Extracting and understanding urban areas of interest using geotagged photos

Yingjie Hu[1*], Song Gao[1], Krzysztof Janowicz[1], Bailang Yu[2], Wenwen Li[3], Sathya Prasad[4]

[1] STKO Lab, Department of Geography, University of California Santa Barbara
[2] Key Laboratory of Geographic Information Science, Ministry of Education, East China Normal University

[3] GeoDa Center for Geospatial Analysis and Computation, School of Geographical Sciences and Urban Planning, Arizona State University

[4] Applications Prototype Lab, Esri Inc.,

Abstract: Urban areas of interest (AOI) refer to the regions within an urban environment that attract people's attention. Such areas often have high exposure to the general public, and receive a large number of visits. As a result, urban AOI can reveal useful information for city planners, transportation analysts, and location-based service providers to plan new business, extend existing infrastructure, and so forth. Urban AOI exist in people's perception and are defined by behaviors. However, such perception was rarely captured until the Social Web information technology revolution. Social media data record the interactions between users and their surrounding environment, and thus have the potential to uncover interesting urban areas and their underlying spatiotemporal dynamics. This paper presents a coherent framework for extracting and understanding urban AOI based on geotagged photos. Six different cities from six different countries have been selected for this study, and Flickr photo data covering these cities in the past ten years (2004 - 2014) have been retrieved. We identify AOI using DBSCAN clustering algorithm, understand AOI by extracting distinctive textual tags and preferable photos, and discuss the spatiotemporal dynamics as well as some insights derived from the AOI. An interactive prototype has also been implemented as a proof-of-concept. While Flickr data have been used in this study, the presented framework can also be applied to other geotagged photos.

Keywords: Areas of interest; AOI; Social media; Flickr; DBSCAN; Chi-shape; Tag extraction; Photo analysis; Data mining;

1 Introduction

Urban areas of interest (AOI) refer to the areas within an urban environment which attract people's attention. Such areas may contain city landmarks, commercial centers, and recreational zones, or may simply provide a scenic view of the city. The concept of urban AOI is different from *urbanized area*, as the former puts additional emphasis on people's interests. Consequently, an urbanized area (e.g., a regular residential neighborhood) may not necessarily also be an AOI. Unlike the well-defined

Corresponding author: Yingjie Hu, yjhu.geo@gmail.com

administrative districts, the boundaries of urban AOI are vague. This is because urban AOI are subjective: given a familiar city, most people will have a list of interesting areas in mind; yet, their lists may differ due to different ages, cultures, education backgrounds, personal interests, and so forth. Similarly, agreeing on certain AOI does not imply agreeing on their spatial extents and delineations. In this respect, AOI are related to the concept of *vague place* (Cohn and Gotts 1996, Montello et al. 2003, Jones et al. 2008, Liu et al. 2010).

Urban AOI have great meanings in multiple application domains. For tourists, AOI highlight the interesting zones within a city, and can therefore be used to support trip planning of travelers. For city planners, AOI reveal the regions which receive high exposure among the general public. Accordingly, these regions could be assigned higher priorities when there are only limited resources for urban planning projects, such as city beautification (Espuche et al. 1991, Gandy 2006). Since AOI are often visited by a large number of people, transportation analysts can examine these regions to understand traffic flows and human mobility patterns (Batty 2007, Yuan and Raubal 2012). In addition, information service providers can display targeted information based on AOI (e.g., highlighting the hotels within the AOI of a city).

AOI exist in the perception of people, and as a result, it is difficult to capture AOI using traditional data collection methods. In urban studies, remote sensing data have been often used to monitor the status of a city (Shi et al. 2014, Hsu et al. 2013, Yu et al. 2010). While good at detecting physical phenomena (e.g., land use types), remote sensing data are unable to observe interests of people. Alternatively, human participant survey, such as the one employed by Montello et al. (2003), could be used to uncover AOI. While such surveys provide valuable insights, they are labor-intensive, time-consuming, and do not scale well.

Social media, such as Twitter and Flickr, record the interactions between people and their surrounding environment (McKenzie et al. 2013). Compared to remote sensing images, social media data contain valuable information about the behavior of people in geographic space. In most cases, data from social media platforms can be retrieved through their public APIs at low costs. While social media data have often been criticized for the representative issue, i.e., the users may not constitute a representative sample of the entire population (Chou et al. 2009), they are nevertheless generated by millions of people from different countries throughout the world.

Among the many types of social media data, geotagged Flickr photos possess a high suitability for exploring urban AOI. One major advantage of Flickr data is that they reflect the interest of people towards locations (Kennedy et al. 2007, Crandall et al. 2009, Li and Goodchild 2012). This can be distinguished from some other social media data, such as geotagged tweets, which are not necessarily related to the locations they originate from. For example, a user may tweet about a humanitarian crisis, such as a particular drought, in East Africa from her office in Santa Barbara, California. While the location of her office is attached to that tweet, her real interest is in the events in Africa. In addition, the openness of the Flickr API allows the retrieval of publicly available data throughout the world and since the year of 2004. This adds an interesting temporal component to the data. Many other social media data are either constrained by user permissions (e.g., Facebook) or limited API accessibility for long-term data (e.g., Twitter and Foursquare). Besides, existing research shows that a major proportion of Flickr photos were taken in urban areas (Crandall et al. 2009, Hollenstein and Purves 2010), and this gives Flickr data one more advantage for studying urban AOI. Back in March 2013, Flickr already had 87 million registered members and more than 8 billion photos (Jeffries 2013).

This paper aims at extracting urban AOI and understanding them from spatial, temporal, and thematic perspectives. Geotagged Flickr data from six different cities in six different countries have been retrieved for this study. From a spatial perspective, this research examines the locations and extents of AOI in multiple cities and countries. From a temporal perspective, this research investigates the evolution of AOI in the past ten years (2004-2014), and compares the evolution patterns in developed and developing countries. From a thematic perspective, this research extracts the semantics of AOI from the textual tags and user contributed photos, and uncovers the thematic topics underpinning these AOI. The contributions are listed as follows:

- We develop a framework for extracting and understanding urban AOI from geotagged photo data. This framework is not restricted to Flickr data, but can also be applied to other geotagged photos.
- To generate proper polygon representations for AOI from point clusters, we design an experiment to identify an optimal parameter for the chi-shape algorithm, which balances the emptiness and the complexity of the generated polygons.
- We examine the extracted AOI from spatial, temporal, and thematic perspectives. Additional insights, such as the changes of landmark exterior and untypical AOI, are also discovered and discussed.
- We design and implement an online prototype that allows readers to explore the extracted AOI. This prototype can be accessed at: http://stko-exp.geog.ucsb.edu/urbanAOIs/index.html .

The remainder of this paper is organized as follows. Section 2 discusses related work on points of interest, vague places, volunteered geographic information, as well as extracting hot zones and landmarks from spatial footprints. Section 3 describes the dataset used in this work, and section 4 presents the framework for extracting and understanding urban AOI from geotagged photos. Section 5 provides a discussion on the spatiotemporal dynamics of AOI and the insights acquired from the extracted AOI. Section 6 describes the interactive prototype implemented based on the proposed framework. Finally, section 7 summarizes this work and discusses future directions.

2 Related work

2.1 AOI, POI, and vague place

The concept of AOI is closely related to two notions in literature, namely *point of interest (POI)* and *vague place*. POI represent individual locations (e.g., a restaurant or a landmark) which are of interest to people (McKenzie et al. 2014, Yoshida et al. 2010). In contrast, an AOI may contain multiple co-located geographic features, such as the restaurants on a pedestrian street or several nearby landmarks (Elias 2003, Raubal and Winter 2002). AOI may also include the areas that do not have prominent landmarks but simply provide scenic views (e.g., the areas in Paris that provide a good view of the Eiffel Tower). Thus, AOI can incorporate the *reversed viewshed*: unlike the traditional *viewshed* which represents the visible areas from a fixed point, *reversed viewshed* identifies the areas from which a given target can be seen (Fisher 1996, Senaratne et al. 2013). In terms of geometric representations, AOI are typically represented as polygons instead of points. Such a polygon representation has several advantages. First, it enables new functionalities that require spatial relations. For example, applications of geographic information retrieval often need to query information within a specific region (Jones et al. 2008), and AOI, which represent the boundaries of these regions, can be used for more accurate information search. Second, from a computational perspective, it is generally more efficient to perform operations on a polygon than on a set of points (Akdag et al. 2014). In addition, polygons convey information about the shape of a region, and can be employed for shape-based analysis (Li et al. 2014). Finally, from a cognitive perspective, polygons can provide simple and accessible representations for areas compared with clustered points.

The concept of vague boundary is important in the context of AOI. While disagreement may exist on the extent of AOI in a city, Montello et al. (2003) showed that there is often a general consensus on the core area of a place (e.g., *downtown Santa Barbara*). Similarly, in this study, we are interested in identifying the AOI which are agreed upon by a significant number of people. While vague places can often be referred to by vernacular names (Hollenstein and Purves 2010), AOI may not have a particular name due to the co-existence of multiple attractions. In addition to the work from Montello et al., there are also other studies on vague places. For example, Jones et al. (2008) used the place names harvested from Web search to identify the boundaries of vague places based on kernel density estimation. Davies et al. (2009) discussed the user needs and implications for modeling vague places in GIS.

2.2 Volunteered geographic information and spatial footprints

Volunteered geographic information (VGI) provides an alternative data source for many geospatial applications (Goodchild 2007, Elwood 2008, Sui et al. 2012, Hu et al. 2013). Although lacking standard quality control, some VGI has been shown to have equally good quality as authoritative data (Li and Goodchild 2012, Haklay 2010).

Spatial footprint is a special type of VGI generated by people on social media platforms (Cheng et al. 2011). When posting stories or sharing information on social media, people can geo-reference the posts by attaching their locations. Compared with traditional VGI platforms (e.g., OpenStreetMap) on which people directly contribute geographic information (Haklay and Weber 2008), *spatial footprints* can be considered as indirectly contributed VGI, i.e., the major goal of users is usually to share information rather than to contribute data.

The geotagged Flickr photos used in this research are one type of spatial footprints. A number of studies have been conducted based on Flickr data. For example, Hollenstein and Purves (2010), Intagorn and Lerman (2011) as well as Li and Goodchild (2012) have used Flickr data to investigate the boundaries of vague place concepts. Keßler et al. (2009) and Gao et al. (2014) employed Flickr data to enrich gazetteers with new place entries. There are also many other interesting applications of Flickr data, such as event extraction (Kennedy et al. 2007) and movement pattern analysis (Jankowski et al. 2010).

2.3 Extracting meaningful zones, tags, and photos from spatial footprints

With the wide availability of spatial footprints, research been done to identify hot regions as well as to summarize the textual tags and photos from the data. For example, Kisilevich et al. (2010b) proposed P-DBSCAN algorithm which detects attractive areas from geotagged photos based on the density of different people in a region. Cranshaw et al. (2012) extracted social dynamic neighborhood (which they call *livehoods*) by clustering Foursquare venues based on geospatial proximity and social similarity. Research from Ahern et al. (2007), Kennedy et al. (2007), as well as Rattenbury and Naaman (2009) focuses on mining place semantics from the textual tags of Flickr data, and related applications, such as TagMap, have also been developed to display the representative tags for geographic locations (Rattenbury and Naaman 2009). In another direction, researchers have investigated the extraction of landmarks and their photos, such as Jaffe et al. (2006), Chen et al. (2009), Kisilevich et al. (2010a), and Ji et al. (2011). These studies generally first cluster photos based on their geo-referenced locations, and then use visual feature matching techniques to find representative photos for landmarks. While many studies are based on the data from one single city, there is also global scale research that explores the popular cities and landmarks throughout the world (Crandall et al. 2009, Zheng et al. 2009).

Our research differs from the previous studies in several aspects. First, we address the question of deriving proper polygons from point clusters to represent AOI, whereas existing research only uses point clusters or simple convex hulls to identify zones. Second, we investigate and compare the evolution patterns of AOI in the past 10 years using cities in developing and developed countries. Such spatiotemporal evolution has been rarely examined so far. Finally, instead of focusing on one particular component (e.g., extracting textual tags), we propose a coherent framework which connects data processing, AOI generating, tag and photo summarizing, and knowledge discovery.

3 Dataset

Data used in this study have been retrieved using Flickr’s public API (https://www.flickr.com/services/api/). Six cities from six different countries have been selected for this work, which are: New York City (NYC), London, Paris, Shanghai, Mumbai, and Dubai. The first three cities are generally recognized as well-developed cities, while the second three cities have experienced fast development in the past 10 years. We deliberately choose these two groups in order to examine the difference in the growth patterns of their AOI. The data retrieval was performed in July 2014, and we retrieved all publicly available and geotagged Flickr data from June 2004 to June 2014 in order to study the AOI growth patterns in the past 10 years. The data for each city were retrieved using a bounding box containing the city’s administrative boundary.

The retrieved data contain two parts: Flickr photos and their metadata. Flickr photos are the images uploaded by Flickr users, which have been standardized into the JPG format. The metadata contain a rich amount of information about the photos, including photo ID, owner ID, photo title, photo location (latitude and longitude), taken date, textual tags, and some other information, such as the ID of the host server. Among these metadata, photo title, textual tags, and location are optionally provided by users, while the other fields (e.g., photo ID and server ID) are automatically filled by Flickr when the photos were uploaded. Location information is available for each metadata record, since we have only retrieved geotagged photos. However, titles and textual tags are only available for some photos.

Textual tags are often provided by users as descriptions for the photo content, and one photo may have multiple tags. Flickr also standardizes the user-provided tags by removing the space between words and converting letters into lowercase. For example, a user-provided tag like “Statue of Liberty” will be standardized into “statueofliberty”. Locations are assigned to photos in two ways: they can be either recorded by the built-in GPS in the camera device, or manually specified by the user based on an interactive map. Thus, the attached location could be where the photo was taken, or the location of a target in the photo. Locations recorded by a GPS belong to the former case, whereas the manually specified locations could be either of the two situations.

Table 1: the numbers of geotagged Flickr photos and unique users retrieved for this study.

City	Number of photos	Number of Users
New York City	2,761,542	2,751
London	2,876,013	2,357
Paris	1,456,298	3,019
Shanghai	254,123	1,775
Mumbai	55,532	1,901
Dubai	89,457	2,176

The total numbers of the geotagged Flickr photos and unique users (i.e., the same user who took multiple photos is counted only once) in the experimental dataset are summarized in table 1.

4 A three-layer framework for extracting and understanding AOI

4.1 Framework overview

A three-layer framework (Figure 1) has been designed for extracting AOI from geotagged photos and understanding their spatiotemporal dynamics. Learning from the DIKW (data, information, knowledge, and wisdom) Pyramid (Rowley 2007), the proposed framework aims at deriving knowledge from data following a bottom-up paradigm. The data layer at the bottom is responsible for retrieving data from Flickr's public API and pre-processing the data for later stages. The spatiotemporal layer, lying in the middle of the framework, focuses on extracting information about the spatial extents as well as the temporal growth of AOI. The semantic layer at the top serves the purpose of discovering knowledge from the extracted AOI, i.e., why these areas are considered as interesting by people and what makes them different from other sub-regions in the city. After applying the framework to the retrieved data, we will also present some wisdoms that can be derived from the AOI in the discussion section.

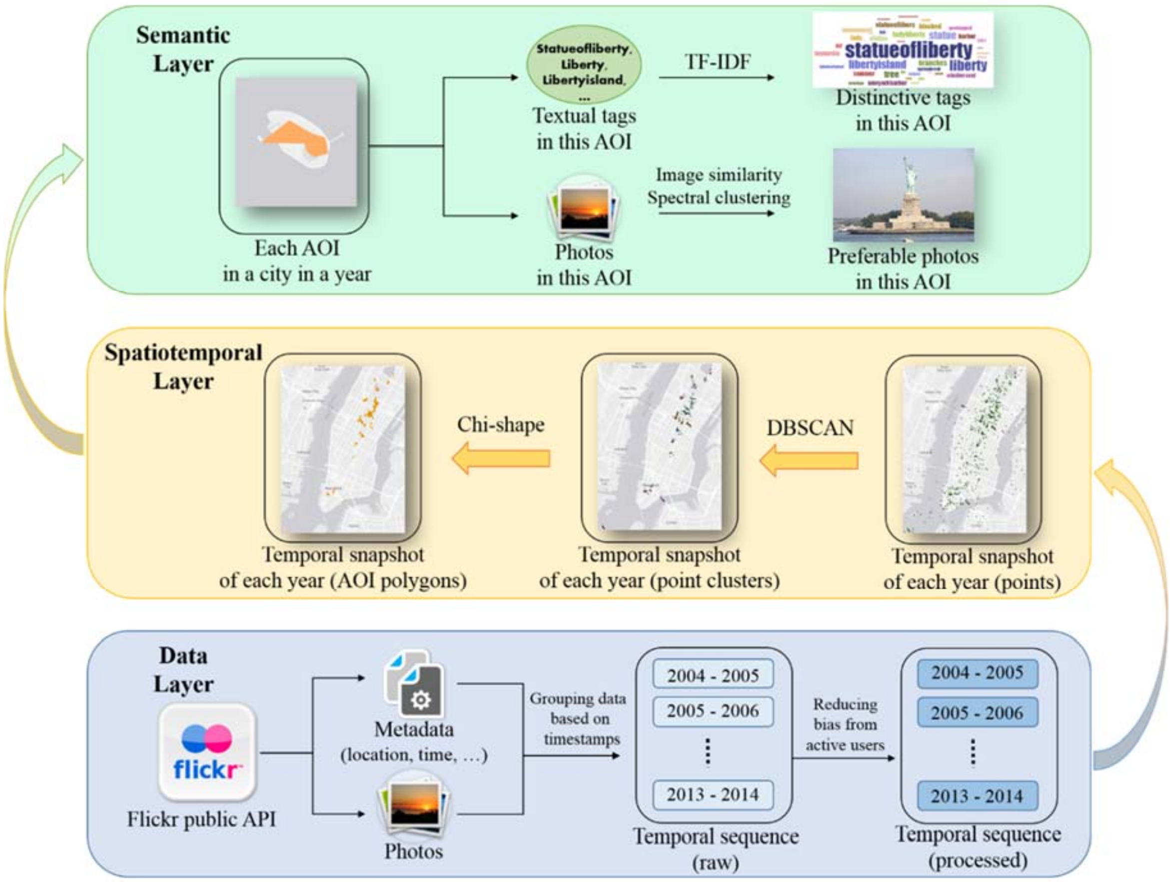

Figure 1. A three-layer framework for extracting and understanding urban AOI from geotagged Flickr data.

4.2 Data layer

The major function of this layer is to prepare data for later stages. Specifically, two preparations have been performed: constructing temporal sequences and reducing data bias.

Temporal sequences, which consist of multiple snapshots ordered by time (Goodchild 2013), have been constructed to examine the evolution of AOI. To study annual changes, we utilize a one-year time window in this research, and the geotagged photos in each city have been divided into 10 snapshots. Each snapshot contains the records starting from the June of last year and ending at the June of the next year (since the latest Flickr data we have retrieved are in June 2014). Accordingly, the last temporal snapshot in this study is from June 2013 to June 2014.

The data layer also addresses the bias issue existing in Flickr data. As suggested by Hollenstein and Purves (2010), some active Flickr users have uploaded a large number of photos, while those less active users have only uploaded a few. This power-distribution is characteristic for many social media data sources. Consequently, if the raw data are directly used, the extracted AOI will be dominated by the behaviors of active users. To reduce this bias, we retain only one record for each user who had uploaded multiple photos within a neighborhood radius. Specifically, we design a spatial filter which maintains the locations and user IDs for photos in a year. When processing the raw data, the spatial filter only keeps the photos which do not have any existing photo from the same user within the neighborhood radius, thereby reducing the dominance effect from active users. The neighborhood radius is determined based on the search radius of the clustering method in the spatiotemporal layer.

4.3 Spatiotemporal layer

4.3.1 The problem of AOI extraction

This layer extracts AOI based on the locations of geotagged photos. We consider the problem of AOI extraction as a majority voting process: AOI are formed at areas where a significant number of different Flickr users have taken photos. The emphasis of this definition is on *different* and *significant*: AOI should be derived based on a common agreement among *different* users, and meanwhile, there should be a *significant* number of Flickr users who took photos in the AOI. Our data pre-processing removes the additional records from the same user in a neighborhood, and helps to ensure that the AOI are derived based on the opinions of *different* users. Our next steps need to ensure that the extracted AOI reflect the behavior of a *significant* number of users. Based on this analysis, we abstract AOI extraction into a clustering problem, i.e., identifying significant point clusters from the pre-processed data.

4.3.2 Identifying point clusters using DBSCAN

DBSCAN (Density-based spatial clustering for applications with noise) is a density-based clustering method (Ester et al. 1996). It is configured by two parameters *Eps*, the search radius, and *MinPts*, the minimum number of points within the search radius. These two parameters together define a minimum density threshold, and clusters are identified at locations where the density of points is larger than the threshold.

Compared with some other clustering methods, such as K-Means or K-Medoids, DBSCAN possesses several advantages for extracting urban AOI. First, DBSCAN does not require a pre-determined number of clusters. In this study, the number of clusters is equivalent to the number of AOI, which are difficult to estimate for different cities in different years. Second, DBSCAN is good at detecting clusters in different shapes. In an urban environment, AOI can be in any arbitrary shape: a pedestrian street or a beach may show an elongated AOI, whereas a commercial plaza or a landmark building may show a square-like AOI. DBSCAN captures these arbitrary shapes by identifying clusters based on the density connectivity of points instead of their distances to the centroid. Finally, DBSCAN is robust to data noises that can be commonly found in Flickr photos and other social media data. Figure 2 compares the performances of K-means and DBSCAN.

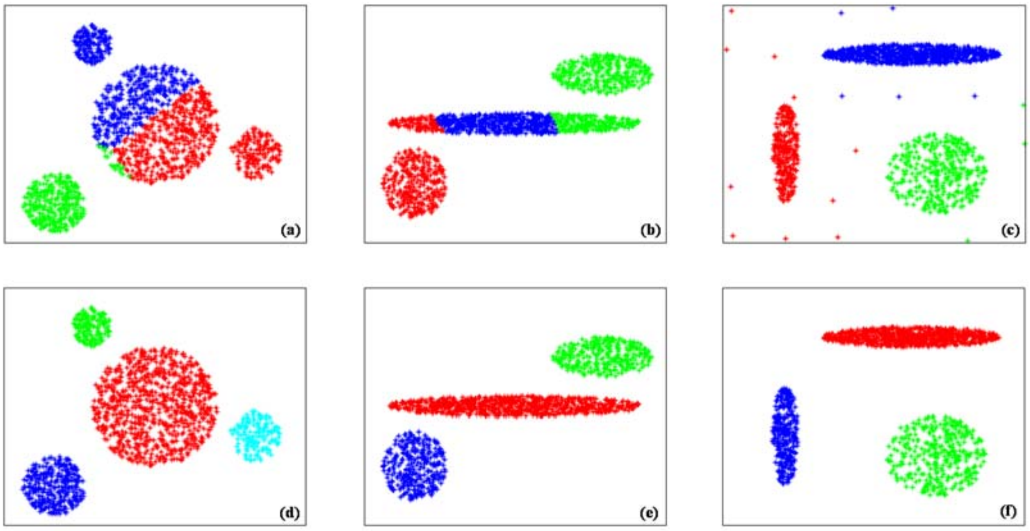

Figure 2. Comparison of K-means and DBSCAN; (a) (b) (c) are the results of applying K-means; (d) (e) (f) are the results of applying DBSCAN;

To apply DBSCAN, proper values need to be selected for *Eps* and *MinPts*. *Eps* can be determined by the geographic scale of the studied problem. Generally, a larger *Eps* produces AOI covering a broader region, while a smaller *Eps* creates AOI in smaller areas. *MinPts* defines the minimum number of points required for a cluster, and determines the significance of the extracted AOI. A larger *MinPts* can help ensure a higher significance for the detected clusters, but may exclude some interesting areas. A smaller *MinPts* can extract more clusters, but may also include noises. Due to the varying numbers of Flickr users and photos in different cities and different years, a single absolute value for *MinPts* may not be suitable. Thus, we handle this variation issue by setting *MinPts* as a percentage of the Flickr users who have visited that city in that year.

To identify proper values for *Eps* and *MinPts*, we use two cities, NYC and Shanghai, as the references for calibration. These two cities are selected because the authors are relatively familiar with them and can use background knowledge to verify the clustering result. Besides, these two cities are from the developed and developing countries respectively, and a calibration based on them can help study the two city groups. Since this research aims at extracting neighborhood-level AOI, we iteratively experimented with *Eps* from 100 to 500 meters and with *MinPts* from 1% to 5%. In each iteration, we first use the value of *Eps* as the neighborhood radius to pre-process the data so that the dominance effect from active users is reduced. Then, we input the pre-processed data to DBSCAN which identifies clusters in the city. After that, we compare the clustering results with the well-known popular areas in these two cities (e.g., Times Square in NYC and The Bund in Shanghai). In total, we have experimented with 25 different combinations of the two parameters. With high *Eps* and low *MinPts* (e.g., 500 meters and 1%), very large clusters have been identified from the data. In the case of NYC, points on the entire Manhattan Island become one big cluster. With low *Eps* and high *MinPts* (e.g., 100 meters and 5%), only a few clusters covering small areas are detected. In the case of Shanghai, small clusters are identified in The Bund area, Pudong district, and People Square which cover only the hottest sightseeing spots. Based on the experimental results, we select 200 meters for *Eps* and 2% for *MinPts*, since they produce generally significant AOI which cover the popular areas in the cities. The two parameters define the meaning of the extracted AOI. In this study, AOI are the areas that satisfy the two criteria: 1) minimum user criterion: these areas have attracted at least 2% of the total Flickr users who have visited that city in that year; 2) user density criterion: for any neighborhood with a 200 m radius within these areas, there should also be at least 2% of different Flickr users.

After setting the parameters, we apply the data pre-processing and DBSCAN to the retrieved geotagged photo data. Clusters are identified, and noisy points are removed. Figure 3a and Figure 3b show the clustering result using an example of NYC. Although there are six different cities in our experimental dataset, we use the same set of parameters for DBSCAN to extract AOI. This is because one goal of our study is to compare the AOI in different cities and years, and using the same parameters ensures that the extracted AOI are defined based on the same criteria, namely 2% of different users and 200 meters of search radius. An alternative approach is to find a specific set of parameters for each city. However, such an approach will generate AOI based on different criteria, which are not comparable. For example, an AOI extracted using 1% of different users and 500 meters of search radius essentially has a different definition for *areas of interest*, and therefore cannot be directly compared with the AOI extracted using the criteria in this work. However, if a study only investigates the AOI in a single city in multiple years, then it would be suitable to identify a set of specific parameters for the target city.

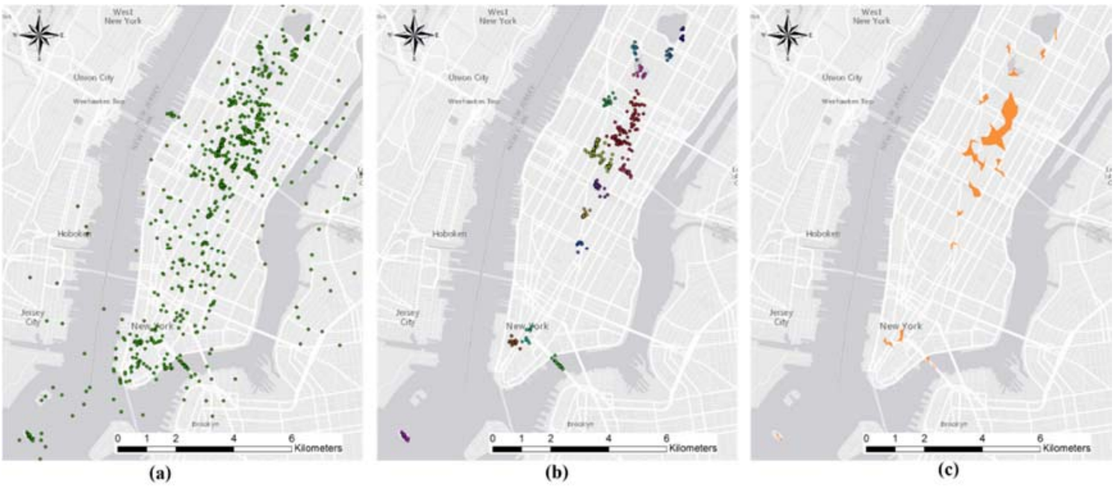

Figure 3: Extracting AOI from photo locations using an example of NYC in 2004 - 2005; (a) locations of Flickr photos; (b) point clusters detected by DBSCAN; (c) AOI formed using chi-shape algorithm.

4.3.3 Constructing AOI from point clusters using chi-shape algorithm

While point clusters have been identified from photo locations, one more step is necessary to derive areas (polygons) from the clustered points. Convex hull is a typical method for finding the minimum bounding shape based on a set of points, and has been used in many applications (Barber et al. 1996, Jarvis 1973, Yu et al. 2014, Frontiera et al. 2008). While providing unique and often computationally efficient results, convex hulls can contain large empty areas that are not occupied by the original point set (Akdag et al. 2014). To delineate the shapes of point clusters more accurately, Duckham et al. (2008) proposed an algorithm that identifies a non-convex polygon termed as *chi-shape* (or *concave hull*). However, the chi-shape algorithm requires a normalized length parameter λ_P in [1, 100], which determines the threshold of the longest edge of the generated polygon.

In order to find a suitable value for λ_P, we employ the fitness function proposed by Akdag et al. (2014) as in Equation 1:

$$\Phi(P, D) = Emptiness(P, D) + C * Complexity(P) \tag{1}$$

where Φ is the fitness function, P represents the polygon generated from the point set, and D is a set of triangles generated based on the point set using Delaunay triangulation. $Emptiness(P, D)$ is the emptiness function based on P and D. $Complexity(P)$ quantifies the complexity of a polygon based on the number of notches, the total length of perimeter, and the deviation from the corresponding convex hull (Brinkhoff et al. 1995). C is a parameter which balances the weights of the two parts, and we assign a value of 0.35 to C, as suggested by Akdag et al. (2014). Equation 1 will achieve its minimum value when a polygon has reached the best balance between emptiness and complexity.

We implement the fitness function, and employ the point clusters of the six cities in 2014 as the experimental data. We iterate λ_P from 1 to 100, and calculate the average fitness of the generated polygons. Figure 4 shows the resulted curve plot, with x axis being the normalized length parameter λ_P and y axis being the average fitness. The minimum value of the fitness function is achieved when λ_P equals to 32.

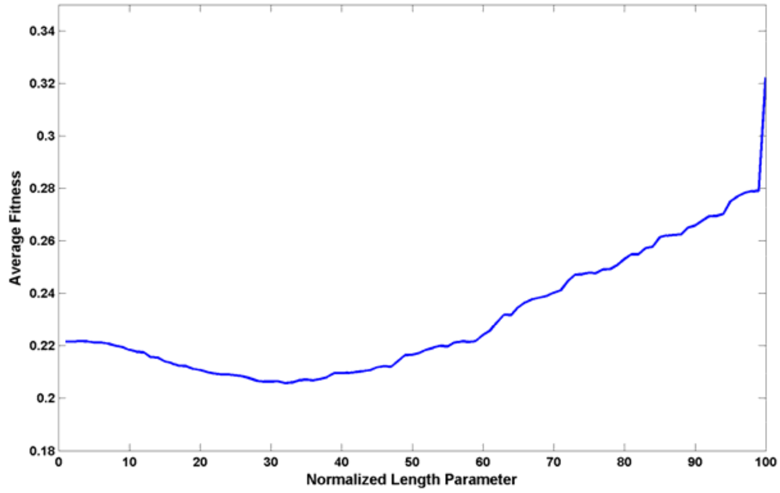

Figure 4: curve plot of the normalized length parameter and the average fitness.

Figure 5 shows an example in the Bund area of Shanghai, in which different polygons are constructed from the same point cluster when λ_P is assigned different values. As can be seen, the generated polygon has a shape that is close to the point cluster when λ_P equals to 1, but this polygon also has spiky edges and sharp angles (i.e., high complexity). With the increase of λ_P, we observe smoother polygons with larger empty areas. When λ_P equals to 100, the constructed polygon is equivalent to a convex hull, and some noisy areas (e.g., part of the river) have also been included into the polygon.

Based on the experimental result, we use the optimal λ_P=32 for the chi-shape algorithm. Figure 3b and Figure 3c illustrate the process of constructing AOI from point clusters.

4.4 Semantic layer

While AOI have been constructed, the reasons why these areas attract people are still unknown. The semantic layer aims at discovering useful knowledge for interpreting AOI. Specifically, we sum up the textual tags and photos within each AOI based on the pre-processed data (i.e., the dominance effect of the active users has been reduced), and identify the distinctive tags and preferable photos in these AOI.

4.4.1 Detecting distinctive tags

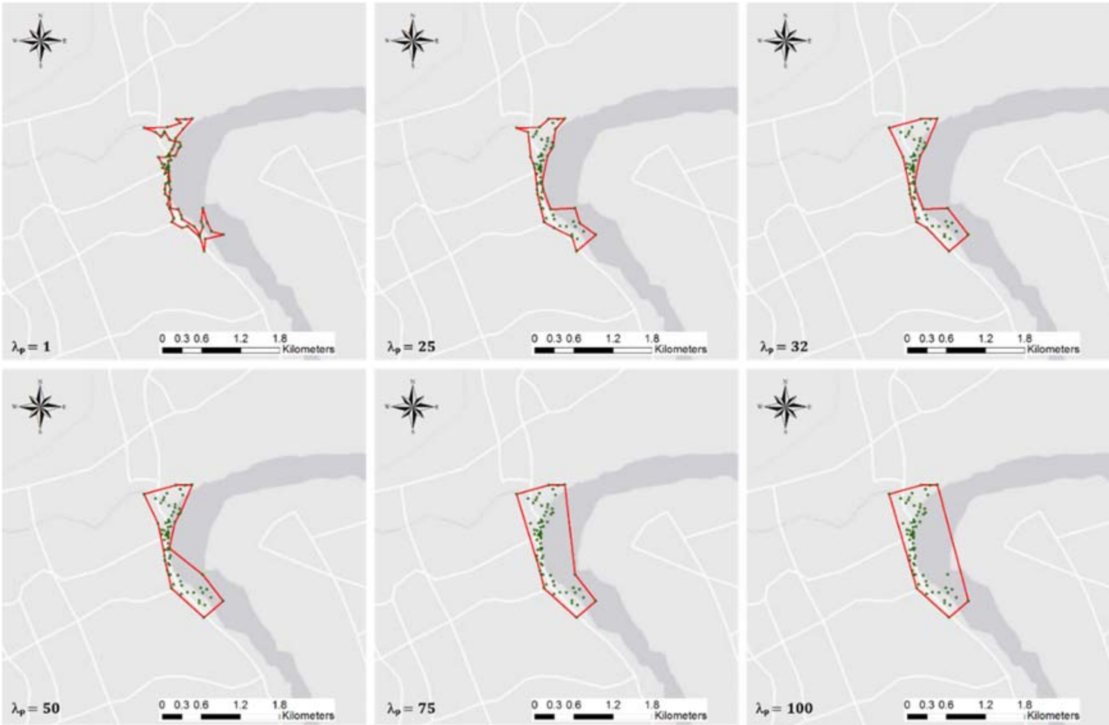

Figure 5: polygons generated using the chi-shape algorithm under different λ_P values.

Flickr tags contain valuable information about the photo content, and therefore have been used to discover interesting targets in AOI. However, some common tags can be found in almost any AOI within a city. For example, the tags "Paris" and "France" have been observed in many AOI in Paris. Thus, it is necessary to highlight the tags that are specific to the local regions while reducing the importance of the commonly used terms. To achieve this goal, we employ a method, namely term frequency and inverse document frequency (TF-IDF), which has been widely used in information retrieval (Salton and Buckley 1988). TF-IDF can be calculated using equation (2):

$$w_{ij} = tf_{ij} \times \log\frac{N}{df_j} \tag{2}$$

where w_{ij} is the weight of tag T_j in AOI A_i; tf_{ij} is the frequency count of tag T_j among all tags in A_i; N is the total number of AOI in a city, and df_j is the number of AOI that contain the term T_j.

TF-IDF captures the importance of the tags which are frequently mentioned by people within a particular AOI. Meanwhile, it reduces the significance of tags which can be commonly found in many AOI. Consequently, high weights will be given to tags which not only have a high frequency in the local region but also are rarely mentioned in other AOI. Figure 6 shows the tag clouds generated for two AOI in two cities.

4.4.2 Selecting preferable photos

While distinctive tags provide insight on the topics that people talk about within an

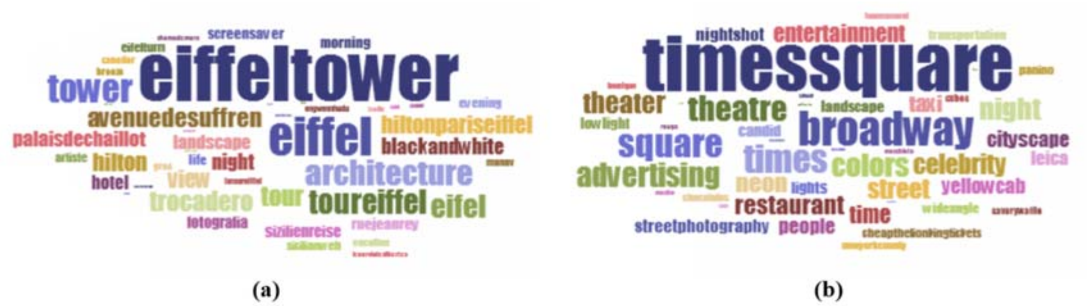

Figure 6: two tag clouds for two AOI respectively; (a) an AOI around the Eiffel Tower; (b) an AOI around Times Square.

AOI, the vast number of Flickr photos provide the potential to understand what people are looking at in AOI. However, one AOI may contain many photos with varied qualities and motives: some photos capture the good views within an AOI, whereas some others are more personal photos (e.g., family pictures), or photos of random targets. Consequently, simple methods, such as randomly selecting several photos for each AOI, will not work.

Thus, our goal is to develop a method that can select photos representing a preferable view of an AOI. To achieve this goal, we design a workflow based on the methods from Crandall et al. (2009). The rationale behind this workflow is that if a photo captures a preferable view of an AOI, then similar views should be captured by a number of other persons. For example, almost everyone who travels to Paris will take a photo of the Eiffel Tower, whereas it is less likely for different people to capture the same random shoot. Figure 7 illustrates the designed workflow.

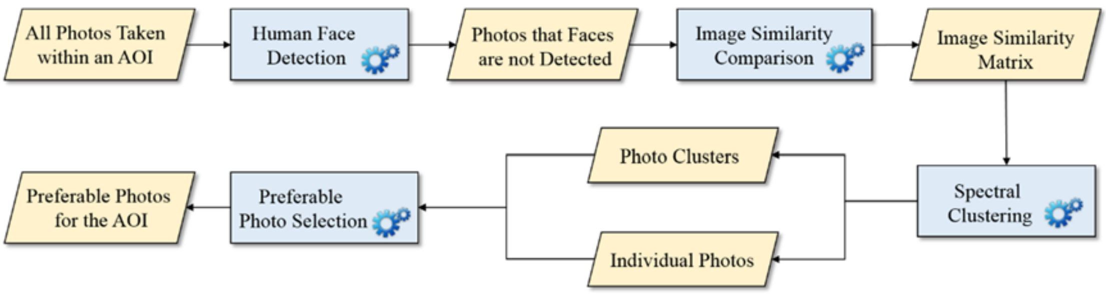

Figure 7: workflow for extracting preferable photos from an AOI. Blue rectangles with gears represent software modules, while yellow rhombuses are data files.

In this workflow, we first apply a human face detection algorithm to remove the personal photos in an AOI. The face detection library used in this step is OpenCV 2.4.9. For photos in which faces are not detected, an image comparison algorithm is applied to calculate the distance matrix for each photo pair. It is worth noting that image comparison itself is an ongoing research topic, and designing a sophisticated comparison algorithm is beyond the scope of this work. Thus, we employ a moderate algorithm proposed by Santos (2010), which compares images based on *patches* instead of *pixels*. Such a method divides a single photo into 25 RGB patches, and calculates the Euclidean distance between these patches (see Figure 8 and equation (3)).

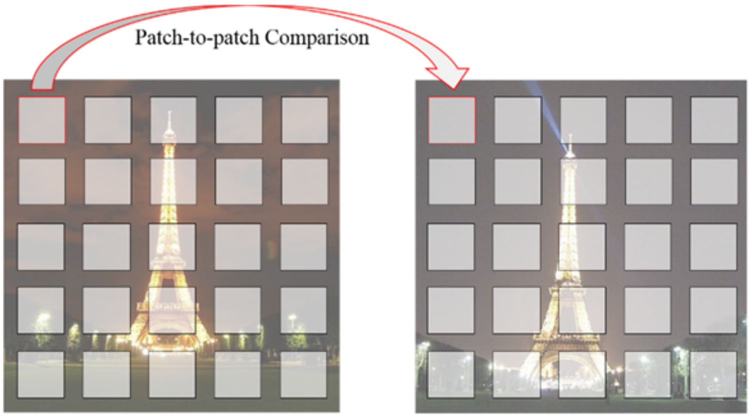

Figure 8: an illustration for the patch-based image comparison method.

$$d(x, y) = \sum_{i=1}^{25} \sqrt{(x_{ir} - y_{ir})^2 + (x_{ig} - y_{ig})^2 + (x_{ib} - y_{ib})^2} \qquad (3)$$

where x, y represent two photos, and $d(x, y)$ is the distance between them. x_{ir} represents the *red* band value for patch *i* in photo x, while x_{ig} and x_{ib} represent the *green* and *blue* bands respectively.

Based on the generated photo distance matrix, we apply spectral clustering (Shi and Malik 2000) to identify photo clusters. Such a method converts the photo distance matrix into a graph, with photos as nodes and photo similarities as edge weights. Then, photos, which contain views shared by multiple people, are grouped into clusters, whereas the other photos, which are often random shoots, are excluded as noises. Finally, in a photo cluster, the photo that is most similar to all others is selected as the preferable photo. Two special situations need to be handled. In some AOI, no photo clusters can be detected. This happens when only a small number of photos are left after the human face filtering, and consequently it becomes less likely to find a shared view among the limited data. For these AOI, our workflow records their identities, and we manually select one photo from their small candidate pool. In some other AOI, multiple photo clusters can be identified due to the situations that multiple landmarks are co-located, or the same target may have multiple preferable views from different distances or perspectives. For these AOI, our workflow automatically selects one preferable photo for each cluster. As a result, some AOI may have multiple preferable photos that capture different landmarks or different views.

5 Results and discussion

Applying the framework to the retrieved Flickr data, we have extracted AOI for the six cities in the past ten years. In this section, we examine these results, and present some insights that can be derived from the AOI. We also discuss the importance and potential applications of the derived insights.

5.1 Spatial extents of AOI

The spatial extents of AOI delineate the boundaries of hot regions within a city, and can be used as an additional data layer in geographic information systems to support decision making. Most of the extracted AOI cover areas where one or more prominent landmarks are located. This result corresponds to our empirical knowledge that important landmarks generally attract more people than regular areas. To provide a more concrete discussion, we examine two examples, namely NYC (2013 - 2014) and Shanghai (2008 - 2009). Examples about other cities and years are also available via our online prototype. Figure 9 shows the spatial extents of the extracted AOI.

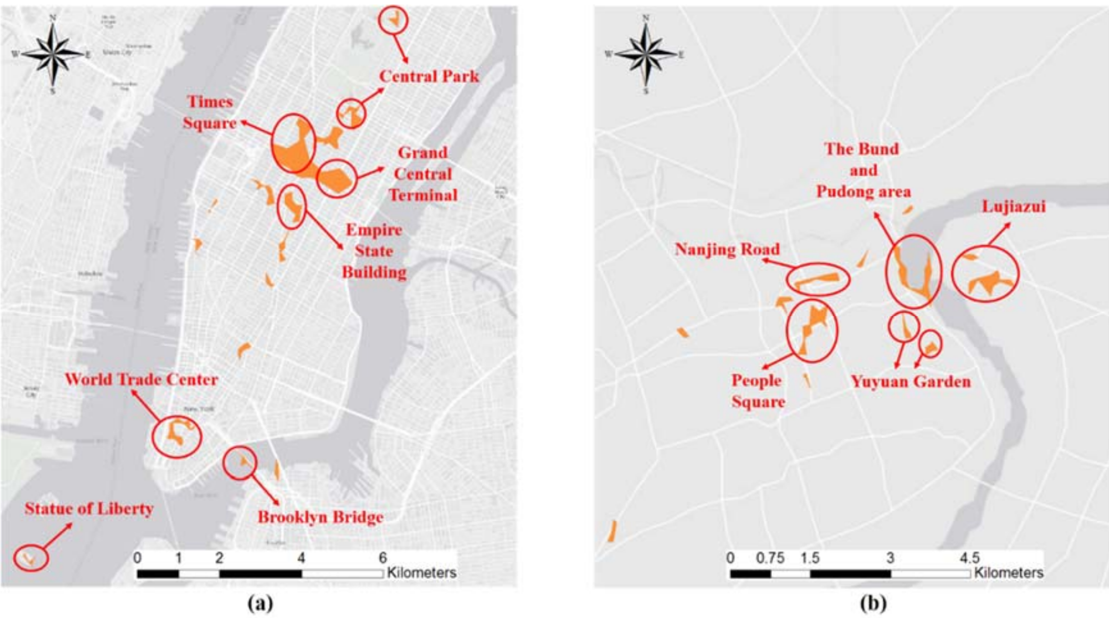

Figure 9: spatial extents of AOI in two cities; (a) New York City (2013-2014); (b) Shanghai (2008-2009).

In NYC, the extracted AOI cover popular tourist zones, including Times Square, Central Park, and the Statue of Liberty, to name just a few. The most significant AOI is formed around the Times Square area, where landmarks, such as Grand Central Terminal and Chrysler Building, are co-located. The extracted Times Square AOI ranges from 3rd avenue to 9th avenue, and is displayed as an elongated shape. Depending on where people took photos in that year, one large AOI (when people took photo continuously in the general area) or multiple smaller AOI (when photos were taken closely near the landmarks) are formed. Therefore, in some other years (e.g., in 2007-2008; see the online demo), the big Times Square AOI in Figure 9 is divided into several smaller areas.

In the example of Shanghai, popular areas are also covered by the extracted AOI, including the Bund area, Pudong district, Nanjing Road commercial area, Yuyuan Garden and others. The most significant AOI in this case is the Bund-and-Pudong area. Such an AOI consists of two smaller areas separated by the Huangpu River, which are the Bund, where a lot of Shanghai’s historical landmarks are located, and Pudong, where most of the city's modern skyscrapers are built. With *old* on one side and *new* on the other side, this region has been the *must see* for visitors for many years. There are also cruise tours on the Huangpu River, and therefore we see Flickr photo locations on the river. Consequently, the two smaller areas can be connected in some years.

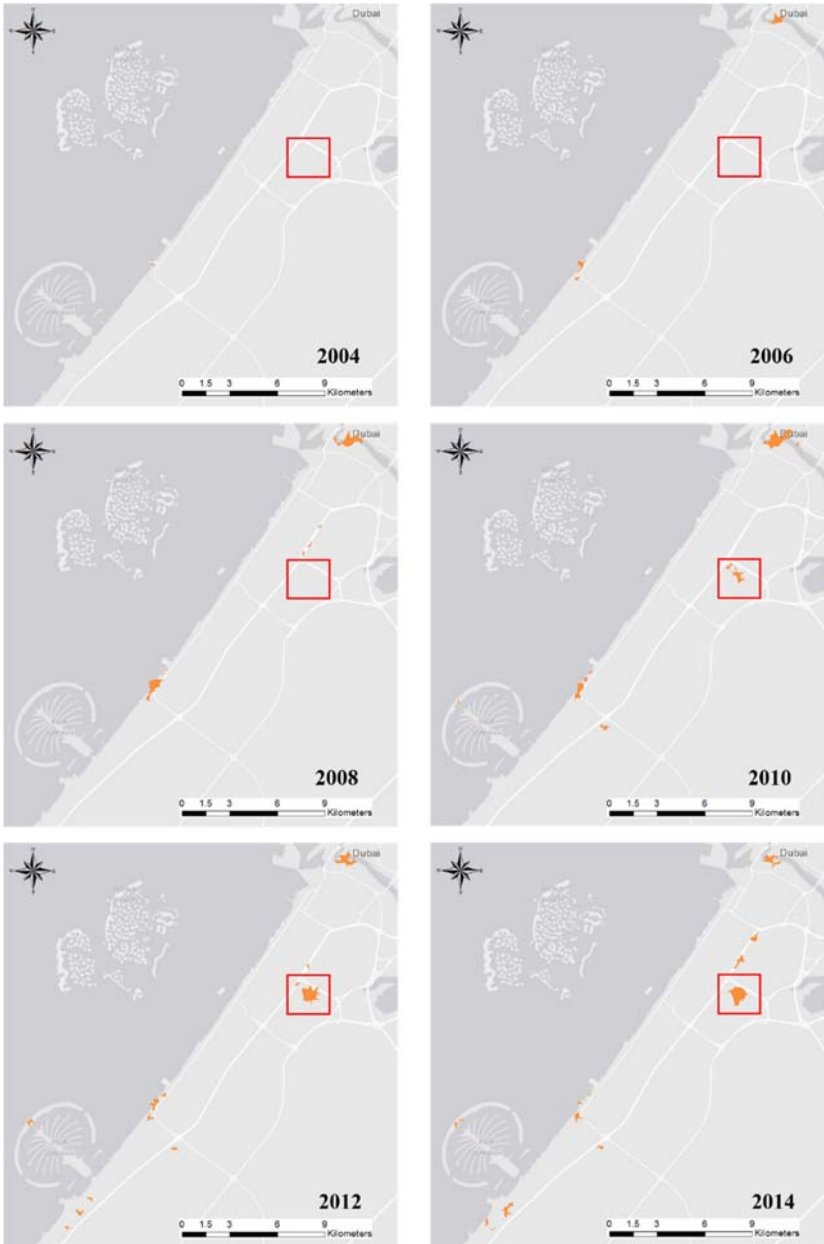

Figure 10: The evolution of AOI in Dubai from 2004 to 2014. The region in the red rectangle contains the skyscraper Burj Khalifa which officially opened in January 2010. Due to the lack of data, the basemap is from 2014; back to 2004, the palm tree island did not yet exist.

5.2 Spatiotemporal evolution of AOI in a city

Since the extracted AOI have been organized as a temporal sequence, we can also investigate their evolution. The spatiotemporal dynamics of AOI can help reveal the relation between city development and the growth of its attractive regions. As a newly developed urban area may not necessarily become an AOI, examining the spatiotemporal evolution can help answer the questions, such as *which areas are more likely to become an AOI in near future?*

To study the spatiotemporal evolution of AOI, we select the city of Dubai as an example which has experienced significant growth in the past 10 years. According to the data from the National Bureau of Statistics in UAE (http://www.uaestatistics.gov.ae), the population of Dubai has increased from 4,106,427 to 8,264,070 from 2005 to 2010. Such a fast growth of the city also brought a significant increase of the AOI (see Figure 10; to save space, we only show the AOI maps every other year).

The spatiotemporal dynamics of AOI in Dubai also provides insight on how AOI are formed. It can be seen from Figure 10, the AOI within the red rectangle only begins to appear since 2010, and stays there since. By manually examining that area, we find out such AOI contains the iconic skyscraper Burj Khalifa whose construction finished in October 2009 and which officially opened in January 2010. Such an example indicates prominent landmarks can facilitate the formation of AOI.

Besides landmarks, important events can also help form AOI. Figure 11 shows the AOI evolution in Shanghai from 2009 to 2011. It can be observed that two AOI showed up in 2010 within the red rectangle, while they did not exist in the other two years. In 2010, Shanghai held a major international event, Shanghai Expo, and the locations of the AOI are consistent with the location of the event.

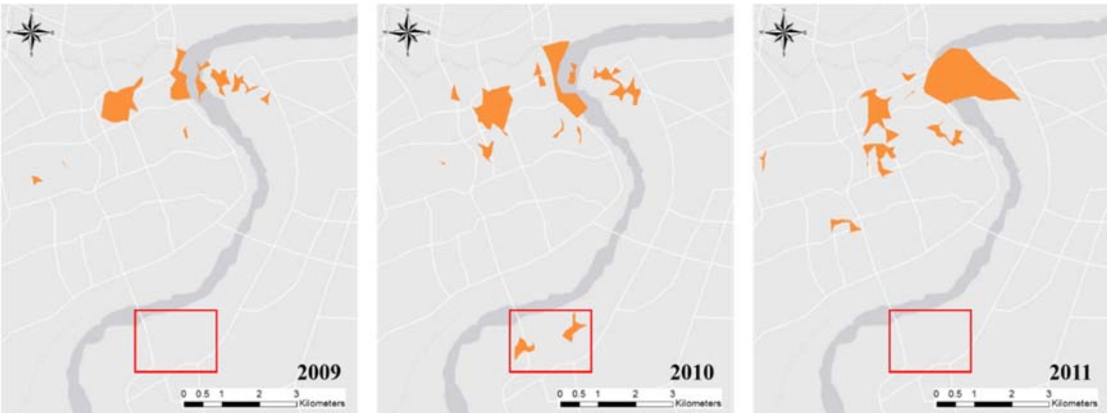

Figure 11: AOI formed in 2010 due to the Shanghai Expo event.

5.3 Comparison of AOI in fast-growing and well-developed cities

While a newly developed area may not necessarily become an AOI, are new AOI more likely to emerge in cities undergoing fast development? The intuitive answer is yes, since more development often brings new attractive features for the city. As this study has selected both fast-growing and well-developed cities, we can verify this answer by comparing the AOI growth patterns in the two city groups.

To perform the comparison, we sum up the total area value of the extracted AOI in each city and each year, and plot out the results (see Figure 12). While there are fluctuations in the total area values, different growth patterns can still be observed between the well-developed cities (in the top row) and the fast-growing cities (in the bottom row). Generally, the three well-developed cities start from a relatively large area values, and grow with a relatively slow rate (an evident example is Paris). In contrast, the three fast-growing cities begin with much lower initial values, but show a significant increase in the total area values of AOI (an evident example is Dubai). All of the three fast-growing cities end up with more than 7 times larger AOI compared with their initial values in the 2004-2005 time window, while such huge increases do not happen to the three well-developed cities.

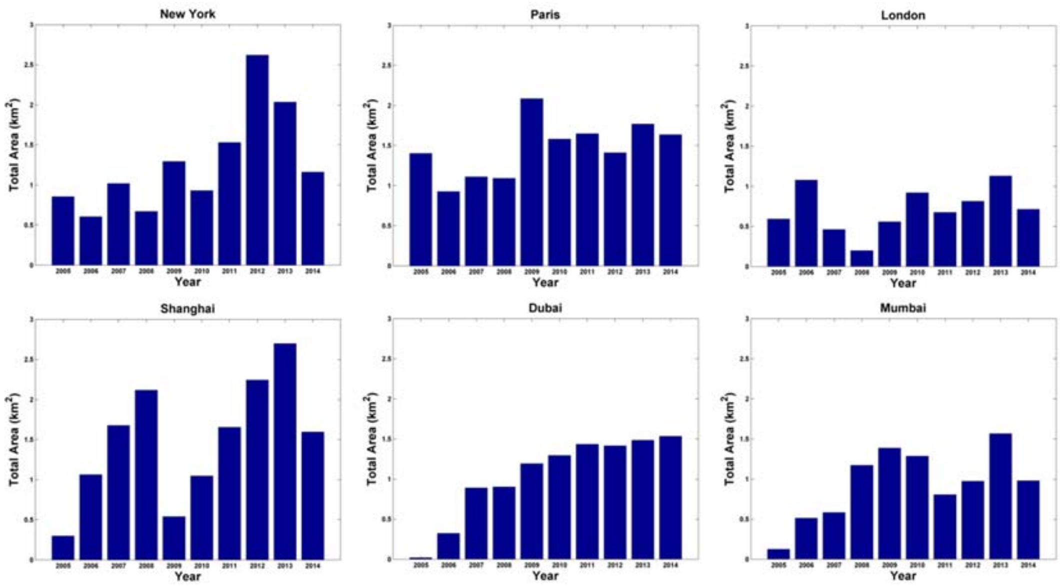

Figure 12: area values of AOI in 6 cities in 10 years; top row contains the three well-developed cities: New York City, Paris, and London; bottom row has the three fast-growing cities: Shanghai, Dubai, and Mumbai.

Since Flickr photo sharing service started from 2004, one can argue that such a significant growth of AOI in fast-growing cities may be due to the increasing popularity of the Flickr service in developing countries. While the increased popularity can have potential influence on AOI expansion, a wider usage of Flickr service does not necessarily lead to the corresponding increase of AOI. Figure 13 provides a comparison between the total area of AOI and the number of photos taken using two examples, Shanghai and Dubai. It can be seen that the area of AOI in Shanghai 2009 is significantly smaller than the area in 2008, while the year of 2009 actually has more photos. Similarly, in Dubai, there is a significant increase in the number of photos in 2013 compared with 2012, but such a big increase cannot be observed in the total area in the corresponding year. To further understand the possible reason for the drop of AOI in Shanghai 2009, we manually examine the generated AOI as well as the original photo locations. We notice that most photos in 2009 were taken in locations closely surrounding landmarks, whereas many photos in some other years (e.g., 2008) were also taken in the areas between landmarks. As a result, these interim areas were also included into the 2008's AOI, whereas the AOI in 2009 only focused on the local attractive regions. While such interim areas can still be considered as AOI, the result indicates that geotagged photo data are influenced by the behavior variation of people in different years.

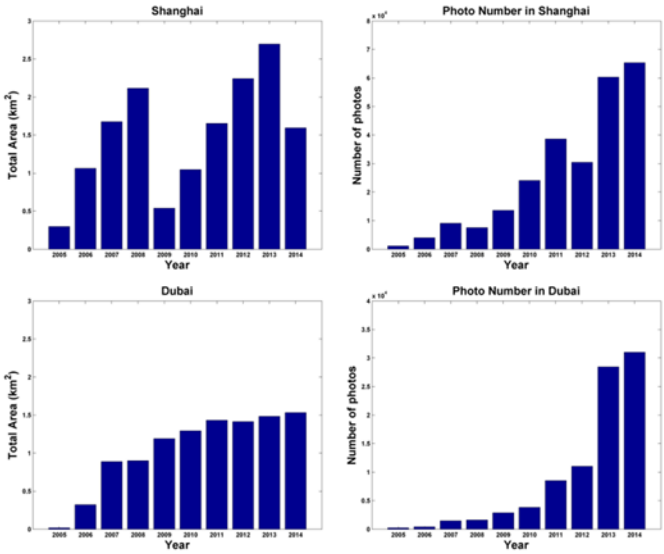

Figure 13: comparing the total area values of AOI with the numbers of photos using the examples of Shanghai and Dubai.

5.4 Historical slideshows for persistent landmarks in AOI

For landmarks persisting in an AOI over years, this study captures their preferable photos in a temporal sequence. Such temporal photos enable the creation of a *historical slideshow* which records the changes of the landmark appearances. As a result, the historical slideshows can be used as valuable documentaries for governments and museums. In addition to the traditional photos from journalists, these documentaries capture the views contributed and shared by the general public.

(a) (b) (c)

Figure 14: a historical slideshow of the Eiffel Tower using the preferable photos in three different years; (a) 2004; (b) 2008; (c) 2013.

Figure 14 shows an example of historical slideshows using the Eiffel Tower in three different years. In 2008, the Eiffel Tower was decorated as blue to celebrate the

French presidency in the European Union (Reuters 2008). Such an event was recorded by the lens of social media. Interestingly, our method also extracts consistent textual tags, such as “blue”, “bleu” (“blue” in French), and “Europe”, in 2008, while these terms are not observed before and afterwards.

5.5 AOI without aesthetic views

While AOI usually provide appealing views towards iconic landmarks or popular zones, is aesthetic view a prerequisite for an AOI to be formed? With the distinctive tags and preferable photos extracted in each AOI, we can further examine the various factors underlying AOI. Figure 15 shows an AOI in Mumbai which is different from our general expectation, and two extracted photos as well as a tag cloud are displayed.

(a) (b) (c)

Figure 15: photos and a tag cloud extracted from the untypical AOI in Mumbai.

It can be seen that the extracted photos in this area were not taken due to their aesthetics. However, such photos are extracted because these views are shared by many people. From the tag cloud, we can see that the important terms are “dhobi”, “ghat”, and “laundry”. A quick search of “dhobi ghat” in Wikipedia reveals that this area is in fact the world's largest outdoor laundry place which has been selected for *World Amazing Records*. This example indicates that AOI can be formed due to a variety of reasons (e.g., people’s curiosity), and providing aesthetic views is not a prerequisite. This result also demonstrates that our AOI extraction method goes beyond identifying the typical landmarks that one can generally imagine.

6 Prototype

While we have discussed some AOI, there are many other interesting areas in our result. Instead of describing them one-by-one, we develop an online prototype (http://stko-exp.geog.ucsb.edu/urbanAOIs/index.html), and invite the readers to interactively explore the AOI and examine the discussed insights. Thus, this prototype has been designed for two purposes: 1) it serves as a supplementary material which provides additional content for the current paper; and 2) it acts as a proof-of-concept for the presented framework. A screenshot is shown in Figure 16.

To implement this prototype, we first extract AOI, the distinctive tags, and preferable photos offline using the presented methods and the retrieved Flickr data. The point clustering and polygon construction algorithms take less than 10 minutes on average to process the data of one city on a Dell desktop computer with Core i5 processor and 8G memory. However, photo comparison and photo clustering algorithms take around 30 hours on average to compare the photos in one city (using the same computer), due to the large number of pixels involved. Then, we publish the extracted AOI as Esri's feature services, and use ArcGIS Javascript API to visualize the results on a Web map. The graphic user interface (GUI) is designed using the Dojo Javascript framework. There are three main parts in the GUI. The map in the center shows the extracted AOI, as well as the locations where people took photos (additional photos from the same user within a radius of 200 meters have been removed). At the bottom is a row of AOI displayed as thumbnails, and the panel on the right shows information about the city, the distinctive tags, and the preferable photos. Not only delineating the boundaries of AOI, this prototype also shows the significance level of AOI (i.e., how much percentage of different Flickr users have visited the area) using graduated colors. By clicking on the AOI thumbnails at the bottom, users can see the number of photos taken in this AOI, percentage of different users, distinctive tags, as well as the preferable photos. Users can also click the *play* button next to the year slider to explore the spatiotemporal dynamics of AOI.

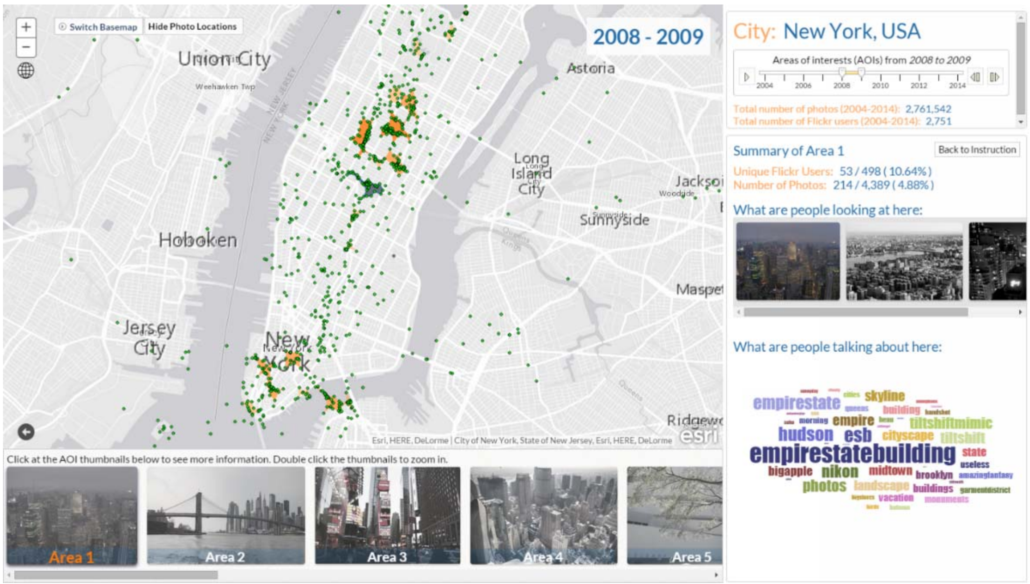

Figure 16: a screenshot of the interactive online prototype.

7 Conclusions and future work

In this study, we define urban AOI as the areas within a city that attract people's attention. A variety of reasons can contribute to the formation of AOI, such as prominent landmarks, commercial zones, and scenic views. The concept of AOI can be applied to multiple domains, including urban planning and location-based services, and can also be used as an additional layer in a GIS to support spatial queries. This study extracts AOI from geotagged photos and seeks a better understanding of how areas of interest form over time. Geotagged Flickr photos from six different cities in the past ten years have been retrieved as the experimental data, and a three-layer framework has been designed to extract and understand AOI. While the individual components (e.g., DBSCAN) of the framework are well known, we connect these methods into a coherent framework for AOI studies, which covers data pre-processing, point clustering, area construction, and semantics enrichment. In addition, we have also designed an experiment to derive proper polygons from point clusters, which achieves a balance between emptiness and complexity.

Detecting, delineating, and annotating AOI is important for various reasons. For example, understanding the evolution of AOI in the past years can help answer planning- and tourism-related questions, such as *which areas are more likely to become AOI in near future?* Meanwhile, the distinctive tags and preferable photos allow us to examine the underlying driving factors of AOI, and to investigate the strategies to turn a regular area into an attractive region. In this study, we have discovered real-world examples that indicate iconic landmarks, significant events, and even unique features can facilitate the formation of AOI. In addition, since the extracted preferable photos are also organized in a temporal sequence, they can be used as documentaries recording the changes of historical landmarks. To broadly share the extracted AOI and enable an interactive exploration, we develop an online platform to visualize the AOI in six cities.

Although Flickr data have been used in this study, the presented framework is general and can be applied to geotagged photos from other social media, such as Instagram and Panoramio. Compared with traditional human participant survey, data from social media provide an alternative solution with rich information and lower cost. However, these datasets remain biased towards the social media users who are only a fraction of the entire population. This representative issue can also vary, as the user bases of social media platforms may change over the years. As a result, the presented work cannot capture the behavior of some demographic groups, such as those who do not use social media. Nevertheless, the analysis result from this work, as well as those from other social media studies, do reveal useful knowledge based on the large number of users.

This research can also be extended in future work. For example, so far we have used a one-year time window to capture the annual changes of AOI. In future work, it would be interesting to use a one-month time window to investigate seasonal variability, since some AOI may show up or disappear in different seasons (e.g., some cities can become hot tourist destinations during summers, but may not be very popular in winters). In addition, our current clustering process has only used spatial proximity of photo locations. It would be interesting to add semantics (e.g., textual tags) into the clustering process. In that way, we expect the spatially-close but semantically-different points may be grouped into different clusters, and therefore one continuous AOI could further split into several sub regions based on their semantics.

Acknowledgement

The authors would like to thank the three anonymous reviewers for their constructive comments and feedbacks.

References

Ahern, S., Naaman, M., Nair, R., and Yang, J. H. I.., World explorer: visualizing aggregate data from unstructured text in geo-referenced collections. ed. *Proceedings of the 7th ACM/IEEE-CS joint conference on Digital libraries*, 2007, 1-10.

AKDAG, F., EICK, C. F. and CHEN, G., 2014. Creating Polygon Models for Spatial Clusters. *Foundations of Intelligent Systems.* Springer, 493-499.

BARBER, C. B., DOBKIN, D. P. and HUHDANPAA, H. 1996. The quickhull algorithm for convex hulls. *ACM Transactions on Mathematical Software (TOMS),* 22(4), 469-483.

BATTY, M., 2007. *Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals.* The MIT press.

Brinkhoff, T., Kriegel, H. P., Schneider, R., & Braun, A., Measuring the Complexity of Polygonal Objects. ed. *ACM-GIS*, 1995, 109-118.

Chen, W. C., Battestini, A., Gelfand, N., and Setlur, V., Visual summaries of popular landmarks from community photo collections. ed. *Signals, Systems and Computers, 2009 Conference Record of the Forty-Third Asilomar Conference on*, 2009, 1248-1255.

Cheng, Z., Caverlee, J., Lee, K., and Sui, D. Z., 2011. Exploring Millions of Footprints in Location Sharing Services. *ICWSM,* 2011, 81-88.

Chou, W. Y. S., Hunt, Y. M., Beckjord, E. B., Moser, R. P., and Hesse, B. W., 2009. Social media use in the United States: implications for health communication. *Journal of medical Internet research,* 11(4).

COHN, A. G. and GOTTS, N. M. 1996. The ‘egg-yolk’representation of regions with indeterminate boundaries. *Geographic objects with indeterminate boundaries,* 2, 171-187.

Crandall, D. J., Backstrom, L., Huttenlocher, D., & Kleinberg, J., Mapping the world's photos. ed. *Proceedings of the 18th international conference on World wide web*, 2009, 761-770.

Crandall, D. J., Backstrom, L., Huttenlocher, D., & Kleinberg, J., The Livehoods Project: Utilizing Social Media to Understand the Dynamics of a City. ed. *ICWSM*, 2012.

Davies, C., Holt, I., Green, J., Harding, J., & Diamond, L., 2009. User Needs and Implications for Modelling Vague Named Places. *Spatial Cognition & Computation,* 9(3), 174-194.

Duckham, M., Kulik, L., Worboys, M., & Galton, A., 2008. Efficient generation of simple polygons for characterizing the shape of a set of points in the plane. *Pattern Recognition,* 41(10), 3224-3236.

ELIAS, B., 2003. Extracting landmarks with data mining methods. *Spatial Information Theory. Foundations of Geographic Information Science.* Springer, 375-389.

ELWOOD, S. 2008. Volunteered geographic information: future research directions motivated by critical, participatory, and feminist GIS. *GeoJournal,* 72(3-4), 173-183.

Espuche, A. G., Guardia, M., Monclús, F. J., & Oyon, J. L., 1991. Modernization and urban beautification: The 1888 Barcelona world's fair*. *Planning Perspective,* 6(2), 139-159.

Ester, M., Kriegel, H. P., Sander, J., & Xu, X., A density-based algorithm for discovering clusters in large spatial databases with noise. ed. *Kdd,* 1996, 226-231.

FISHER, P. F. 1996. Extending the applicability of viewsheds in landscape planning. *Photogrammetric Engineering and Remote Sensing,* 62(11), 1297-1302.

FRONTIERA, P., LARSON, R. and RADKE, J. 2008. A comparison of geometric approaches to assessing spatial similarity for GIR. *International Journal of Geographical Information Science,* 22(3), 337-360.

GANDY, M. 2006. 4 Urban nature and the ecological imaginary. *In the nature of cities: Urban political ecology and the politics of urban metabolism*, 63.

Gao, S., Li, L., Li, W., Janowicz, K., & Zhang, Y., 2014. Constructing gazetteers from volunteered big geo-data based on Hadoop. *Computers, Environment and Urban Systems*.

GOODCHILD, M. F. 2007. Citizens as sensors: the world of volunteered geography. *GeoJournal,* 69(4), 211-221.

GOODCHILD, M. F. 2013. Prospects for a Space–Time GIS. *Annals of the Association of American Geographers,* 103(5), 1072-1077.

HAKLAY, M. 2010. How good is volunteered geographical information? A comparative study of OpenStreetMap and Ordnance Survey datasets. *Environment and planning. B, Planning & design,* 37(4), 682.

HAKLAY, M. and WEBER, P. 2008. Openstreetmap: User-generated street maps. *Pervasive Computing, IEEE,* 7(4), 12-18.

HOLLENSTEIN, L. and PURVES, R. 2010. Exploring place through user-generated content: Using Flickr tags to describe city cores. *Journal of Spatial Information Science,* (1), 21-48.

HSU, F.-C., ELVIDGE, C. D. and MATSUNO, Y. 2013. Exploring and estimating in-use steel stocks in civil engineering and buildings from night-time lights. *International Journal of Remote Sensing*, 34(2), 490-504.

Hu, Y., Lv, Z., Wu, J., Janowicz, K., Zhao, X., & Yu, B., 2013. A multistage collaborative 3D GIS to support public participation. *International Journal of Digital Earth,* 8(3), 212-234.

INTAGORN, S. and LERMAN, K., Learning boundaries of vague places from noisy annotations. ed. *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 2011, 425-428.

Jaffe, A., Naaman, M., Tassa, T., & Davis, M., Generating summaries and visualization for large collections of geo-referenced photographs. ed. *Proceedings of the 8th ACM international workshop on Multimedia information retrieval*, 2006, 89-98.

Jankowski, P., Andrienko, N., Andrienko, G., & Kisilevich, S., 2010. Discovering landmark preferences and movement patterns from photo postings. *Transactions in GIS,* 14(6), 833-852.

JARVIS, R. A. 1973. On the identification of the convex hull of a finite set of points in the plane. *Information Processing Letters,* 2(1), 18-21.

JEFFRIES, A., 2013. *The man behind Flickr on making the service 'awesome again'* [online]. [Accessed 7.28 2014].

Ji, R., Gao, Y., Zhong, B., Yao, H., & Tian, Q., 2011. Mining flickr landmarks by modeling reconstruction sparsity. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM),* 7(1), 31.

Jones, C. B., Purves, R. S., Clough, P. D., & Joho, H., 2008. Modelling vague places with knowledge from the Web. *International Journal of Geographical Information Science,* 22(10), 1045-1065.

Kennedy, L., Naaman, M., Ahern, S., Nair, R., & Rattenbury, T., How flickr helps us make sense of the world: context and content in community-contributed media collections. ed. *Proceedings of the 15th international conference on Multimedia,* 2007, 631-640.

Keßler, C., Maué, P., Heuer, J. T., & Bartoschek, T., 2009. Bottom-up gazetteers: Learning from the implicit semantics of geotags. *GeoSpatial semantics.* Springer, 83-102.

Kisilevich, S., Mansmann, F., Bak, P., Keim, D., & Tchaikin, A., Where would you go on your next vacation? A framework for visual exploration of attractive places. ed. *Advanced Geographic Information Systems, Applications, and Services (GEOPROCESSING), 2010 Second International Conference on,* 2010a, 21-26.

KISILEVICH, S., MANSMANN, F. and KEIM, D., P-DBSCAN: a density based clustering algorithm for exploration and analysis of attractive areas using collections of geo-tagged photos. ed. *Proceedings of the 1st international* *conference and exhibition on computing for geospatial research & application*, 2010b, 38.

LI, L. and GOODCHILD, M. F., Constructing places from spatial footprints. ed. *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information*, 2012, 15-21.

Li W., Chen T., *Wentza E. A. and Fan C.*, 2014. NMMI: A Mass Compactness Measure for Spatial Pattern Analysis of Areal Features. *Annals of the Association of American Geographers*, 104(6), 1116-1133.

Liu, Y., Yuan, Y., Xiao, D., Zhang, Y., and Hu, J., 2010. A point-set-based approximation for areal objects: A case study of representing localities. *Computers, Environment and Urban Systems*, 34(1), 28-39.

MCKENZIE, G., ADAMS, B. and JANOWICZ, K., 2013. A thematic approach to user similarity built on geosocial check-ins. *Geographic Information Science at the Heart of Europe*. Springer, 39-53.

McKenzie, G., Janowicz, K., Gao, S., Yang, J. A., & Hu, Y., 2014. POI Pulse: A Multi-Granular, Semantic Signatures-Based Information Observatory for the Interactive Visualization of Big Geosocial Data. *Cartographica*, 50(2), 71-85.

Montello, D. R., Goodchild, M. F., Gottsegen, J., & Fohl, P. 2003. Where's downtown?: Behavioral methods for determining referents of vague spatial queries. *Spatial Cognition & Computation*, 3(2-3), 185-204.

RATTENBURY, T. and NAAMAN, M. 2009. Methods for extracting place semantics from Flickr tags. *ACM Transactions on the Web (TWEB)*, 3(1), 1.

RAUBAL, M. and WINTER, S., 2002. *Enriching wayfinding instructions with local landmarks*. Springer.

REUTERS, 2008. *Eiffel Tower to turn blue for French EU presidency* [online]. Available from: http://www.reuters.com/article/2008/06/20/us-france-eiffeltower-idUSL2066543720080620 [Accessed 2014-8-25 2014].

ROWLEY, J. E. 2007. The wisdom hierarchy: representations of the DIKW hierarchy. *Journal of Information Science*, 33, 163-180.

SALTON, G. and BUCKLEY, C. 1988. Term-weighting approaches in automatic text retrieval. *Information processing & management*, 24(5), 513-523.

SANTOS, R. 2010. Java Image Processing Cookbook. *Online: http://www.lac.inpe.br/JIPCookbook/*.

SENARATNE, H., BRÖRING, A. and SCHRECK, T. 2013. Using Reverse Viewshed Analysis to Assess the Location Correctness of Visually Generated VGI. *Transactions in GIS*, 17(3), 369-386.

SHI, J. and MALIK, J. 2000. Normalized cuts and image segmentation. *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* 22(8), 888-905.

SHI, K., *et al.* 2014. Evaluating the ability of NPP-VIIRS nighttime light data to estimate the gross domestic product and the electric power consumption of China at multiple scales: a comparison with DMSP-OLS data. *Remote Sensing,* 6(2), 1705-1724.

SUI, D., ELWOOD, S. and GOODCHILD, M., 2012. *Crowdsourcing geographic knowledge: volunteered geographic information (VGI) in theory and practice.* Springer Science & Business Media.

YOSHIDA, D., SONG, X. and RAGHAVAN, V. 2010. Development of track log and point of interest management system using Free and Open Source Software. *Applied Geomatics,* 2(3), 123-135.

Yu, B., Liu, H., Wu, J., Hu, Y., & Zhang, L. 2010. Automated derivation of urban building density information using airborne LiDAR data and object-based method. *Landscape and Urban Planning,* 98(3), 210-219.

YU, B., *et al.* 2014. Object-based spatial cluster analysis of urban landscape pattern using nighttime light satellite images: a case study of China. *International Journal of Geographical Information Science,* 28(11), 2328-2355.

YUAN, Y. and RAUBAL, M., 2012. Extracting dynamic urban mobility patterns from mobile phone data. *Geographic Information Science.* Springer, 354-367.

ZHENG, Y.-T., *et al.*, Tour the world: building a web-scale landmark recognition engine. ed. *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, 2009, 1085-1092.