of interests based on various metadata annotated with a photograph from photo-sharing sites. Although several social-based techniques for extracting hotspots have been proposed using photographic location, those most methods cluster photographs based solely on the density of geographic proximity. However, in almost cases, a hotspot and shooting point where photographs were taken are distant. Also, when a photograph was taken, an angle of view, which the breadth of a subject as seen by a camera system, was measured by a camera. Therefore, we propose to extract the area of interests using photographic location, orientation and angle of view in geo-referenced and oriented photographs. We demonstrate our approach by extracting the area of interests using photographs annotated with those metadata from Flickr.

Keywords: Area of interest, Shooting spot, Photograph location, Photograph orientation, Clustering

1 INTRODUCTION

According to the increasing popularity of mobile devices such as digital cameras and smartphones, numerous photographs taken by photographers have been uploaded to photo-sharing web services such as Flickr [21] and Panoramio [22]. Recently those devices have included embedded global positioning system (GPS). Using them, photographers can readily take photographs with photographic metadata. A photographic location which is one of a type of the metadata observed by GPS shows a place at which photographer took a photograph. Also, photographic orientation indicates the direction in which the photograph was taken from the photographic location. Particularly, photographs with a photograph-orientation feature have become numerous recently. Also, many photographs on photo-sharing sites have metadata that are annotated by users through social tagging.

Many people might take photographs of subjects or landscapes satisfying their own interests. Then, they upload those photographs to the sites. As places at which many photographs have been taken, these locations might also be interesting places for many people to visit. In this paper, we define such places as a hotspot. Also, we can extract the interesting places using photographs obtained from photo-sharing sites. Even if it is in a famous tourism spot, all areas in the spot are not necessarily worth for sightseeing. Therefore, some methods have been proposed to extract hotspots based on photographic locations from photographs at photo-sharing sites [8], [14], [17], [23], [24]. The extracted hotspots might reflect people's interests, or be useful for marketing research, spatial analysis, and so on [13], [30]. Analyzing such areas is necessary for industries such as those related to tourism [12],[13] . Furthermore, tourist attraction recommendation systems such as [10], [12] can use this approach. By presenting hotspots to people who visit a city for the first time, our approach assists tourism.

A hotspot is classifiable into two types: area of interest (a place captured in the photographs), or shooting spot (a place to take photographs). Figure 1 shows examples of shooting spots and area of interests. In Fig. 1, the gray circle shows photographic location. The break line shows pseudo triangle calculated by the photographic orientation and angle of view. The cell surrounded by a solid line represents a part of the area. Also, the cell filled by gray shows shooting spots, and an area of interest. We define a shooting spot as one type of hotspot in . When a photographer takes a photograph of attractive spots such as landmarks or landscapes, they take the photographs at a place which is distant from the spots. Also, an area of interest (or point of interest) of the other type of a hotspot is attractive as tourist spots for many people (e.g., Colosseum, Statue of Liberty). In such areas, many photographers take a lot of photographs inside or nearby from distant places. Such places are also extracted as hotspots and are defined as an area of interest. In addition, hotspots occur because of an event that might occur. When an event such as reworks display happens, many people take photographs related to the event.

Although many methods to extract and visualize the area of interest from photo-sharing sites have been proposed, those studies extract area of interest using photographic location where photographs were taken. Almost researchers to discover area of interests extract places where the density of photographic location is higher than other places using the density-based clustering algorithm like Density-based spatial

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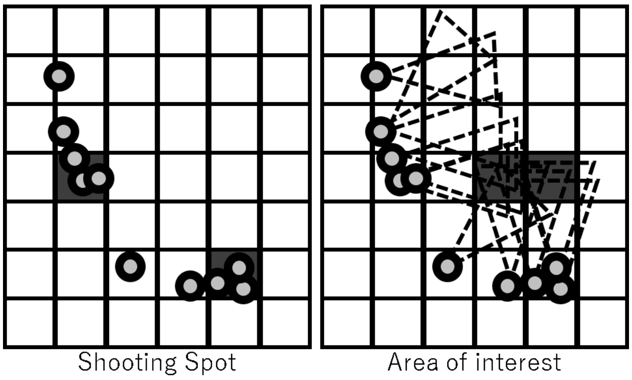


Figure 1: Example of area of interest and shooting spot using photographic location and pseudo triangle.

clustering of applications with noise (DBSCAN) [5] and P-DBSCAN [5].

However, in almost case, a photographic subject of a photograph is several meters away from a place where a photographer took the photo, like Fig. 1. As a result, a place extracted based on the density of photographic location is not the area of interest, but shooting spot. Therefore, we extract area of interests using photographic orientation and angle of view of a photograph. Modern cameras and smartphones equipped with a digital compass can add the metadata of photographic orientation taken by a user. Photographic orientation presents the direction in which the photograph was taken. Also, the angle of view is the angular degree of a given scene that is included in the photograph taken with a camera.

In this paper, we propose a novel clustering method to extract area of interests using photographic orientation and angle of view. In our approach, we use pseudo triangle which is created by the photographic orientation and angle of view. We classify the area into an area of interest or not based on the degree of overlap of the triangles.

The remainder of the paper is organized as follows. Section 2 presents works related to extracting hotspots and area of interests. Section 3 presents a description of our proposed method to extract area of interests using photographic orientation and angle of view. 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 Clustering Algorithms to Extract Hotspots

Some methods have been proposed to extract hotspots from the many photographs with the photographic location which are available on photo sharing sites. There are two main approaches to extract hotspots using the photographic location.

First approach is the density-based clustering algorithm such as DBSCAN [5] or mean shift [40] to extract hotspots from a dataset which includes huge photographs annotated with photographic location. Crandall et al. presented a method to extract hotspots using mean shift based on many photographs annotated with photographic location from the photo-sharing site [4]. Kisilevich et al. proposed P-DBSCAN, which a density-based clustering method improved DBSCAN for the definition of reachable point, to extract hotspots using the density of photographic locations [8]. Ankerst et al. proposed a clustering method of OPTICS which is a variation of DBSCAN to create a cluster using different subspaces extracted from various parameter [34]. Sander et al. proposed GDBSCAN of generalized DBSCAN which extends to enable the corresponding to both spatial and their non-spatial features [33]. Shi et al. proposed density-based clustering method to extract places of interest using spatial information and the social relationships between users [24].

The other approach to extract hotspots is grid-based clustering algorithm. Grid-based clustering is that the data space is quantized into a finite number of cells which is formed by the grid structure. Also, in the grid-based clustering, identifying which a cell is a cluster or not is the number of data included in the cell. The main advantage of the algorithm of grid-based clustering is a fast processing time, which most of the algorithms achieve a time complexity $O(n)$ of where n is the number of data (e.g. DBSCAN is $O(nlog(n))$ using kd-tree) [32]. Also, the performance of clustering depends only on the size of the grids which is usually much less than the data objects [31]. Additionally, almost grid-based clustering algorithms are easy to extent parallelization, because each cells are independent when the algorithm detects whether the cell is defined as a cluster or not. Agrawal et al. proposed CLIQUE to extract clusters within subspaces of the dataset using apriori-like technique [36]. Wang et al. present STING which represents a grid-based and density-based approach [35]. Chang et al. proposed Axis-Shifted Grid-Clustering algorithm, which is a dynamic adjustment of the size of the original cells in the grid and reduction of the weakness of borders of cell [3].

Our proposed method to extract area of interests calculates the density of the area which photographers took photographs. We extract clusters as hotspots based on density in a grid space. To calculate a density of each cells in the grid, we use overlaps of the area taken by photographers, calculated by photographic location, orientation, and angle of view of photographs. In this paper, our proposed method adopts the number of overlaps of pseudo triangles at which photographs were taken in each cells to identify a cell is the area of interests or not. The location is a point, but calculated pseudo triangles present an area. Therefore, the amount of data obtained from the pseudo triangles applied to clustering algorithm is more huge, comparing to the approach using photographic location. Therefore, the time complexity of the advantage of the grid-based approach is important to treat huge photographs.

2.2 Extraction of Hotspots Based on Photograph Orientation

According to photographs with a photographic orientation have become more commonly available, photographic orientation is used for extracting hotspots. Lacerda et al. proposed a method for extracting hotspots using photograph orientations [9]. This method calculates the intersections between lines of photographic orientation of many photographs. The intersections are clustered using DBSCAN. Also, Thomee et al. proposed a method for consideration of inaccuracies affecting GPS location measurements [17].

However, those methods to extract hotspots using photographic orientation do not consider the angle of view of photographs. The angle of view is important information which shows an area of user interest. Therefore, we propose a method to extract area of interests considering both photographic orientation and angle of view.

In the related literature, some methods to estimate the photograph orientation have been presented, even for photographs that appear to have no photograph orientation [11], [7]. Our method uses the photographs with photograph orientation to extract area of interests. Therefore, we expect to use the estimated photograph orientation to increase the accuracy of our method.

2.3 Analysis of Extracted Hotspots

Some researchers study the approach to analyze hotspots obtained from large data annotated with various metadata like photographic location.

The method to extract hotspots is used to find or detect geographical characterization. Spyrou et al. proposed a method to understand the underlying semantics of extracted hotspots using user-generated tags [25]. Omori et al. evaluate georeferenced photographs annotated with user-generated tags related to coastlines show actual coastline [37]. Hu et al. proposed a method to understand urban areas from extracted hotspots using user-generated tags, and choice preferable photos based on image similarity of photographs in the hotspot [39].

Also, there are some methods to extract the relationship between a hotspot to another hotspot such as the relationship of photographic subjects and shooting spots. Shirai et al. proposed a method to extract a hotspot using DBSCAN and to calculate the relation of hotspots [14], [42]. To discover a wide area of interest, this approach infers the relation among hotspots based on the photograph location and orientation. Hirota et al. proposed a method to detect and visualize various relationship of hotspots using photographic orientation and social tagging [6]. Those researchers extract some relationships from extracted hotspots.

The area of interests extracted by our proposed method represents photographic subjects at which many people took photographs. In other words, comparing to previous methods to extract hotspots, our methods can extract hotspots reflecting interests of users. Therefore, our approach might contribute researchers to characterize the region and extract relationships using hotspots.

3 PROPOSED METHOD

We propose a method to extract the area of interests using photograph location, orientation, and angle of view obtained from photo-sharing sites. Our approach includes the following steps.

1. For a particular area, we obtain vast numbers of photographs from photo-sharing site.

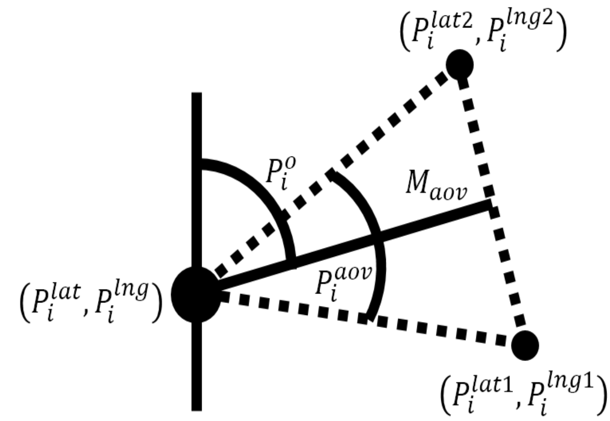


Figure 2: The symbols of pseudo triangle calculated by photographic orientation, location, and angle of view.

2. Generation of a pseudo triangle of a photograph, which represents photograph area which a photographer was taken, based on photographic location, orientation, and angle of view.
3. From photographs which we use to analyze the particular area, we create grid space and cells which the size specified by a user.
4. We count the number of the pseudo triangles in each cell, and define the number is more than the threshold as the area of interest.

We describe details related to the respective steps below.

3.1 Calculation of Pseudo Triangle of a Photograph

We describe calculation of a photograph triangle which represents photograph area using photographic orientation, location and angle of view. Here, Fig. 2 shows the symbols for following equations to calculate the pseudo triangle of a photograph. The pseudo triangle consists photographic location, orientation, and angle of view.

The angle of view is the angular degree of a given scene that is included in the photograph taken with a camera. The angle of view p_i^{aov} of photograph p_i in photographs $P = \{p_1, p_2, ..., p_n\}$ is calculated from focal length p_i^f and the image sensor size p_i^l as follow.

$$p_i^{aov} = 2 * tan^{-1}\left(\frac{p_i^l}{2 * p_i^f}\right) \quad (1)$$

To calculate the pseudo triangle of a photograph, we detect the three points of the triangle. The triangle of photograph p_i consists of vertex, angle of the vertex, photographic orientation p_i^o, and the other two points. The vertex of the triangle is the photographic location of latitude and longitude obtained from GPSLatitude and GPSLongitude in Exchangeable image file format (Exif). The angle of the vertex is angle of view p_i^{aov} of the photograph p_i. The other two points are calculated based on photographic location and orientation p_i^o, the angle

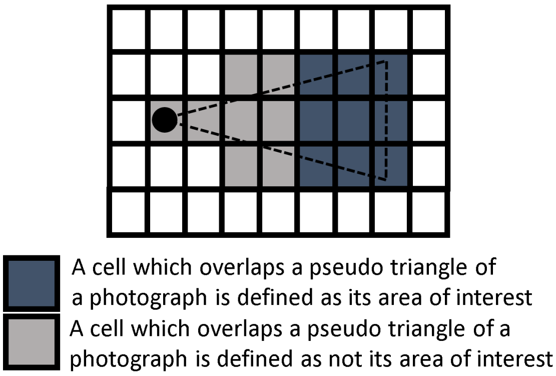


Figure 3: The definition of overlaps of cells and pseudo triangle of a photograph.

of view, and the distance of the photographic subject. We calculate the two points (p_i^{lat1}, p_i^{lng1}) and (p_i^{lat2}, p_i^{lng2}) using following equations.

$$p_i^r = \frac{(p_i^o + p_i^{aov} * 0.5) * \pi}{180} \tag{2}$$

$$d_i^{lat} = M_{aov} * \cos(p_i^r) \tag{3}$$

$$d_i^{lng} = M_{aov} * \sin(p_i^r) \tag{4}$$

$$p_i^{lat1} = p_i^{lat} + d_i^{lat} * \frac{180}{\pi * ER} \tag{5}$$

$$p_i^{lng1} = p_i^{lng} + d_i^{lng} * \frac{180}{\pi * ER * \cos(\frac{p_i^{lat1} * \pi}{180})} \tag{6}$$

Here, ER is radius of earth. Also, M_{aov} shows the parameter how meter distant from latitude p_i^{lat} and longitude p_i^{lng} of photographic location of a photo p_i. (p_i^{lat2}, p_i^{lng2}) are calculated by the same procedure that the direction changes $p_i^o + p_i^{aov} * 0.5$. to $p_i^o - p_i^{aov} * 0.5$.

3.2 Calculation of Grid

To identify places of area of interest which many people have taken in the photograph, we specifically examined the number of overlaps extracted pseudo triangle of photographs. We create a two-dimensional grid which consists square cells. Here, the area which we want to analyze is much wider than the pseudo triangle of one photograph. Therefore, first, we map photographs which have a photograph location to the grid. Also, using the assigned coordinate of the grid, we count the number of the number of extracted pseudo triangle of photographs.

$$y_i = M_{height} - \frac{(p_i^{lat} - Lat_{min}) * M_{height}}{Lat_{max} - Lat_{min}} \tag{7}$$

$$x_i = M_{width} - \frac{(p_i^{lng} - Lng_{min}) * M_{width}}{Lng_{max} - Lng_{min}} \tag{8}$$

Here, Lat_{max}, Lat_{min}, Lng_{max}, and Lng_{min} respectively denote the maximum and minimum values in $\{p_1^{lat}, p_2^{lat}, ..., p_n^{lat}\}$ and $\{p_1^{lng}, p_2^{lng}, ..., p_n^{lng}\}$. Additionally, M_{height} and M_{width} are the number of horizontal and vertical cells. These parameters are decided by how many meters to make one side of a cell. For example, when the length of height of a cell is $m = 50$ meters, M_{height} are calculated as follow.

$$M_{height} = \frac{h(Lat_{max}, Lat_{min})}{m} \tag{9}$$

Here, $h(Lat_{max}, Lat_{min})$ is Hubeny distance between the Lat_{max} and Lat_{min} (Because these are actually points, either Lng_{min} or Lng_{max} is used for this calculation, but there is almost no difference in the result). M_{width} is calculated by the same procedure.

Consequently, each cells in the obtained grid include a photograph taken in the range.

3.3 Extraction Area of Interest

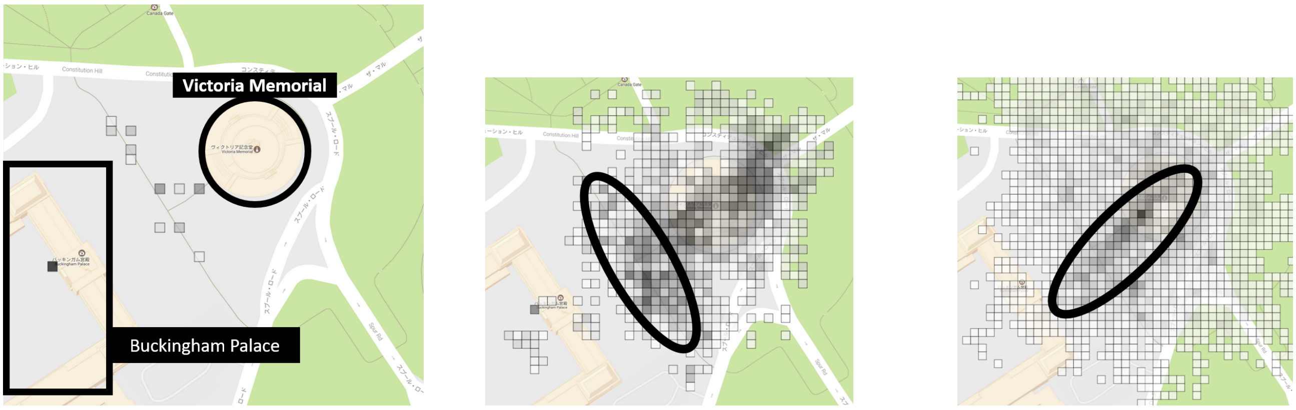
We discover the area of interest from the obtained cells using the overlaps of pseudo triangle extracted in previous steps. Figure 3 shows the overlapped cells of the pseudo triangle of a photograph. In the figure, the black circle shows the photographic location. Dashed lines of triangle consist of the pseudo triangle of a photograph. Here, the cells filled with light gray or dark gray are overlapped to the pseudo triangle. We detect the overlaps of the dashed line and cells based on photographic location and the vertexes of pseudo triangle of a photograph using Bresenham's line algorithm [43]. In this paper, we use the cells filled with dark gray as the user's interests shown by a photograph. The reason why our approach does not use some cells close to the photographic location is we think those cells might present the shooting spot, not the interests. Although some cell which might be extracted as a shooting spot includes many photographs, and the number of overlaps in such cells may be higher than other cells like not a shooting spot. As a result of the case that we do not eliminate the cells filled with light gray, almost extracted cells are not the area of interests which our approach wants to extra, but shooting spot. Therefore, in this paper, our approach only uses cell filled with dark gray to extract the area of interest.

We classify whether a cell show interests of a photograph by three cases. First, a cell includes the triangle. Second, the triangle includes a cell. Finally, a line segment of the triangle intersects the line segments of a triangle. Additionally, we remove the cells close to the photographic location, from classified cells. The criterion for close cells is the distance based on photographic location and M_{aov}. In this paper, eliminated cells are closer than $0.5 * M_{aov}$ like the cells filled with light gray in Fig. 3.

We apply this procedure to the cells of all photographs and count the number of cells detected as the interests. If the number of photographs in a cell is greater than threshold $minP$, then the cell is classified as an area of interest. Finally, we visualize the extracted area of interest on Google Maps [20].

4 EXPERIMENTS

This section presents a description of experiments conducted using our proposed method. We present and discuss several examples of detection of visualization of area of interest.



(a) Shooting spot **(b)** Our method **(c)** Compass clustering

Figure 4: The results obtained from photographs which were taken around Buckingham palace and Victoria Memorial.

4.1 Datasets

We describe the dataset for experiments for visualizing the area of interests. Photographs for experiments are obtained from photographic search results of Flickr. Those photographs have Exif metaadata of latitude (GPSLatitudeRef, GPSLatitude), longitude (GPSLngitudeRef, GSPLongitude), orientation (GPSImgDirection, GPSImgDirectionRef), and focal length. We obtained 5,842,337 photographs taken during 1 January 2005 - 20 20 May 2016 and taken in London.

4.2 Comparison Method

We use compass clustering [9] as comparison method. This clustering method uses the intersections of pseudo orientations of a photograph to extract people's interests. DBSCAN clusters extracted intersections, and the calculated clusters are defined as the area of interests in the method. To simplify comparison between our method and the compass clustering, we change grid-based clustering from the procedure of clustering the intersections. Therefore, we map the intersections into cells of a grid and extract the cells which include the number of photographs than a threshold of $minP$ as the area of interests.

4.3 Visualization of Area of Interests

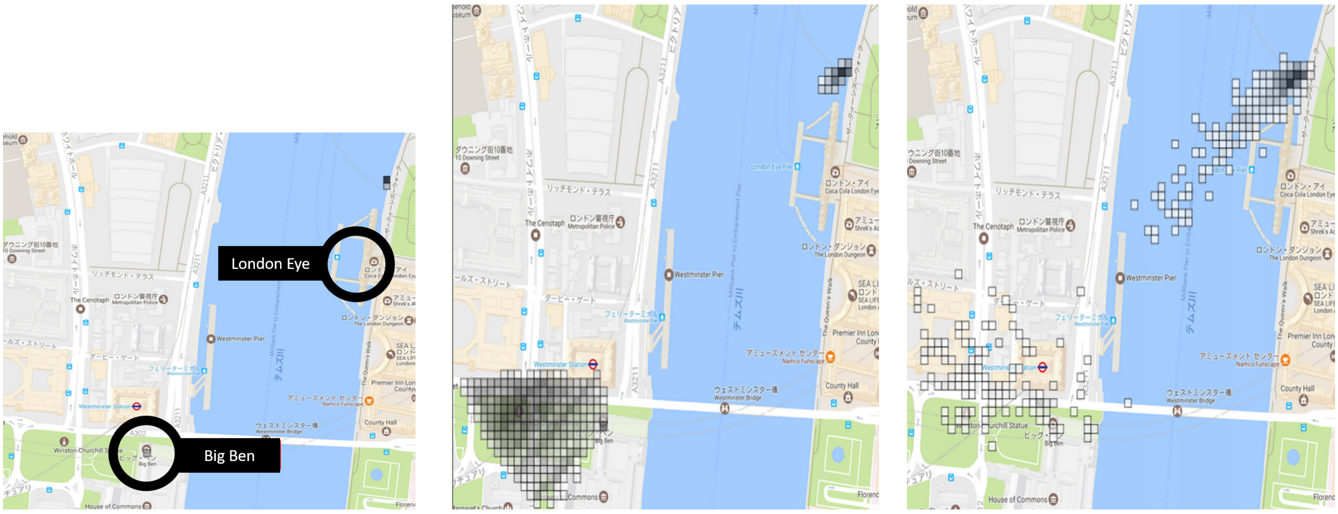
Figure 4 presents results of hotspots extracted from photographs in the area of Buckingham Palace, using our proposed method, compass clustering, and shooting spots. We used 2,023 photographs taken in the area (latitude: -0.145 - -0.138 and longitude: 51.506 - 51.499). The clustering parameters are set as $minP = 40$, $M_{aov} = 100$ meters, and $m = 5$ meters. Here, in this paper, we set the value of parameters manually with confirming the experimental results. In those figures, the polygon shows the place extracted as a hotspot. In Fig. 4(b) and Fig. 4(c), the more dark color of a polygon from white to black, the cell includes more numbers of the photographic area of photographs. Also, in Fig. 4(a), the more dark color of a polygon from white to black, the more photographs were taken in the area. Also, in those figures, black circle shows the area of Victoria Memorial, and black rectangle shows the area of Buckingham Palace.

Figure 4(a) shows the one shooting spot in Buckingham palace, and eleven shooting spots around Victoria Memorial. The shooting spots include the photographs taken of those subjects. However, although the Victoria Memorial is one of the famous monument and photographic subject, its place is not extracted as shooting spot. The reason is when people may take a photograph of the subject, they take apart from the subject. On the other hand, in Fig. 4(b) and Fig. 4(c), the extracted area of interests shows the more wide area than shooting spots of Fig. 4(a), because those methods use the line of photographic orientations or pseudo triangles.

In result of compass clustering of Fig. 4(c), there are the dark polygons linearly from Victoria Memorial to Buckingham Palace. Because compass clustering extracts the area of interest using the pseudo orientation of photographs, the method tends to extract the area of interests linearly. On the other hand, in the result of our proposed method in Fig. 4(b), there are the black polygons widely in the black ellipse. Here, the gate of Buckingham Palace exists over a wide range in the area of the ellipse. Therefore, many people take photographs of the gate and Buckingham Palace, and our proposed method discover the place as the area of interests in result shown in Fig. 4(b). Our approach uses the angle of view to discover the area of interests to consider the region of the interests. As a result, our proposed method can extract the broad subject as the area of interests.

Next, we show another result in the case that the distance between the area of interests and shooting spots is farther away. Figure 5 presents results of hotspots extracted from photographs around Big Ben and London Eye. There is a Themes river between Big Ben and London Eye. Thus, the distance between those spots is about 500 meters. We used 704 photographs annotated with tags related Big Ben, and taken in the area (latitude: -0.130 - -0.105 and longitude: 51.598 - 51.518). The clustering parameters are set as $minP = 40$, $M_{aov} = 100$ and $m = 10$ meters.

In Fig. 5(a), two shooting spots are extracted around London Eye. Therefore, the result shows there is interest from the place to Big Ben. In Fig. 5(b), and 5(c), both method extracted the area of interests around London Eye and Big Ben. However, the area of interests by compass clustering method



(a) Shooting spot **(b)** Our method **(c)** Compass clustering

Figure 5: The results obtained from photographs which were taken around Big Ben and London Eye.

is a few that our method around Big Ben, and the compass clustering added heavyweights to the places around London Eye. This reason is that the compass clustering method uses the intersections calculated by the pseudo orientation. In this case, because the area of interests which we want to visualize is far from shooting spots, the points of the intersects is more diverse, and the extraction of the interests is more difficult. On the other hand, because our method calculates the interests using the pseudo triangles which show the users interest, even if the distance is far, our approach can extract overlaps of users interests.

Next, we discuss the parameter M_{aov} of the distance between photographic subject and location of a photograph. In Fig. 5(b), and 5(c), there are some defined cells as the area of interests beyond Big Ben. We assume this reason is the diversification of distance between photographic subject and location in our approach and the compass clustering. Therefore, the photographic areas extracted by our approach have some errors based on the distribution of photographic location.

Figure 6 show the result of area of interest obtained from the same dataset of Fig. 5, when extracting the area of interest using both the cells which close cells from the photographic location (the cells filled with light gray in Fig. 3) and cells which we use to extract area of interest in Section 3.3 (the cells filled with dark gray in Fig. 3). This result shows many photographers took photographs to Big Ben from London Eye. Therefore, the cell with the most significant number of overlaps of pseudo triangles is the area around London Eye. Also, the color of cells changes black into white from London Eye to Big Ben. This shows that the number of the overlaps is decreasing from London Eye to Big Ben. As a result, although fig. 6 shows the result that many photographers took photographs from London Eye and Big Ben, the black cells do not show the area of interests about Big Ben but shooting spots about Big Ben, compared to Fig. 5(b). Therefore, the procedure of excluding the cell which is close to photographic location is important for extracting the accurate area of interest.

We summarize the visualization result obtained by our proposed method and discuss the performance improvement. Comparing to the area of interest extracted using compass clustering, our proposed method extracts more wide area as the area of interest, shown in Fig. 4. Also, we extract the area of interest around Big Ben, but compass clustering extracted area of interest near London Eye, shown in Fig. 5(c). This reason is intersections of pseudo orientation in compass clustering are concentrated around the shooting spot near London Eye. On the other hand, our proposed method shown in Fig. 5(b) extracted area of interest around Big Ben. This advantage is the pseudo-triangle and the eliminated cells described in Section 3.3. To make extraction of the area of interests more accurate, we should estimate the distance between the photographic location of a photograph and each subject in the photograph.

5 CONCLUSIONS

We proposed a method to extract and visualize the area of interests using photograph metadata of photographic orientation, location, and angle of view obtained from photo-sharing sites. Our approach identifies a cell in grid mapped from photographs into the area of interest or not, using the overlaps of pseudo triangles extracted by the photograph metadata. We presented some examples of results obtained from Flickr using our proposed method. Comparing to the other method to extract the area of interests based on photographic orientation, our proposed method can extract the area of interests at more widely, and it is possible to visualize the contents of the area of interests more importantly.

Future studies will be conducted estimate metadata such as photographic orientation, the distance between the photographic location and the subjects of photograph. Regarding photographic orientation, the applicability of our approach depends on the number of photographs with the metadata and their accuracy. Also, in this paper, we set manually the parameter M_{aov} of distance between subjects of a photograph and

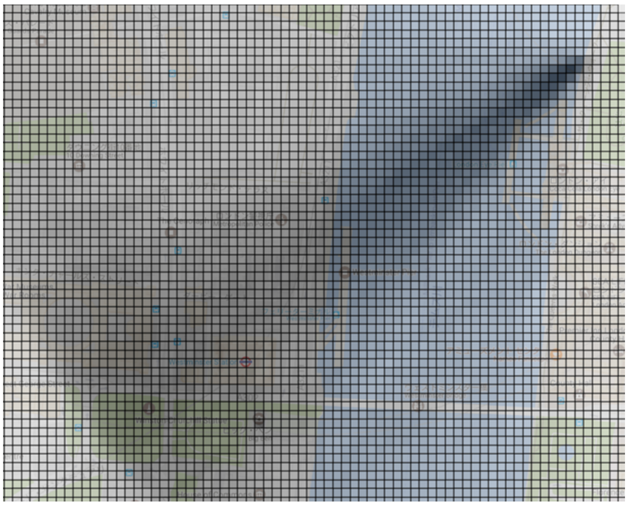


Figure 6: The result of area of interests without excluding the close cells from photographic location (i.e. the result is extracted from light and dark gray cells 3).

photographic location. The parameter M_{aov} depends on the situation of a photographer took a photograph. Therefore, to extract the accurate area of interests extracted by our proposed method, we should set appropriate parameter. Additionally, we will recommend travel routes considering shooting spots and area of interests, because we think that such places which can take photographs around famous landmarks are important for tourism.

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