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DOI: <https://doi.org/10.1109/ITNG.2010.62>

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Citation

RAZIKIN, Khasfariyati; GOH, Dion Hoe-Lian; LIM, Ee Peng; SUN, Aixin; THENG, Yin-Leng; KIM, Thi Nhu Quynh; CHATTERJEA, Kalyani; and CHANG, Chew-Hung. Managing media rich geo-spatial annotations for a map-based mobile application using clustering. (2010). *International Conference on Information Technology: New Generations (ITNG 2010)*. 138-143. Research Collection School Of Information Systems.

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Managing Media Rich Geo-spatial Annotations for a Map-based Mobile Application using Clustering

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Abstract

With the prevalence of mobile devices that are equipped with wireless Internet capabilities and Global Positioning System (GPS) functionality, the creation and access of user-generated content are extended to users on the go. Such content are tied to real world objects, in the form of geospatial annotations, and it is only natural that these annotations are visualized using a map-based approach. However, viewing maps that are filled with annotations could hinder the serendipitous discovery of data, especially on the small screens of mobile devices. This calls for a need to manage the annotations. In this paper, we introduce a mobile application, MobiTOP, which enable users to create multimedia geospatial annotations and employs a map-based visualization for users to explore the annotations. We propose the adoption of clustering approaches to manage the volume annotations on the map. Two approaches of clustering techniques, namely incremental clustering and DBScan (Density based spatial clustering applications with noise), are proposed and compared with a baseline approach in our evaluation. Implications of our findings are discussed.

Key Words: Geospatial annotations, map-based visualization, mobile applications, mobile visualization.

1. Introduction

User-generated content is no longer limited to content created using Web 2.0 applications such as blogs and wikis. The ubiquitous nature of mobile devices has brought about a new medium for content creators to contribute and share information. Users are now able to create content on the go instead of having the need to be behind a computer. As mobile devices are now equipped with wireless Internet access capabilities (e.g. 3G, GPRS) and Global Positioning System (GPS) functionality, contributors are now able to generate and access content at any given location. For example, mobile applications such as Shozu (<http://www.shozu.com>) and Zonetag (<http://zonetag.research.yahoo.com/>) allow uploading of photos from users' mobile devices to their Flickr accounts.

The concept of content creation on the go with mobile devices has created a new dimension in terms of mobility [9]. Such content are no longer tied to virtual content like HTML pages but to real world objects. Other than the geographical coordinates of the object, an annotation that has been created on mobile devices can be made up of textual contents such as tags or augmented with multimedia content like images and videos [9]. Since these annotations are associated with geographical coordinates, it is only natural that they are visualized using maps on the mobile device, similar to Web-based approaches. A map-based visualization allows users to explore a representation of the physical space. The zoom levels provides different levels of perspectives to the users that ranges from a global view that shows the world map to a micro level perspective where the area of interest is displayed at a high resolution. This approach enables the users to relate the geospatial annotation to a real world object at a particular location [6]. However, this map based approach becomes ineffective when it is full of annotations. The map becomes cluttered, and in turn impedes users' searching and browsing actions [11]. This is further aggravated when the map is viewed from a mobile device that has a limited screen size [4].

Here, we propose the adoption of clustering methods to assuage the problems of visualization of map-based annotations on mobile devices. Annotations that are located close together will be grouped in the same cluster, thus adhering to the cluster hypothesis. Put differently, these annotations are grouped together as they share similar characteristics relative to their location. When the zoom level changes, the number of clusters will vary as it depends on the distance between the objects. The granularity of the clusters thus changes at different zoom levels. This enables users to have a good idea of the spread of clusters over the area. However, different clustering methods differ in their techniques, so it is necessary to identify the best approach to manage geospatial annotations. Our contribution to this area is to determine the most useful clustering technique to manage annotations on small visual displays by comparing two existing clustering techniques.

In this paper, we describe a mobile application, MobiTOP, where users are able to create geospatial annotations. We extend existing research by exploring the different clustering techniques that would be applicable for use in MobiTOP. The application offers a map interface where users are able to explore the annotations. This system serves as a platform where our proposed clustering algorithms will be evaluated. Two clustering techniques namely, incremental clustering [3] and DBScan (Density based spatial clustering applications with noise) [7] are compared in terms of their performance.

This paper is organized as follows. The following section will describe the related work done. This will be followed by an introduction to MobiTOP mobile application. The subsequent section will elaborate on the methodology adopted for evaluating the clustering techniques and the proceeding section will report the results of the evaluation. The paper will conclude with a discussion on the implications of the results obtain as well as the limitation of our work.

2. Related studies

In this section, we first give an overview of mobile applications with the ability to create geospatial annotations. This is then followed by a discussion on studies that had used clustering approaches with geospatial objects. Finally, the selected clustering techniques are given an in depth treatment.

With the prevalence of mobile applications that utilizes GPS functions, there has been a growing body of work that has investigated the use of such devices in varying areas. Applications have been implemented for use in diverse areas from education (e.g. [18, 16]) to leisure activities (e.g. [8, 5]).

Studies of using mobile devices in an educational context involve students harnessing the portability of mobile devices their learning. Such learning often takes place outside the classroom in the form of fieldwork. In such cases, relevant geospatial annotations are created to reinforce the learning concepts. ButterflyNet [18] was used by university level students for their field biology practices. Students doing fieldwork are able to annotate their field notes using mobile devices. In another study, high school Geography students collected data to study the outdoor microclimate around their school's campus. Using Mobile G-Portal [16], they recorded their readings of their fieldwork study.

An example of mobile annotations applications for leisure activities is MobiSpray [8]. This application enables graffiti artists to mark locations with their virtual graffiti imprints. This unique application uses RFID tags attached to physical objects for the artists to mark the object with their graffiti by using the phone. The RFID tags stores the pre-uploaded designs from the Web so that it can be viewed by other people with the mobile application. Applications for creating mobile annotations have also found a place as museum guides. MobiTags [5] allows museum visitors to explore and annotate museum exhibits. The users are able to express their opinions, both objectively and subjectively, through tags. Other museum visitors are able to express their agreement with the tags by voting.

Various works have been done on the clustering of tags for geo-referenced images available from Flickr. Ahern et al [2] determined representative tags by clustering the tags in the map's area. Using TF-IDF, the most representative tags of the area were determined. This study used K-means clustering approach. In a more recent work by Crandall et al [6], highly photographed places in the world were obtained by clustering techniques. In their work, the authors made use of a more dynamic mean shift clustering that takes into consideration the scale of the map to elicit the popular tags of the area in question.

K-means is a fixed cluster approach that is problematic for spatial data as it tends to be biased towards densely populated areas. Also, it is largely dependent on heuristics. The mean shift technique employed in Crandall et al's [6] work made use of bucketing techniques. That is to say, instead of relying on pre-computed parameters, incremental and DBScan [7] clustering approaches adopted in this work uses dynamically generated parameters. This generalizes the algorithm making it adaptable for use in different contexts.

Incremental clustering [3] is a type of hierarchical clustering that merges clusters that are within the cluster's maximum distance. DBScan [7], on the other hand, groups the data by density and it is able to cluster any arbitrary shape. It has been known to be suited for large spatial databases. Incremental clustering performs at $O(n \log n)$. Similarly, DBScan has an average runtime complexity of $O(n \log n)$. There has been various works that had adopted these two techniques. Incremental clustering has been used in geospatial domain (e.g. [15]) as it is able to handle dynamic data. On the other hand, DBScan has been applied to mainly spatial data. Some of related works in this area include cluster social aspects from GPS [1] and queries from user logs [17]. This algorithm was selected for these studies as it is able to handle both large and sparse data and does not require in-depth domain knowledge.

3. MobiTOP mobile application

MobiTOP [13] is a mobile application that allows users to contribute and share geospatial multimedia annotations. The annotations are made up of locations, multimedia content, and textual content comprising tags, titles and descriptions. This mobile application was implemented primarily for Nokia N95 8GB smart phones. The application uses the global positioning system (GPS) feature available in the phone to determine the current location of the user. MobiTOP adopts a map-based visualization to support the exploration and

creation of geospatial multimedia annotations (see Figure 1). The system was developed using the Java Platform, Micro Edition (J2ME) and the map based visualization implemented with the J2ME Map API (<http://j2memap.landspurg.net/>).

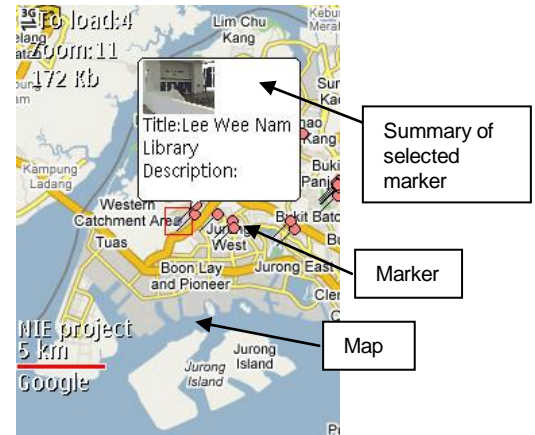


Figure 1 Map interface of MobiTOP mobile application.

Figure 1 shows the map based visualization of the annotations. A marker indicates that an annotation has been created on the location. Similar to maps available on Web applications, the map is able to zoom in or out depending on the users' wish to view the different levels of view on the map. Annotations are created using either accessing a form or by selecting a location on the map. Additionally, multimedia content can be associated with the annotations by attaching existing content on the phone or capturing content via the phone's camera. Figure 2 shows the details of one such multimedia annotation. More information about MobiTOP can be found at Nguyen et al [13].

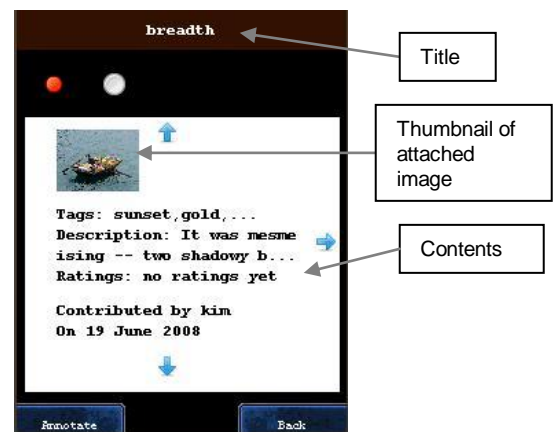


Figure 2 Annotation details interface of MobiTOP mobile application

With the limited size of the mobile phone’s screen, there is a necessity to address the issue on the management of visualizing the annotations on the map. A map that is cluttered with annotations would impede the user’s navigation and in turn would make the mobile application unusable. By implementing an appropriate clustering technique for annotations, we expect that users will be able to explore the map easily, especially when there are large numbers of annotations. In our approach, different zoom levels of the map would result in a different number of clusters depending on the location of the annotations. At higher zoom levels, annotations which are closer in relative distance would be grouped in the same cluster. In contrast, at lower zoom levels, the same annotations would be in different groups depending on their distances apart.

4. Evaluation methodology

An investigation was done on comparing different clustering approaches to determine the best approach to be adopted in MobiTOP. As discussed, two algorithms, incremental clustering and DBScan were compared.

The dataset utilized in this study is similar to the one used by Nguyen et al [14]. Our dataset consists of 197,126 geospatial multimedia annotations harvested from Flickr between November 2007 and December 2007. Each annotation consisted of an image, title of the image, user contributed tags as well as its latitude and longitude. The dataset consisted of 134,496 unique tags submitted by 21,586 contributors. On average, each contributor uploaded 9.13 (SD = 33.58) photos. Each photo was assigned 13.07 (SD = 7.56) tags on average.

We made use of a modified implementation of incremental clustering as used by Nguyen et al [14]. Their clustering algorithm did not specify the number of clusters to be maintained that is in contrast to the original implementation by Charikar et al [3]. Instead, it has defined the maximum allowable distance between two clusters that are dependent on the zoom level of the map. As each zoom level of the map presents different resolution of the area, this algorithm has taken advantage of the zoom level to dynamically define the diameter of the cluster. The resulting clusters displayed on the screen have a fixed diameter regardless of the zoom level. The diameter of the clusters is defined by $2^{5-zoom\ level}$. The modified algorithm merges a point into a cluster whenever the distance between the point and the centroid of the cluster is less than the diameter of the cluster. At each merging of the points to the cluster, the centroid is updated.

For the implementation of DBScan, two parameters *eps* and *minPts*, need to be defined. *Eps* defines the

maximum distance of a point with other points while, *minPts* is the minimum number of points that are in the cluster. For each point in the data, the algorithm first expands the cluster based on the parameters defined earlier. By expanding the clusters, points which are density reachable, i.e., within the *eps* distance of the current point, are added to the clusters. However, the cluster could be expanded further if there are other points which have a distance less than *eps* with the points that had been just added to the cluster. We made use of the same formula defined by Nguyen et al [14] for the diameter of the cluster to be used as *eps*. As our implementation does not require any elimination of noise points, we set the minimum number of points in the cluster to one. The reason for this is because users would also be interested with clusters that have a single annotation.

We created a ground truth collection due to an absence of a baseline collection for comparison. Fifteen different tags were selected for evaluation purposes, and were selected based on the different concepts of landmarks, places or objects. These concepts were selected as users searching for local information on a map application would likely be selecting these query terms. Table 1 lists the different tags grouped by its concepts. The tags were used as queries to retrieve a set of annotations that had been annotated with that tag. The different algorithms were used to cluster the set of images based on their locations. The clustered images resulting from the different algorithms were then compared with a baseline approach that did not adopt any clustering feature. Here, the baseline approach listed images depending on the order retrieved in the database. This is in contrast to the clustering algorithms where the resulting images were grouped based on their geospatial locations.

Table 1 Tag selected for evaluation

Query Type	Query
Landmarks	Castle, Bridge, Museum, Ruins, Tower
Places	City Hall, Library, Temple, Restaurant, Garden
Objects	Statue, Train, Fountain, Lake, Fireworks

Given the set of clusters returned for each query (tag), we employed a rational user model to determine which would be selected for further analysis. Specifically, we assume that when a user is presented with a search result that has been clustered, they would select the largest

cluster [10] to explore. Users will also expand one cluster at most [12]. Following this tenet, we selected the top 50 images from the largest cluster based on the outcomes of the different algorithm. The clusters from the different algorithms were selected as close as possible in the same region to ensure consistency in the evaluation. Here, we took the location of the largest cluster from the DBScan approach as a guide for the other approaches as this algorithm is deemed to be more accurate in clustering spatial data.

In order to evaluate the usefulness of the different approaches, the top 50 images from the different clusters were evaluated for their relevancy by four human judges. The judges were presented with a list of images resulting from the different queries. WordNet definitions were provided to provide guidance to the evaluators. At the same time, the standard for relevance was also provided. In other words, the concept relevance in relation to the dataset was made known to the judges. This enabled the judges to maintain a standard level between them. Additionally, the judges were not told which algorithms generated the clusters to ensure there were no biases involved.

We used the precision value at the top N of the list of image computed by Precision@N = No of relevant results in N / N, where N = 5, 10, 25, 50. Precision at N determines the proportion of relevant images in the list, averaged over the number of photos. For instance Precision@5, is the proportion of relevant first five images in the list.

5. Results

Table 2 shows the average values of the algorithms' performance at the different precision levels. The values in bold show the highest value obtained for the average at the different levels. Due to space constraints, precision values are not shown for the individual queries. As observed from the table, DBScan showed the best performance among the different algorithm at all levels. However, the difference in precision values between DBScan and incremental clustering were not statistically insignificant, as the differences ranged only from 6% to 1.55%. Nevertheless, both algorithms significantly outperformed the baseline approach (no clustering). More specifically, a one-way, between algorithms ANOVA was conducted to compare the differences in precision among the three approaches, namely Baseline, Incremental and DBScan. There was a significant difference in precision across the different algorithms [$F(2, 177) = 7.697, p < 0.01$]. Post hoc comparisons using Tukey HSD test indicated that the mean score for the Baseline ($M = 0.511, SD = 0.304$) was significantly different from

DBScan ($M = 0.684, SD = 0.213$), $p < 0.01$ and Incremental ($M = 0.662, SD = 0.265$), $p < 0.01$. However there was no significant difference between DBScan and Incremental.

Table 2 The values obtained by the different clustering algorithm for the different levels in precision. The bolded values are the highest value obtained for all levels.

Precision level	Baseline	Incremental	DBScan
Precision @ 5	0.533	0.667	0.693
Precision @ 10	0.533	0.647	0.680
Precision @ 25	0.491	0.693	0.709
Precision @ 50	0.488	0.644	0.655

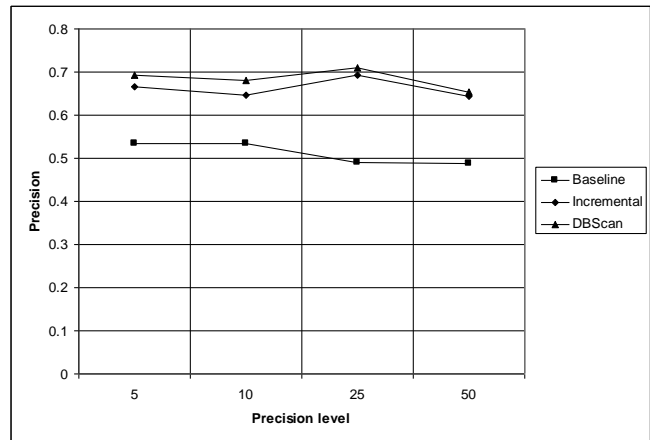


Figure 3 The performance of all the clustering algorithms at different precision levels.

Figure 3 illustrates the precision values of the three algorithms. It is interesting to note that both the results of incremental clustering and DBScan produce an atypical outcome compared with the baseline results. The baseline results are typical of that for precision values. This is because the number of irrelevant data increases as the more data is included. The reasoning for this is that the tags used are uncontrolled hence yielding such results. Both incremental clustering and DBScan exhibit similar trends.

The performance showed a slight degradation between the precision values precision@5 and precision@10. However, there is an increase between precision@10 and precision@25. The precision values then decreases for precision@50.

6. Discussion and conclusion

To reiterate, the aim of this paper is to compare clustering algorithms that can manage annotations on a map-based visualization on the MobiTOP system. The algorithms were evaluated by the precision of the clustering results, and our findings indicate that both incremental and DBScan perform better than the baseline (no clustering) approach. However, there is no statistical difference between the incremental clustering and DBScan algorithms, although DBScan seems to perform marginally better. Put differently, our results show that clustering annotations yield better performance than those that are not clustered.

Our results show that DBScan has performed better than incremental clustering techniques. Thus, this algorithm is selected for the clustering the annotations in MobiTOP's mobile application. However, the clustering process is done on the server before the clustered data is sent over to the mobile application in order to optimize the process. In the mobile device, each cluster is represented by a marker on the map. The users select a marker by panning the map to centralize the marker. After doing so, a small window containing a summary of the annotations in the cluster will be displayed.

There are limitations in our work that could be addressed in future research. In this present study, we evaluated potential clustering algorithms that could help in the logical grouping of annotations. A future direction is to implement the algorithm in the MobiTOP mobile application and evaluate users' performance in using the clustered annotations for browsing. Next, the current algorithms did not employ any ranking mechanisms that would help users discern the relevancy of the annotations returned in each cluster. Hence, the next step would be to investigate ranking techniques which would be applicable to rank annotations within clusters.

Acknowledgments. This work is partly funded by A*STAR grant 062 130 0057.

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