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Discovering Hotspots with Photographic Location and Altitude from Geo-tagged Photographs

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***Abstract*—A hotspot is an interesting place where many people go sightseeing. A place where many photographs have been taken (which we call a hotspot) might be an interesting place for many people to visit. Analyzing such places is important to promote industries such as those related to tourism. To identify hotspots, most existing research applies a grid-based or density-based clustering algorithm, such as density-based spatial clustering of applications with noise (DBSCAN) or mean shift. When applying such methods to hotspot detection, the features used for clustering are latitude and longitude. Therefore, the identified hotspots are visualized in a two-dimensional space. However, large areas, landmarks, and buildings may include elevated hotspots or multiple hotspots with different altitudes, which cannot be distinguished by latitude and longitude. Therefore, in this research, we propose methods for identifying hotspots based on altitude, in addition to latitude and longitude, and visualizing these hotspots in a three-dimensional space. We propose two types of method, based on density-based and grid-based clustering, that use these features. The first method is one that improves ST-DBSCAN, which clusters data based on spatial and time features. The other method is an extension of general grid-based clustering using these features. As an example application, we classified the identified hotspots as shooting spots, observation spots, areas of interest, and others. We demonstrate our approach by identifying hotspots in a three-dimensional space using photographs obtained from Flickr, and discuss the usefulness of detecting hotspots using altitude in addition to latitude and longitude.**

Keywords*–*area of interest; density-based clustering; grid-based clustering; photograph location; clusteing.

I. Introduction

A considerably shorter pre-version of this paper has already been published in [1].

Owing to the increasing popularity of mobile devices, such as digital cameras and smartphones, numerous photographs have been uploaded to photo-sharing web services, such as Flickr [2], Instagram [3], and Google Photos [4]. In addition, these digital devices have recently been equipped with Global Positioning System (GPS) sensors. Thus, many photographs are annotated with latitude and longitude information, which shows the place where the photograph was taken. If many people take photographs in the same area, this may be an area of interest. As described in this paper, we define such areas as hotspots. The identified hotspots are used to analyze urban areas [5] and tourist behavior [6].

Many methods have been proposed to identify hotspots [7], [8], [9], [10], [11]. Most existing research on detecting hotspots is based on a density-based or grid-based clustering method, such as density-based spatial clustering of applications with noise (DBSCAN) [12] and mean shift [13]. The studies that apply these methods use latitude and longitude as features to identify high-density areas as clusters, and the detected clusters are then defined as hotspots. However, clusters obtained by such a method, only using latitude and longitude, do not consider altitude. Therefore, there are some cases where multiple hotspots, at different altitudes, are identified as one hotspot. For example, in a sightseeing location such as the Eiffel Tower, the latitude and longitude for the observatory and the area around the tower are almost the same, but there are several hotspots with different altitudes. Even if the altitude is different, because these latitudes and longitudes are almost equal, it is difficult to distinguish between these hotspots.

In our previous research [1], we proposed a method for detecting hotspots, using ST-DBSCAN [14], which deals with the time when the photograph was taken, in addition to latitude and longitude. When we apply ST-DBSCAN in this paper, we use altitude instead of time to detect hotspots, thereby considering the height of the hotspot. In this paper, as an alternative approach, we propose a method using grid-based clustering. Previous research has been conducted on grid-based clustering for detecting hotspots in two-dimensional space. In this paper, we extend the method to three-dimensional space. In addition, this paper compares the two types of proposed method, by the visualization results and execution time.

The remainder of this paper is organized as follows. Section II describes the difference of extracted hotspots on 2D or 3D. Section III describes work related to this topic. Section IV presents our two types of proposed method for detecting hotspots based on altitude. Section V presents several examples of visualization results, and experiment on execution time by our proposed methods. Section VII concludes the paper with a discussion of the results and future work.

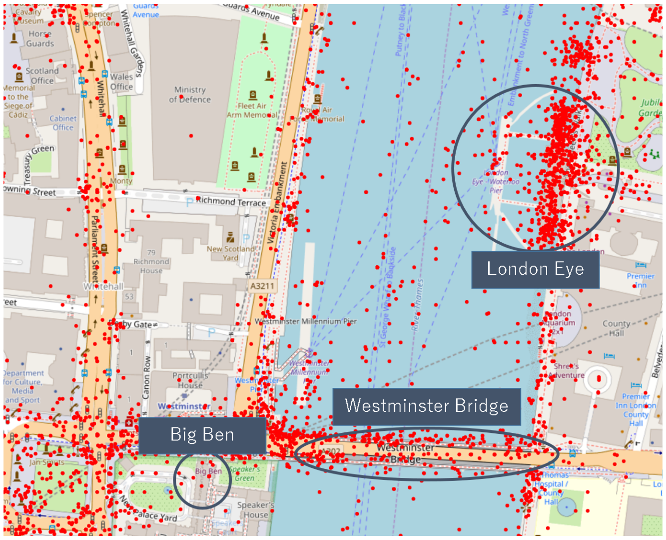

Figure 1. Visualization of photograph location on 2D.

TABLE I. Famous landmarks in London.

Name	Latitude	Longitude
Big Ben	51.500729	−0.124625
London Eye	51.503324	−0.119543
Westminster Bridge	51.500942	-0.121874

II. Extracting hotspots on 2D and 3D

In this section, we discuss the difference between extracted hotspots using methods on 2D and 3D.

Figure 1 visualizes the photographs obtained from Flickr. According to the latitude and longitude, we superimposed these photographs on a map of OpenStreetMap [15]. These photographs were taken in London. There are several famous buildings in this area, which are listed in Table I. The red points in the figure show locations of photographs (obtained from Flickr) that were taken around Big Ben, the London Eye, and Westminster Bridge. The number of photographs is 5,000, which we randomly selected from the obtained photographs. There are some areas around the three tourist attractions that have a high density of points.

We applied DBSCAN to these data and detected 23 clusters. Figure 2 shows the clustering result. The points in this figure show the photograph locations that were classified as belonging to clusters. Each color in the figure represents one cluster (the colors are only used to distinguish visually between the clusters). Figure 3 shows the visualization results of the same photograph location data as in Figure 1, but using latitude, longitude, and altitude in a three-dimensional space. The blue points in this figure show the photograph locations. This figure clearly shows the diversity of the altitudes of the photograph locations. The red points in Figure 1 around the London Eye have a high density. Figure 3 shows that there are actually two high-density groups of locations in the area of the London Eye: at the top of the wheel and at ground level. We believe that these two groups should be identified as distinct clusters. However, in Figure 2, these photograph locations are regarded as a single cluster. If hotspots are identified using latitude and longitude, distinction between those hotspots is difficult, but using altitude information makes it possible to distinguish them.

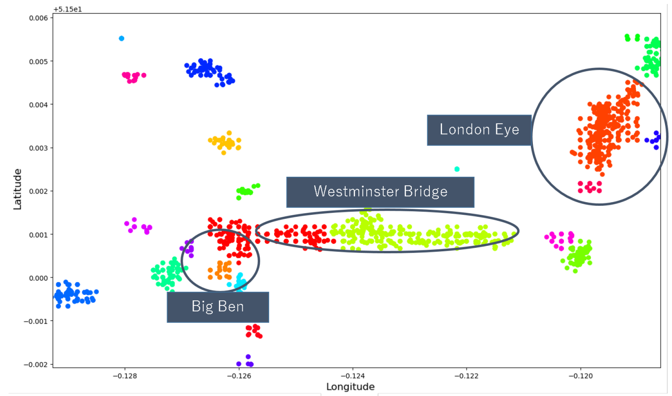

Figure 2. Clustering result by DBSCAN.

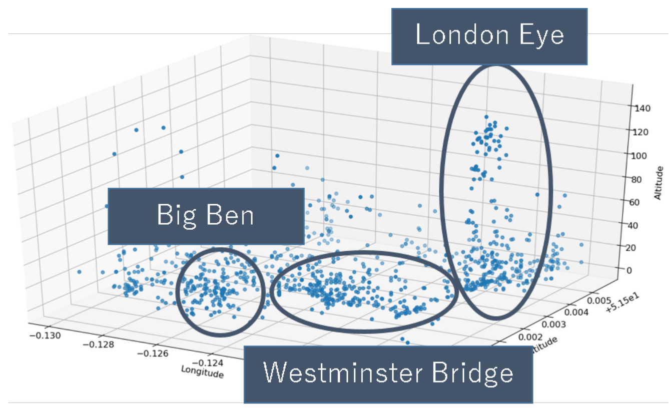

Figure 3. Visualization of photograph location on 3D.

Common methods for detecting hotspots such as DBSCAN and mean shift treat the distance between two points as one dimensions using latitude and longitude. We believe that these methods are inappropriate for clustering with three-dimensional metadata. In this research, we propose approaches that considers not only the area of a hotspot, represented by latitude and longitude, but also the height of the hotspot, by adding the altitude.

Additionally, hotspots can be classified into three types: an area of interest, a shooting spot, and an observation spot [16], [17]. Areas of interest include tourist attractions (for example, the Colosseum or the Statue of Liberty). In such areas, many photographs have been taken inside the site or at a nearby location. However, when people take a photograph of such an attraction, they will take it at a place that is at some distance from the attraction itself. Such places are also identified as hotspots, and are defined as shooting spots. Finally, observation spots are hotspots for photographing the surroundings of the hotspot. In this research, we classify hotspots, detected considering the altitude in addition to latitude and longitude, into three classes by considering multiple information sources, such as the direction of photography, and we then visualize the results.

III. Related Work

In this section, we discuss some work related to our study, including detecting hotspots and analyzing the detected hotspots.

A. Detection of hotspots

Various methods have been proposed to detect hotspots in a large dataset using location information. In the case of detecting hotspots from large datasets of photographs annotated with location metadata, two main approaches are used: density-based clustering algorithms, such as DBSCAN [12] and mean shift [13], and grid-based clustering algorithms.

Crandall et al. presented a method to detect hotspots using mean shift based on many photographs annotated with photograph location [18]. Kisilevich et al. proposed P-DBSCAN, an improved version of DBSCAN, for the definition of a reachable point, to detect hotspots using the density of photograph locations [19]. Ankerst et al. proposed a clustering method OPTICS, which is a variant of DBSCAN used to create a cluster using different subspaces extracted from various parameters [20]. Sander et al. proposed GDBSCAN, which extends DBSCAN to enable correspondence to both spatial and non-spatial features [21]. Shi et al. proposed a density-based clustering method to detect places of interest using spatial information and social relationships between users [22]. Chen et al. proposed a clustering method for massive sets of spatial points based on density peaks and connect [23]. Yang et al. proposed a method to identify human mobility hotspots using kernel density estimation to evaluate convergent and dispersive hotspots [10]. Yang et al. proposed an algorithm to detect hotspots of various sizes using self-tuning spectral clustering [8]. Kulkarni et al. proposed a parameter-free method for detecting hotspots from spatiotemporal trajectories without any *a priori* assumptions [9].

Another famous approach to detecting hotspots is the grid-based clustering algorithm. In grid-based clustering, the data space is quantized into a finite number of cells, which are formed by the grid structure. Whether a cell is a cluster is determined by the number of data points included in the cell. The main advantage of grid-based clustering algorithms is a fast processing time: most of the algorithms achieve a time complexity of $O(n)$, where n is the number of data points (compared with, for example, DBSCAN, whose complexity is $O(n \log n)$ using tree algorithm such as a k-dimensional tree [24]) [25]. Moreover, the performance of grid-based clustering depends only on the size of the grid, which is usually much less than the number of data points [26]. Additionally, most grid-based clustering algorithms are easy to parallelize because each cell is independent when the algorithm detects whether the cell is defined as a cluster. Agrawal et al. proposed CLIQUE, to detect clusters within subspaces of the dataset using an *a priori*-like technique [27]. Wang et al. presented STING, which combined grid-based and density-based approaches [28]. Chang et al. proposed the axis-shifted grid-clustering algorithm, which performs a dynamic adjustment to the size of the original cells in the grid and a reduction in the weakness of the borders of cells [29].

The studies outlined above detect hotspots using a density-based clustering method, such as DBSCAN, or a grid-based clustering method, both based on latitude and longitude. However, in some cases, actual hotspots include the concept of height and are distributed in three-dimensional space, rather than a two-dimensional space. In this paper, we propose two new types of approach to detecting and visualizing hotspots using ST-DBSCAN or grid-based clustering, by adding altitude to latitude and longitude.

B. Detecting hotspots based on photograph orientation

As photographs with a photograph orientation have become more commonly available, photograph orientation has been increasingly useful for detecting hotspots.

Photograph orientation is an important information source, because it constitutes information about the user's interests. The photographer shoots a subject of his or her own interest from some location. The direction of the subject is combined with the photograph location. Therefore, hotspots are likely to exist in the directions taken by users.

Lacerda et al. proposed a method for detecting hotspots using photograph orientations [30]. This method calculates intersections between the lines of the orientations of many photographs. The intersections are then clustered using DBSCAN. In addition, Thomee et al. proposed a method for considering the inaccuracies affecting GPS location measurements [31]. Hirota et al. proposed a method for determining the areas of hotspots using the orientation and angle of view of photographs [32]. This method determines the area from the overlaps of pseudo-triangles calculated by photograph orientation, location, and some other metadata.

The above methods focus on photograph orientation to detect areas where the users' interest is concentrated. Therefore, in this paper, our approach classifies the types of detected hotspots based on the photograph orientation and the users' interest.

C. Analysis of detected hotspots

Some researchers have studied approaches to analyze hotspots obtained from large photograph datasets annotated with various metadata, such as location.

The method to detect hotspots is used to find or detect geographical characteristics. Spyrou et al. proposed a method to understand the underlying semantics of detected hotspots using user-generated tags [33]. Omori et al. evaluated georeferenced photographs annotated with user-generated tags related to coastlines, to show the actual coastline [34]. Hu et al. proposed a method to understand urban areas from detected hotspots using user-generated tags, to choose preferable photographs based on the image similarity between photographs of the hotspot [35]. Chen et al. proposed a framework to detect boundaries of hotspots from geotagged data, and used them to construct spatiotemporal profiles of areas [36]. Zhu et al. proposed a method for analysis of emotions of detected hotspots [37].

There are also some methods to detect the relationship between a hotspot and another hotspot, such as the relationship between photograph subjects and shooting spots. Shirai et al. proposed a method to detect a hotspot using DBSCAN and to calculate the relation between hotspots [38], [16]. To discover a wide area of interest, this approach infers the relation between hotspots based on the photograph location and orientation. Hirota et al. proposed a method to detect and visualize various relationships between hotspots using photograph orientation and social tagging [17]. The above researchers have extracted various relationships from detected hotspots.

The areas of interest detected by our proposed method represent areas in which many people took photographs. We apply these studies to detected hotspots and expect to be able to analyze the results in more detail.

IV. Proposed Method

In this section, we describe our two types of proposed method for detecting hotspots considering the altitude, in addition to the latitude and longitude, of photographs. We also describe our proposed method for classifying the hotspots into three types: area of interest, shooting spot, and observation spot, using photograph location and orientation.

A. Extracting hotspots with altitude using ST-DBSCAN

Here, we explain why we adopt ST-DBSCAN to detect hotspots with altitude, in addition to latitude and longitude. In most of the previous research, DBSCAN has been used for detecting hotspots. Until now, latitude and longitude have been used as features for calculating the distance between two points. Because we now need to consider altitude to detect hotspots, we infer that neither DBSCAN nor mean shift is an appropriate method for this purpose. This is because Eps, which is the parameter of those methods for evaluating the distance between two points, is a one-dimensional threshold. As previously described, there are hotspots with different altitudes but almost equal latitude and longitude. Therefore, although those methods are appropriate for using latitude and longitude as one feature for evaluating the distance between two points, it is not appropriate to add altitude to the feature. As a result, altitude should be regarded as a different feature from latitude and longitude, and we adopt ST-DBSCAN to achieve this.

Moreover, when applying DBSCAN, there is an approach to evaluate distances between photographs using the three features of latitude, longitude, and altitude with one distance function, and detect the cluster with one Eps threshold. However, this is an inappropriate approach for our purposes. The values of latitude and longitude have similar characteristics, but altitude is different from them. Therefore, in this paper, rather than considering latitude, longitude, and altitude as a single feature, we detect hotspots using latitude and longitude as one feature and altitude as the other feature.

ST-DBSCAN is one of the improved methods of DBSCAN that considers time in addition to the spatial feature of latitude and longitude. ST-DBSCAN has three parameters—$Eps1$, $Eps2$, and $MinP$—where $Eps1$ is a threshold of distance between the spatial features of two photographs, $Eps2$ is a threshold of distance between other features, such as the difference between the times when two photographs were taken, and $MinP$ is a threshold of the number of photographs included in the cluster.

Here, we describe the procedure of ST-DBSCAN.

- The method extracts the core data points such that the number of neighborhood data points within $Eps1$ and $Eps2$ is greater than $MinP$.
- The method evaluates the distance between the core data points and others.
- If the distance is less than $Eps1$ and $Eps2$, these data points are connected. The method defines connected data as a cluster.
- The data points for which the number of neighborhood data points (within $Eps1$ and $Eps2$) is less than $MinP$ are defined as noise data and not included in any cluster.

Figure 4 shows an overview of detecting hotspots using ST-DBSCAN. In this figure, the red points are regarded as core data and detected as a cluster, whereas the blue points are regarded as noise data

In this research, we apply ST-DBSCAN, with $Eps1$ as latitude and longitude and $Eps2$ as altitude.

In the implementation of ST-DBSCAN, we use a k-dimensional tree [24] to search neighborhood data. Here, because ST-DBSCAN needs two types of distance, this method constructs two k-dimensional trees: one for latitude and longitude and another for altitude.

B. Detecting hotspots with altitude using grid-based clustering

Our second method for detecting hotspots uses the grid-based clustering approach. Figure 5 shows the procedure of grid-based clustering. This method constructs a three-dimensional grid space with latitude, longitude, and altitude. We map photographs to the grid and count the number of photographs. We extract voxels that contain many photographs and connect the extracted adjacent voxels. The connected voxels are regarded as hotspots.

First, we map the photographs that have a photograph location to the grid. Using the assigned grid coordinate, we count the number of photographs. Photograph p_i is mapped to coordinates (x_i, y_i, z_i), as shown below.

$$z_i = M_{alt} - \frac{(p_i^{alt} - Alt_{min}) * M_{alt}}{Alt_{max} - Alt_{min}} \tag{1}$$

$$y_i = M_{lat} - \frac{(p_i^{lat} - Lat_{min}) * M_{lat}}{Lat_{max} - Lat_{min}} \tag{2}$$

$$x_i = M_{lng} - \frac{(p_i^{lng} - Lng_{min}) * M_{lng}}{Lng_{max} - Lng_{min}} \tag{3}$$

Here, Alt_{max}, Lat_{max}, and Lng_{max} denote the maximum values of altitude, latitude, and longitude, respectively; Alt_{min}, Lat_{min}, and Lng_{min} denote the corresponding minimum values. M_{alt}, M_{lat}, and M_{lng} are the height, length, and width of the grid. (This is decided using a parameter m to adjust the number of cells required in this procedure. In this paper, we set these parameters to be the same as the ST-DBSCAN parameters $Eps1$ and $Eps2$.) 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 included in the cell is greater than the threshold $MinP$.

At this stage, having determined whether each individual cell is a hotspot, we connect any extracted hotspots that are in adjacent cells. We calculate the distance $D(c_p, c_q)$ between cells c_p and c_q as the Chebyshev distance, as follows.

$$D(c_p, c_q) = max_i(\|c_{pi} - c_{qi}\|) \tag{4}$$

where c_{pi} and c_{qi} represent the feature value of c_p and c_q, respectively, in the i-th dimension. We connect the two cells if $D(c_p, c_q)$ is 1, which means that those cells are adjacent; otherwise the cells are not adjacent.

Finally, each group of joined cells is defined as a hotspot.

C. Classification of hotspot

In this paper, a hotspot is classified as an area of interest, a shooting spot, or an observation spot (as shown in Figure 6) using the orientation annotations of the photographs included

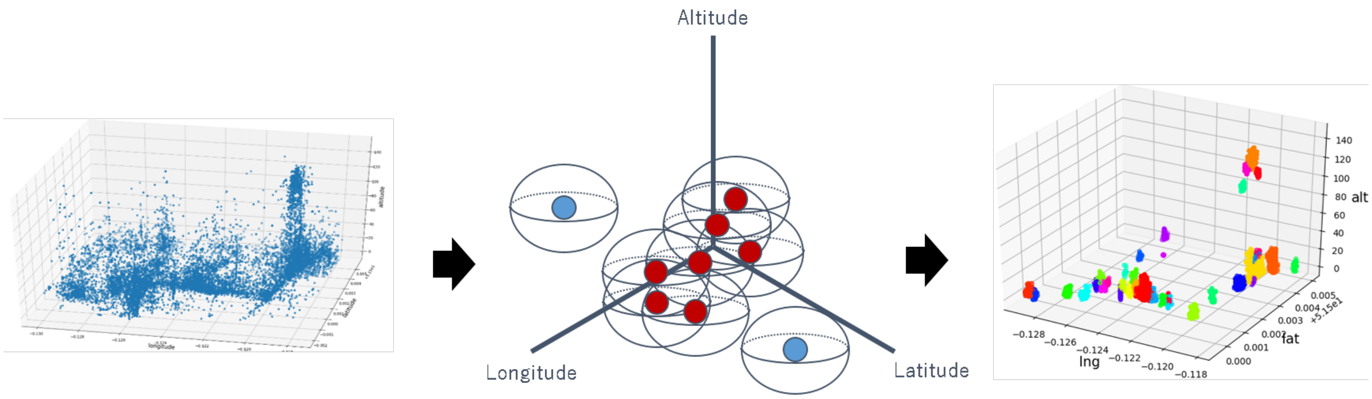

Figure 4. An overview of clustering by ST-DBSCAN.

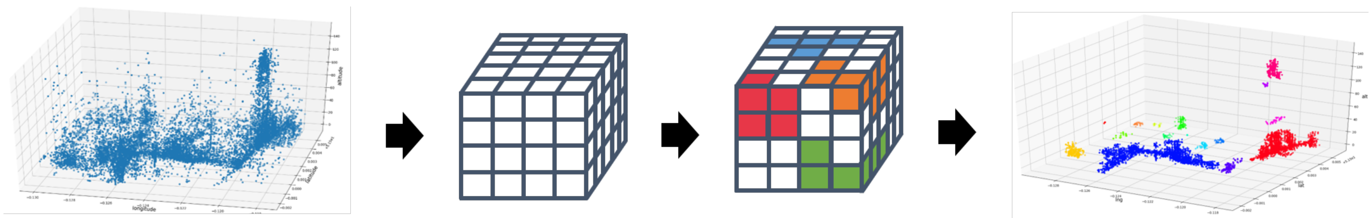

Figure 5. An overview of grid-based clustering.

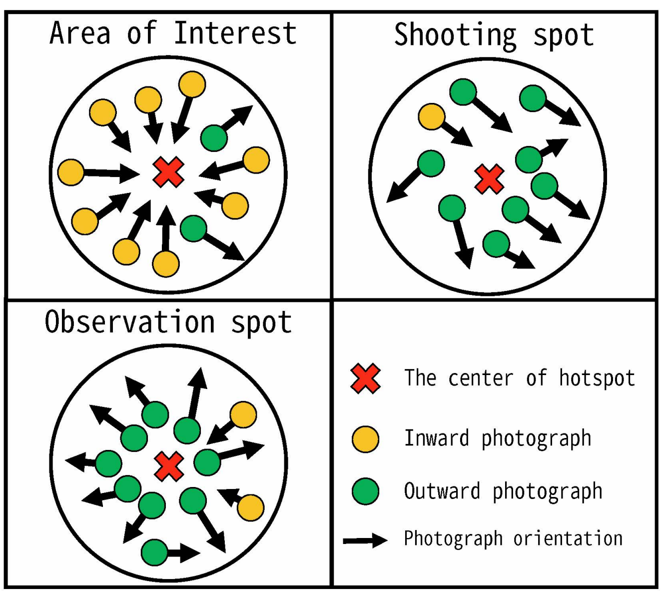

Figure 6. Classification of hotspots.

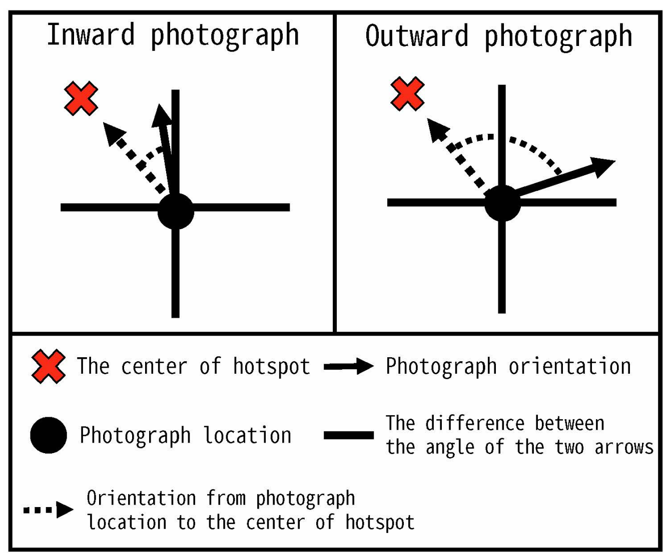

Figure 7. Inward photograph and outward photograph.

in the detected hotspots. However, the number of photographs with a known photograph orientation (in addition to latitude and longitude) is minuscule compared with the number of photographs with only latitude and longitude. As a result, the classification of hotspots that have few photographs may be difficult. Therefore, we classify hotspots into four groups: areas of interest, shooting spots, observation spots, and others. In this research, we classify hotspots that have less than 10 photographs with a known orientation as “other”, and we do not perform the following processes on them.

First, we decide whether each hotspot is a shooting spot. In this case, many photographs are taken with a specific orientation. Therefore, we calculate the bias of the photograph orientation based on its frequency distribution. We divide the value of the photograph orientation by 10 degrees and count the number of photographs in each of the 36 classes. We consider a hotspot to be focused on a specific orientation if the largest class includes at least 15% of the photographs belonging to the hotspot.

In the next step, we classify each remaining hotspot as either an area of interest or an observation spot according to the photograph orientation. Moreover, this classification is based on the ratio of inward to outward photographs in the hotspot. Figure 7 shows examples of inward and outward photographs. In this research, if the photograph orientation and the orientation to the center of gravity of the hotspot are close, we regard the photograph as an inward photograph; otherwise, we classify it as an outward photograph.

We set the orientation (with the true north as 0°) of the photograph to θ_i. If the coordinates (latitude and longitude)of the center of gravity of the hotspot are (x_h, y_h) and the coordinates of the shooting position are (x_i, y_i), θ_d is the orientation from the shooting position to the center. We calculate the orientation θ_d in which (x_h, y_h) exists using the following equation:

$$\theta_d = \tan^{-1} \frac{\cos y_i \times \sin(x_h - x_i)}{\cos y_1 \times \sin y_h - \sin y_i \times \cos y_h \times \cos(x_h - x_i)} \tag{5}$$

Next, we classify each photograph in a hotspot as an inward or outward photograph based on the difference between θ_d and θ_i, as follows:

$$\begin{cases} inward & |\theta_i - \theta_d| < \theta \\ outward & \text{otherwise} \end{cases} \tag{6}$$

In this study, we set the threshold for classifying inward and outward photographs as $\theta = 50$. If the number of photographs classified as inward photographs is larger than the number of outward photographs, the hotspot is classified as an area of interest; otherwise, it is classified as an observation spot.

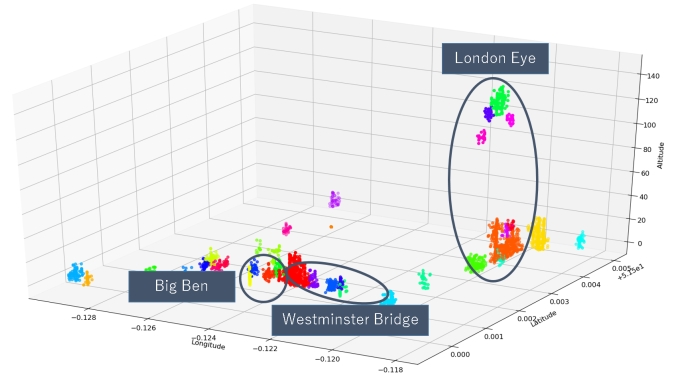

Figure 8. The clustering result in three-dimensional (ST-DBSCAN).

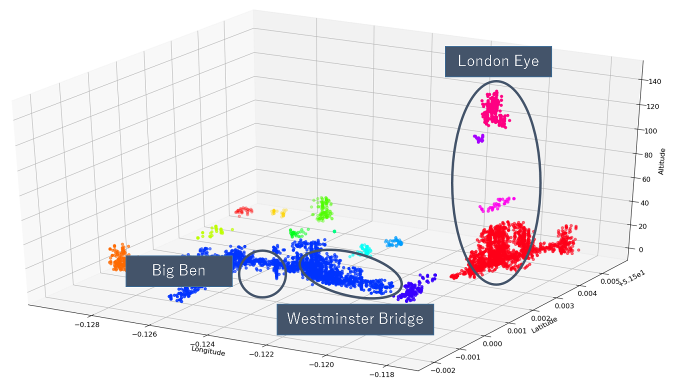

Figure 9. The clustering result in three-dimensional (grid-based clustering).

V. EXPERIMENT

This section presents a description of experiments conducted using our proposed method. We present and discuss several examples of detecting hotspots by density-based and grid-based clustering.

A. Dataset

Here, we describe the dataset for the experiment of detecting hotspots. Photographs for the experiments were obtained from Flickr, and included metadata for latitude, longitude, altitude, and orientation. In this paper, we used the exchangeable image file format (Exif) metadata for latitude (GPSLatitude), longitude (GPSLongitude), altitude (GPSAltitude), and orientation (GPSImgDirection).

The dataset included photographs taken in an area of Westminster in London (latitude: 51.5056 – 51.4979; longitude: −0.1178 – −0.1299). The size of this area is about 1 × 1 km. We obtained photographs taken between January 1, 2011 and May 10, 2016.

To deal with altitude errors, we set a threshold for altitude and removed photographs having an altitude higher or lower than the threshold. In this experiment, we set this parameter based on the height of buildings around the area to be analyzed. In addition, we removed photographs with an altitude of 0 m or less.

Furthermore, we excluded photographs in which the latitude, longitude, and altitude all overlap in the dataset. This might occur as a result of an incorrect GPS position or device configuration. Such points for which there is much inappropriate metadata is excessively evaluated when detecting a hotspot. As a result, the number of photographs used in this experiment was 13,911.

B. Visualization of hotspots

Figure 8 shows the clustering results by ST-DBSCAN, based on the latitude, longitude, and altitude of photographs. The parameters used in ST-DBSCAN and grid-based clustering were $Eps1 = 0.0001$, $Eps2 = 5$, and $MinP = 30$, respectively. Figure 9 shows the clustering results by our proposed grid-based method. The parameters of this method is the same as for ST-DBSCAN. The number of clusters detected by ST-DBSCAN (Figure 8) was 35, and the number detected by grid-based clustering (Figure 9) was 6. In Figures 8 and 9, photograph locations classified as noise are not displayed. In these figures, each color represents a cluster (the colors are only used to distinguish visually between the clusters).

Figure 8 shows that some clusters with different altitudes were detected in areas with almost the same latitude and longitude. In particular, several clusters were detected near an altitude of 130 m, latitude of 51.504, and longitude of −0.120. This is because the highest point of the London Eye is 135 m. Therefore, many people take photographs around there, and the area was detected as a hotspot.

Compared with ST-DBSCAN (Figure 8), the detected clusters were more widespread using grid-based clustering (Figure 9). However, Figures 8 and 9 show that the detected hotspots cover almost the same areas. Instead of evaluating the distance between two photographs by latitude and longitude in DBSCAN, the grid-based clustering detects hotspots by

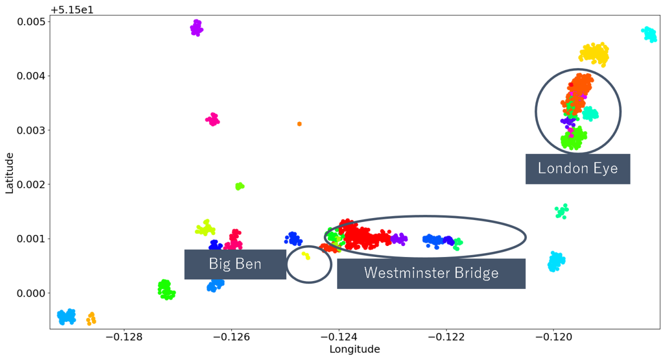

Figure 10. The clustering result in two-dimensional (ST-DBSCAN).

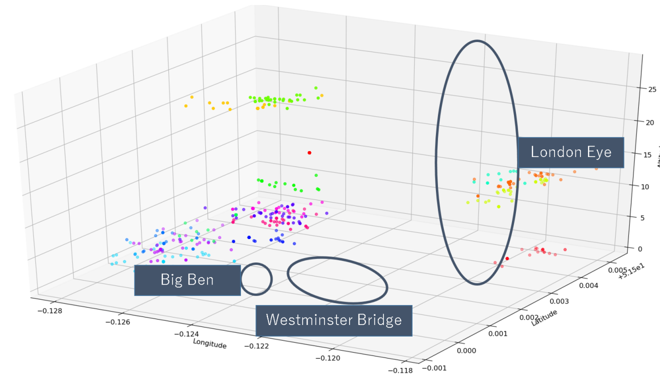

Figure 12. Clustering result by DBSCAN using latitude, longitude and altitude.

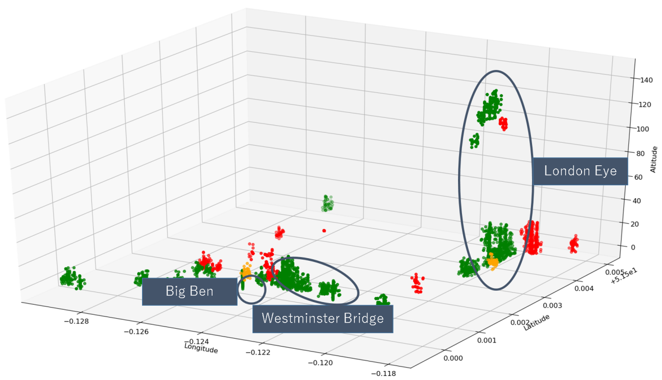

Figure 11. Classification result of hotspot.

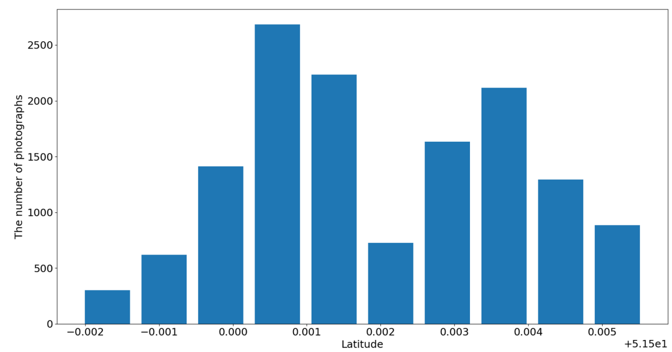

Figure 13. Histogram of Latitude of photographs.

evaluating the relationship between adjacent cells. Therefore, the photograph locations that were classified as multiple clusters by ST-DBSCAN were classified as one cluster by our proposed grid-based clustering method. At this stage, it is not possible to determine which method is better, because quantitative evaluation has not been performed for either method. Therefore, as future work, it is necessary to examine which method can detect hotspots more accurately.

Figure 10 shows a two-dimensional representation of the clustering result by ST-DBSCAN (i.e., the figure shows the clusters in Figure 8 mapped in two dimensions, without altitude). Some clusters are displayed overlapping in multiple areas in this figure. Therefore, in such areas, points with different altitudes should be identified as belonging to distinct hotspots. Naturally, the latitude and longitude of the photographs taken in such areas are almost equal. Unless we detect hotspots by considering the altitude, in addition to latitude and longitude, it is difficult to distinguish between, and correctly detect, these clusters.

Although it may be possible to distinguish these hotspots by clustering with only latitude and longitude in some cases, substantial time and effort would be required to tune the Eps and $MinP$ parameters in DBSCAN. In addition, when photographs annotated with latitude and longitude are used, these metadata often include errors. Therefore, photographs that should belong to different hotspots may erroneously be assigned to the same hotspot. Therefore, in Figures 8 and 10, we show that it is possible to distinguish between hotspots in areas with similar latitude and longitude by considering the altitude, even in such a state.

C. Combination of features

Next, we discuss the advantages of our proposed methods, compared with simply applying DBSCAN and using latitude, longitude, and altitude as one feature. We applied DBSCAN to the London dataset using latitude, longitude, and altitude; Figure 12 shows the clustering results. The parameters of DBSCAN were the same as ST-DBSCAN, except for the threshold $Eps2$ of altitude, and use Euclidean distance to calculate the distance between each pair of data points. The number of detected clusters was 15. The clusters in Figure 12 tend to have a flat shape, because the scale of the features varied greatly.

We show the histograms of latitude, longitude, and altitude in Figures 13, 14, and 15. In this dataset, the high density area is around latitude 51.50001 and longitude -0.120, shown in Figures 13 and 14. The distributions of latitude and longitude depend on areas of high density included in the dataset. However, the distribution and the scale of altitude are very different: altitude varies between about 0 and 140, as shown in Figure 15. This distribution depends on the area being analyzed and the height of the landmarks in that area. In most cases, the distribution of altitude is different from that of latitude and longitude.

As a result, when measuring the distance between data points, altitude becomes a more dominant feature than latitude and longitude. In addition, because the distribution of these features is very different, it is difficult to handle them consistently even if the feature values are normalized.

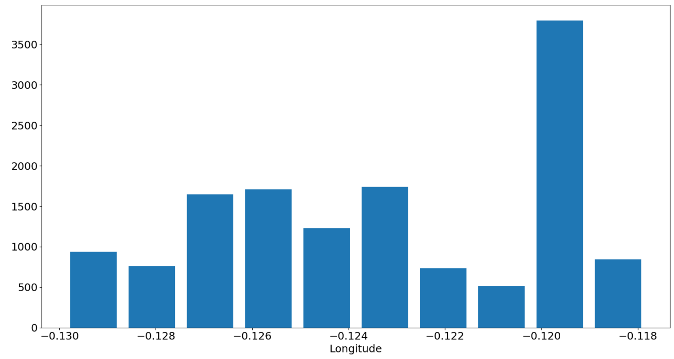

Figure 14. Histogram of Longitude of photographs.

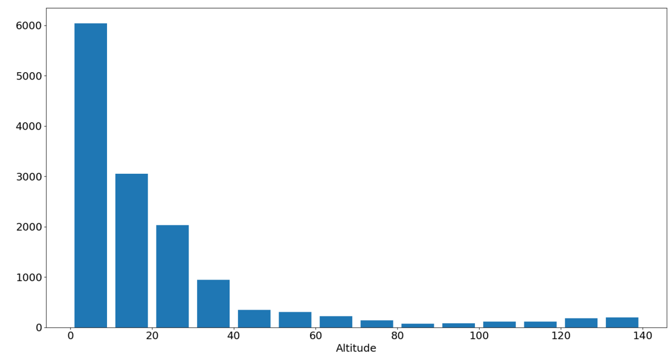

Figure 15. Histogram of Altitude of photographs.

Therefore, when calculating the distance between each pair of data points in our methods for detecting hotspots, we believe that latitude and longitude should be treated together, and altitude treated separately.

D. Execution time

In this section, we compare the execution time for detecting hotspots by each method. We measured the time of DBSCAN and our proposed ST-DBSCAN and grid-based clustering. The experiment used the dataset of London photographs, as described in Section V-A. We used five datasets with varying numbers of photographs, from 2,000 to 10,000. The parameters of these methods were the same as used in Section V-B.

Figure 16 shows the execution times of the three methods: these are the median times for performing each method ten times. In Figure 16, the grid-based clustering is the fastest of the three methods. This reason is that this method has a low computational complexity $O(n)$ (while the complexity of DBSCAN and ST-DBSCAN is $O(n \log n)$. Therefore, as the number of data points increases, the execution time hardly increases, compared with the other methods.

ST-DBSCAN has a smaller execution time than DBSCAN, even though the two methods use almost the same algorithm. ST-DBSCAN uses the latitude and longitude threshold $Eps1$ and altitude threshold $Eps2$. In contrast, DBSCAN uses only the latitude and longitude threshold $Eps1$. Therefore, compared with DBSCAN, because ST-DBSCAN needs to satisfy two conditions when searching for neighborhoods, fewer photographs are classified as belonging to a cluster. As a result, the execution time of ST-DBSCAN is less, because the number of times the algorithm determines connectivity with surrounding data is reduced.

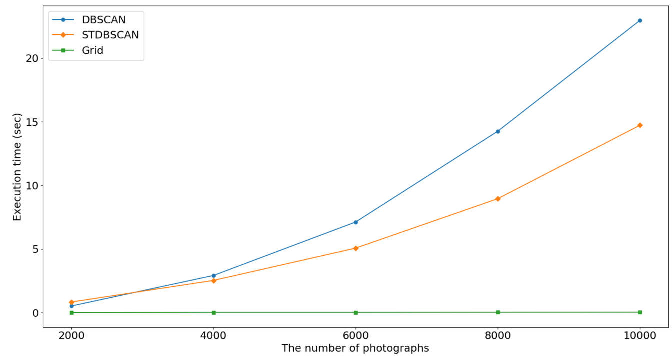

Figure 16. Execution time of each method.

From Figure 16, the grid-based clustering method is much faster than ST-DBSCAN. However, because the grid-based method needs to map photographs to cells when detecting hotspots, the detected hotspots are rougher than those of ST-DBSCAN as shown in Figure 9. Therefore, it is desirable to select these approaches properly, considering this result.

VI. Visualization of Classified Hotspots

In this section, we show the result of classifying hotspots into four types. Figure 11 shows the result of the classification of hotspots which is detected by ST-DBSCAN. In this figure, a green point shows a photograph location in a hotspot classified as an observation spot, a red point is a shooting spot, and an orange point is an area of interest. In Figure 11, many observation spots were detected: for example, the highest location of the London Eye is an observation spot. It seems that people are shooting the view from the top of the Ferris wheel. In addition, there are two clusters of orange points: under the London Eye and around Big Ben. These hotspots should probably be classified as shooting spots because these contents of photographs include the landmarks that is these photographs are shot in the hotspots. The area around latitude 51.502 and longitude -0.121 is detected as a shooting spot because it includes many photographs of Big Ben. It seems that other areas are also classified as shooting spots because they contain many photographs of landmarks, such as the London Eye and Big Ben.

In the above description, we explained the classification results regarding hotspots. At this stage, quantitative analysis of the classification has not been performed. In the results, some hotspots have been misclassified. Therefore, in a future study, there is a need to improve the method for, and evaluation of, the classification of hotspots.

VII. Conclusion

In this paper, we proposed two types of method for detecting hotspots using the geographical coordinates of photographs (latitude, longitude and altitude). The first of our proposed methods uses ST-DBSCAN, which is a density-based clustering method. The other is a grid-based clustering method. We visualized the clustering results using those methods based on the metadata of photographs taken in London. We discussed the detection of separate hotspots that may be detected as a single cluster when considering only latitude and longitude. We compared these proposed methods with DBSCAN, which uses latitude, longitude, and altitude as a single feature of a photograph. As a result, we showed that we can detect hotspots that overlap when we consider only latitude and longitude. In addition, we compared the execution time for detecting hotspots by these methods. Finally, we visualized the clustering results and classified hotspots as areas of interest, shooting spots, and observation spots.

As future work, we aim to compare our approach with clustering methods other than ST-DBSCAN and grid-based clustering. In this paper, these methods have been applied using latitude, longitude, and altitude as features, but it has not yet been revealed to be superior quantitatively to other clustering methods, such as DBSCAN and mean shift. Moreover, our method of grid-based clustering is still naive; we will improve this method to enable it to detect hotspots faster. For example, we can consider the characteristics of features to speed up the decision of whether a cell is a hotspot. We performed classification of hotspots but have not quantitatively evaluated the result yet. The results obtained suggest that further improvements in our proposed classification method are necessary.

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References

[1] M. Hirota, M. Endo, and I. Hiroshi, "A proposal for discovering hotspots using 3d coordinates from geo-tagged photographs," in Proceedings of The Eleventh International Conference on Advanced Geographic Information ystems, Applications, and Services, ser. GEOProcessing 2019, Feb 2019, pp. 59–62, ISBN:978-1-61208-687-3, URL:http://www.thinkmind.org/index.php?view=article&articleid= geoprocessing_2019_4_10_30046.

[2] "Flickr," URL: https://www.flickr.com [accessed: 2019-07-15].

[3] "Instagram," URL: https://www.instagram.com/ [accessed: 2019-07-15].

[4] "Google photos," URL: https://photos.google.com/ [accessed: 2019-07-15].

[5] Z. Xia, H. Li, Y. Chen, and W. Liao, "Identify and delimitate urban hotspot areas using a network-based spatiotemporal field clustering method," ISPRS International Journal of Geo-Information, vol. 8, no. 8, 2019.

[6] Y. Yuan and M. Medel, "Characterizing international travel behavior from geotagged photos: A case study of flickr," PLOS ONE, vol. 11, no. 5, 05 2016, pp. 1–18.

[7] C.-L. Kuo, T.-C. Chan, I.-C. Fan, and A. Zipf, "Efficient method for poi/roi discovery using flickr geotagged photos," ISPRS International Journal of Geo-Information, vol. 7, no. 3, 2018.

[8] Y. Yang, Z. Gong, and L. H. U, "Identifying points of interest by self-tuning clustering," in Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval, ser. SIGIR '11. ACM, 2011, pp. 883–892.

[9] V. Kulkarni, A. Moro, B. Chapuis, and B. Garbinato, "Extracting hotspots without a-priori by enabling signal processing over geospatial data," in Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. SIGSPATIAL '17. ACM, 2017, pp. 79:1–79:4.

[10] X. Yang, Z. Zhao, and S. Lu, "Exploring spatial-temporal patterns of urban human mobility hotspots," Sustainability, vol. 8, no. 7, 2016.

[11] D. Laptev, A. Tikhonov, P. Serdyukov, and G. Gusev, "Parameter-free discovery and recommendation of areas-of-interest," in Proceedings of the 22Nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. SIGSPATIAL '14. ACM, 2014, pp. 113–122.

[12] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, ser. KDD '06, 1996, pp. 226–231.

[13] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 5, 2002, pp. 603–619.

[14] D. Birant and A. Kut, "St-dbscan: An algorithm for clustering spatial-temporal data," Data & Knowledge Engineering, vol. 60, no. 1, 2007, pp. 208–221, intelligent Data Mining.

[15] "Openstreetmap," URL: https://www.openstreetmap.org/ [accessed: 2019-07-15].

[16] M. Shirai, M. Hirota, H. Ishikawa, and S. Yokoyama, "A method of area of interest and shooting spot detection using geo-tagged photographs," in Proceedings of The First ACM SIGSPATIAL International Workshop on Computational Models of Place, ser. COMP '13. ACM, 2013, pp. 34:34–34:41.

[17] M. Hirota, M. Shirai, H. Ishikawa, and S. Yokoyama, "Detecting relations of hotspots using geo-tagged photographs in social media sites," in Proceedings of Workshop on Managing and Mining Enriched Geo-Spatial Data, ser. GeoRich '14. ACM, 2014, pp. 7:1–7:6.

[18] D. J. Crandall, L. Backstrom, D. Huttenlocher, and J. Kleinberg, "Mapping the world's photos," in Proceedings of the 18th International Conference on World Wide Web, ser. WWW '09. ACM, 2009, pp. 761–770.

[19] S. Kisilevich, F. Mansmann, and D. Keim, "P-dbscan: A density based clustering algorithm for exploration and analysis of attractive areas using collections of geo-tagged photos," in Proceedings of the 1st International Conference and Exhibition on Computing for Geospatial Research & Application, ser. COM.Geo '10. ACM, 2010, pp. 38:1–38:4.

[20] M. Ankerst, M. M. Breunig, H.-P. Kriegel, and J. Sander, "Optics: Ordering points to identify the clustering structure," in Proceedings of the 1999 ACM SIGMOD International Conference on Management of Data, ser. SIGMOD '99. ACM, 1999, pp. 49–60.

[21] J. Sander, M. Ester, H.-P. Kriegel, and X. Xu, "Density-based clustering in spatial databases: The algorithm gdbscan and its applications," Data Mining and Knowledge Discovery, vol. 2, no. 2, 1998, pp. 169–194.

[22] J. Shi, N. Mamoulis, D. Wu, and D. W. Cheung, "Density-based place clustering in geo-social networks," in Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data, ser. SIGMOD '14. ACM, 2014, pp. 99–110.

[23] Y. Chen, Z. Huang, T. Pei, and Y. Liu, "Hispatialcluster: A novel high-performance software tool for clustering massive spatial points," Transactions in GIS, vol. 22, no. 5, 2018, pp. 1275–1298.

[24] J. L. Bentley, "Multidimensional binary search trees used for associative searching," Communications of the ACM, vol. 18, no. 9, Sep. 1975, pp. 509–517.

[25] A. K. Mann and N. Kaur, "Survey paper on clustering techniques," International Journal of Science, Engineering and Technology Research, vol. 2, no. 4, 2013, pp. 803–806.

[26] M. Parikh and T. Varma, "Survey on different grid based clustering algorithms," International Journal of Advance Research in Computer Science and Management Studies, vol. 2, no. 2, 2014.

[27] R. Agrawal, J. Gehrke, D. Gunopulos, and P. Raghavan, "Automatic subspace clustering of high dimensional data for data mining applications," in Proceedings of the 1998 ACM SIGMOD International Conference on Management of Data, ser. SIGMOD '98. ACM, 1998, pp. 94–105.

[28] W. Wang, J. Yang, and R. R. Muntz, "Sting: A statistical information grid approach to spatial data mining," in Proceedings of the 23rd International Conference on Very Large Data Bases, ser. VLDB '97. Morgan Kaufmann Publishers Inc., 1997, pp. 186–195.

[29] C.-I. Chang, N. P. Lin, and N.-Y. Jan, "An axis-shifted grid-clustering algorithm," Tamkang Journal of Science and Engineering, vol. 12, no. 2, 2009, pp. 183–192.

[30] Y. A. Lacerda, R. G. F. Feitosa, G. A. R. M. Esmeraldo, C. d. S. Baptista, and L. B. Marinho, "Compass clustering: A new clustering method for detection of points of interest using personal collections of georeferenced and oriented photographs," in Proceedings of the 18th

Brazilian Symposium on Multimedia and the Web, ser. WebMedia '12. ACM, 2012, pp. 281–288.

[31] B. Thomee, "Localization of points of interest from georeferenced and oriented photographs," in Proceedings of the 2Nd ACM International Workshop on Geotagging and Its Applications in Multimedia, ser. GeoMM '13. ACM, 2013, pp. 19–24.

[32] M. Hirota, M. Endo, K. Daiju, and I. Hiroshi, "Discovering hotspots using photographic orientation and angle of view from social media site," International Journal of Informatics Society, vol. 10, no. 3, 2019, pp. 109–117.

[33] E. Spyrou, M. Korakakis, V. Charalampidis, A. Psallas, and P. Mylonas, "A geo-clustering approach for the detection of areas-of-interest and their underlying semantics," Algorithms, vol. 10, no. 1, 2017, p. 35.

[34] M. Omori, M. Hirota, H. Ishikawa, and S. Yokoyama, "Can geo-tags on flickr draw coastlines?" in Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. SIGSPATIAL '14. ACM, 2014, pp. 425–428.

[35] Y. Hu, S. Gao, K. Janowicz, B. Yu, W. Li, and S. Prasad, "Extracting and understanding urban areas of interest using geotagged photos," Computers, Environment and Urban Systems, vol. 54, 2015, pp. 240–254.

[36] M. Chen, D. Arribas-Bel, and A. Singleton, "Understanding the dynamics of urban areas of interest through volunteered geographic information," Journal of Geographical Systems, vol. 21, no. 1, Mar 2019, pp. 89–109.

[37] Y. Zhu and S. Newsam, "Spatio-temporal sentiment hotspot detection using geotagged photos," in Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. SIGSPACIAL '16. ACM, 2016, pp. 76:1–76:4.

[38] M. Shirai, M. Hirota, S. Yokoyama, N. Fukuta, and H. Ishikawa, "Discovering multiple hotspots using geo-tagged photographs," in Proceedings of the 20th International Conference on Advances in Geographic Information Systems, ser. SIGSPATIAL '12. ACM, 2012, pp. 490–493.