A Proposal for Discovering Hotspots Using 3D Coordinates from Geo-tagged Photographs

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***Abstract*—A hotspot is an interesting place where many people go for sightseeing. To extract hotspots, most of the existing research applies a density-based clustering algorithm, such as Density-based spatial clustering of applications with noise (DBSCAN) with latitude and longitude as its features. Therefore, the extracted hotspots are visualized as a two-dimensional space. However, large areas, landmarks, and buildings may include high hotspots or multiple hotspots with different altitudes. Therefore, in this research, we propose extracting hotspots based on altitude in addition to latitude and longitude and visualize these extracted hotspots in a three-dimensional space. To use those features, we apply ST-DBSCAN to extract hotspots and discuss the usefulness of extracting hotspots using altitude. In addition, as an application example, we classified hotspots as shooting spots, observation spots, areas of interest, among others and visualized the results.**

***Keywords*–area of interest;photograph location;photograph orientation**

I. INTRODUCTION

Owing 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 [1]. In addition, these digital devices have been equipped recently with Global Positioning System (GPS) sensors; thus, many photographs are annotated with latitude and longitude information. A photographic location represented by the latitude and longitude shows the place where the photographer took a photograph. If many people take photographs at the same location, this represents an area of interest to users. Analyzing such areas using photographs given a photographic location on social media sites is useful for analyzing geographical characteristics, such as obtaining information on sightseeing spots that the photographer finds interesting.

Many people take photographs of subjects or landscapes that satisfy their own interests. Subsequently, some of them upload their photographs to websites. As places from which many photographs have been taken, these locations might also be interesting places for other people to visit. As described in this paper, we define such places as hotspots. Most of the existing research for extracting hotspots are based on a density-based clustering method, such as density-based spatial clustering of applications with noise (DBSCAN) [2] and mean shift [3]. In addition, those researches that use such density-based clustering methods use latitude and longitude as features to extract hotspots and the extracted 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 wherein multiple hotspots at different altitudes are extracted as one hotspot. For example, in a sightseeing spot such as the Eiffel Tower, the latitude and longitude for the observatory and area around the building are almost the same, but there are some hotspots with different altitudes. Even if the altitude is different, because these latitudes and longitudes are almost equally located, it is difficult to distinguish between these hotspots.

In this research, when extracting a hotspot, we propose not only the width of a hotspot represented by the latitude and the longitude to extract hotspots but also the height of the hotspot by adding the altitude. In recent years, the metadata annotated to a photograph captured by smartphones includes altitude in addition to latitude and longitude. For this reason, in this research, we extract hotspots taking into consideration such metadata using the photographs given the information obtained from Flickr. As DBSCAN and mean shift, which is commonly used for extracting hotspots, treat the distance for evaluating the density around the data as one dimension, we consider those methods inappropriate for clustering with feature quantities with the metadata. Therefore, in this paper, we use ST-DBSCAN [4], which was proposed to deal with time in addition to latitude and longitude. When we apply ST-DBSCAN, we adopt altitude instead of time to extract hotspots, thereby considering the height of the hotspot.

In addition, hotspots can be classified into three types: an area of interest, a shooting spot, and an observation spot [5][6]. The areas of interest for people are tourist spots (e.g., the Colosseum or the Statue of Liberty). In such areas, many photographs have been taken inside the monument or at a nearby location. Also, when people take a photograph of such an area of interest, they will take it at a place that is at a distance from the area of interest. Such places are also extracted as hotspots and are defined as shooting spots. Observation spots are hotspots for photographing the surroundings of the hotspot. In this research, we classify hotspots extracted 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.

The remainder of this paper is organized as follows. Section II presents works related to this topic. Section III describes our proposed method for extracting hotspots based on altitude in addition to latitude and longitude. Section IV explains several examples of visualization result. Section V conclude the paper with a discussion of results and future works.

II. Related Works

Some methods have been proposed to extract hotspots from the many photographs with the photographic location available on social media sites.

Density-based clustering algorithms, such as DBSCAN [2] or mean shift [3] can be used to extract hotspots from a dataset that includes huge numbers of 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 [7]. Kisilevich et al. proposed P-DBSCAN, an improved version of DBSCAN, for the definition of a 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 used to create a cluster using different subspaces extracted from various parameters [9]. Sander et al. proposed GDBSCAN, which extends DBSCAN to enable the correspondence to both spatial and non-spatial features [10]. Shi et al. proposed a density-based clustering method to extract places of interest using spatial information and the social relationships between users [11].

The previously described research extracts hotspots using a density-based clustering method, such as DBSCAN based on latitude and longitude. However, in some cases, actual hotspots have a concept of height and are distributed in a three-dimensional space rather than a two-dimensional space. In this paper, we propose a new approach to extract and visualize hotspots using ST-DBSCAN by adding altitude.

III. Proposed Method

In this section, we describe our proposed method for extracting hotspots considering the altitude in addition to latitude and longitude from photographs and classifying the hotspots into one of three types: area of interest, shooting spot, and observation spot.

A. Extracting hotspots with altitude

Here, we describe why we adopt ST-DBSCAN to extract hotspots with altitude in addition to latitude and longitude. In most of the previous research, DBSCAN has been used for extracting hotspots. At this time, latitude and longitude are used as the features for representing the distance between two points. As we need to consider altitude in this research to extract hotspots, we infer that DBSCAN is not an appropriate method in this case. This is because the Eps, which is the parameter of DBSCAN 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 DBSCAN is an appropriate method to use 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, the altitude should be regarded as a different feature to latitude and longitude, and we adopt ST-DBSCAN to achieve this.

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 distances of spatial features of two data, $Eps2$ is a threshold of distances of other features, and $MinP$ is a threshold of the number of data included in the cluster. In this research, we apply ST-DBSCAN with $Eps1$ as latitude and longitude and $Eps2$ as altitude.

B. 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 1 using the photograph orientation annotated to the photographs included in the extracted hotspots. However, in addition to the latitude and longitude, the number of photographs with the photograph orientation is miniscule compared with the photographs with only the latitude and longitude. As a result, the classification of hotspots that have fewer photographs may be difficult. Therefore, we classify hotspots into four groups: areas of interest, shooting spots, observation spots, and others. In this research, we assume that hotspots with less than 10 photographs with photograph orientation as other, and we do not perform the following processes.

First, we classify a hotspot as a shooting spot or others. In this case, many photographs are taken with a specific orientation. Therefore, we calculate the bias of the photograph orientation based on a frequency distribution related to photograph orientation. We divided the value of photograph orientation by 10 degrees and counted the number of photographs for each class. We consider that these hotspots are focused on a specific orientation if the top class includes 15% of the photographs belonging to hotspots.

Next, we classify the remaining hotspots into either an area of interest or observation spot. This classification is based on the ratio of inward and outward photographs in the hotspot. Figure 2 shows examples of inward and outward photographs. In this research, if the photograph orientation and 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 given to photograph as 0° to θ_i and the coordinates of the center of gravity of the hotspot h for the coordinates (x_i, y_i) of the latitude and longitude at the shooting position. We calculate the orientation θ_d in which (x_h, y_h) exists using the following equation:

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

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:

$$\begin{cases} inward & |\theta_i - \theta_d| < \theta \\ outward & \text{otherwise} \end{cases} \quad (2)$$

In this study, we set the threshold for classifying inward photographs and outward photographs as $\theta = 50$. If the number of photographs classified as inward photographs in a hotspot 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.

IV. EXPERIMENT

A. Dataset

Here, we describe the dataset for the experiment of extracting hotspots using latitude, longitude, and altitude. Photographs for experiments were obtained from Flickr. Those photographs include metadata for latitude, longitude, altitude, and orientation. We obtained photographs taken during January 1, 2011–May 10, 2016. We use the photographs taken in

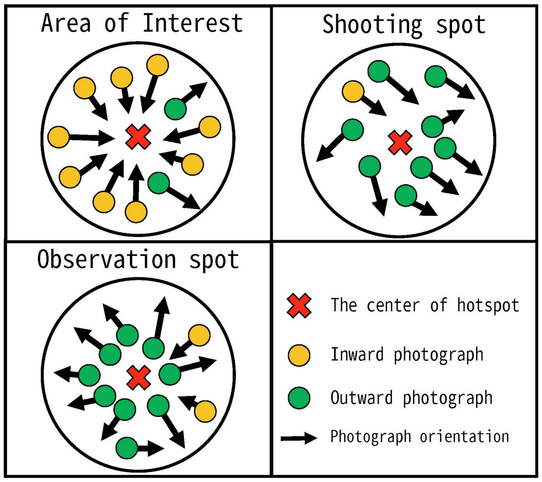

Figure 1. Classification of hotspots.

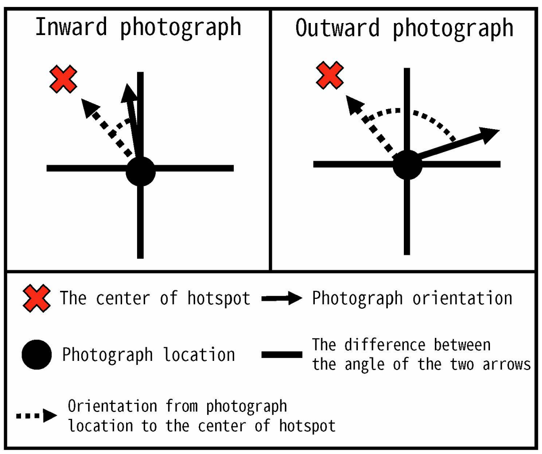

Figure 2. Inward photograph and outward photograph.

the area of Westminster in London. There are some famous landmarks in this area, such as the Big Ben (latitude: 51.500729; longitude: -0.124625) and the London Eye (latitude: 51.503324; longitude: -0.119543).

To deal with altitude errors, we set the threshold of altitude and remove photographs having an altitude higher or lower than the threshold. In this experiment, we set the 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. This might occur as a result of an incorrect GPS positioning or device configuration. The point where there is much inappropriate metadata is excessively evaluated when extracting a hotspot. As a result, the number of photographs used in this experiment is 13,911.

B. Visualization of hotspots

Figure 3 shows the clustering results by ST-DBSCAN based on the latitude, longitude, and altitude of photographs. The parameters used in ST-DBSCAN were $Eps1 = 0.0001$, $Eps1 = 5$, and $MinP = 30$, respectively. The number of extracted clusters in Figure 3 is 35. Each color in this Figure represents a cluster (the colors are only an easy-to-view representation to distinguish between clusters).

In Figure 3, some clusters with different altitudes are extracted from areas with almost the same latitude and longitude. In particular, several clusters were extracted 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 extracted as a hotspot.

Figure 4 is a two-dimensional representation of the clustering result (i.e., the Figure shows that the clusters in Figure 3 map 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 extracted as distinguished hotspots. Naturally, the latitude and longitude of the photographs taken in such areas are almost equal. As a result, unless we extract hotspots by considering the altitude in addition to latitude and longitude, it is difficult to distinguish between and extract these clusters.

Although it may be possible to distinguish these hotspots by clustering with only latitude and longitude in some cases, much time and effort are required to tune parameters of Eps and $MinP$ in DBSCAN. In addition, when latitude- and longitude-annotated photographs are used, those metadata include errors. Therefore, the photographs that should originally belong to different hotspots may belong to the same hotspots erroneously. Therefore, in Figures 3 and 4 we show that it is possible to distinguish between the hotspots in areas of similar latitude and longitude by considering the altitude even in such a state.

Next, Figure 5 shows the result of the classification of hotspots. In this Figure, the green point shows a photograph in a hotspot classified as an observation spot. In addition, the red point is a shooting spot and the orange point is an area of interest. In Figure 5, many observation spots were extracted. For example, the highest location of the London Eye is an observation spot. It seems that people are shooting the periphery from the top of the Ferris wheel. In addition, there are two chunks of orange points: under the London Eye and around the Big Ben. These hotspots should probably be classified as shooting spots because the hotspots include photographs of these landmarks. The area around latitude 51.502 and longitude -0.121 is extracted as a shooting spot as it includes many photographs of the 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 the Big Ben.

In the above description, we explained the classification results regarding hotspots. At this stage, quantitative analysis of the classification is not done. In these results, there are some hotspots misclassified. Therefore, we think the need for improvement of the method and evaluation for classifying hotspots in a future study.

V. Conclusion

In this paper, we have discussed the extraction of hotspots that can be extracted as one cluster when considering only latitude and longitude by using latitude and longitude in addition to the altitude information of a photograph. We used ST-DBSCAN for extracting hotspots while also considering the altitude. In addition, we visualized clustering results using ST-DBSCAN using the metadata of photographs taken in London.

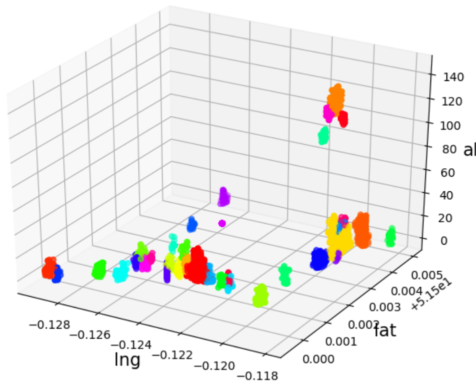

Figure 3. The clustering result in three-dimensional.

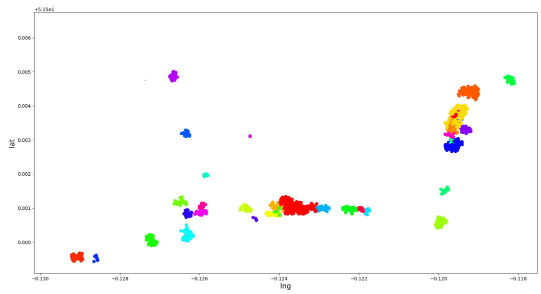

Figure 4. The clustering result in two-dimensional.

In addition, we classified the hotspots as areas of interest, shooting spots, observation spots, and others and visualized the results.

As future work, we aim to compare our approach with density-based clustering methods other than ST-DBSCAN. In this paper, ST-DBSCAN has been applied only using latitude, longitude, and altitude as a feature quantity, and it has not yet been revealed to be superior to other clustering methods, such as DBSCAN. In addition, we performed classification of hotspots in one of the application examples of hotspots and have not been evaluated the result yet. Thus, further improvements in our proposed method is necessary.

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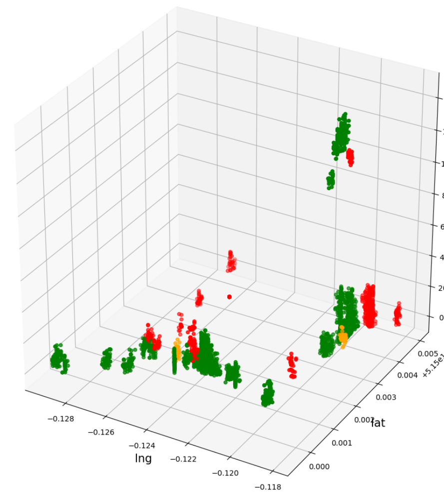

Figure 5. Classification result of hotspot.

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