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Mobile GIS and Location-Based Services

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Abstract

With the fast development of mobile Web and computing technologies, as well as increasingly availability of mobile devices, mobile information technologies have revolutionary influence on the human society. In this chapter, we present a comprehensive review of mobile GIS and LBS concepts, core components and characteristics, technology stack, a variety of applications, and research frontiers. The applications of mobile GIS and LBS face several challenges such as small screen for data visualization, limited bandwidth and high costs of networks for transferring data, battery consuming for positioning and computing capabilities, heterogeneous types and multi-level spatiotemporal resolutions of datasets. This subject itself is also fast developing and advancing. We do hope that this chapter not only educates the next-generation of geographic information systems/science major students with the knowledge but also inspires them to dive into this challenging research areas and make their contributions in the future.

Keywords:

Apps, Field Data Collection, GeoComputation, GPS, GIS, LBS, Location, Mobile Database, Mobile GIS, Positioning, Shareability, Wi-Fi

1 Introduction

With the fast development of mobile Web and computing technologies, as well as increasingly availability of mobile devices, mobile information technologies have revolutionary influence on the human society. News, emails, microblogs, photos, videos, Apps and many other multi-media information can be easily accessed and shared with colleagues and friends through smart phones almost every day. In the era of mobile age, location-based services (LBS) play an important role in people's daily life, such as searching nearby points of interest (POI), way finding and navigation. In the domain of geographic information systems (GIS), advanced mobile information technologies have lowered the traditional enterprise GIS fence and enabled a variety of novel applications which can help improve positioning and tracking accuracy, efficient field data collection, real-time mapping, ground truth validation, location intelligence and decision support, and so on (Lemmens 2011; Abdalla 2016). Geospatial information, spatial analysis, and spatial queries are no longer limited to a fixed environment but can be accessed at any place at any time (Shi et al. 2009). However, mobile GIS and LBS face several challenges such as small screen for data visualization, limited bandwidth and high costs of networks for transferring data, battery consuming for positioning and computing capabilities, heterogeneous types and multi-level spatiotemporal resolutions of datasets. It is necessary for geographic information scientists and researchers to review and summarize recent progresses in this fast developing domain, with highlights on the core concepts of mobile GIS and LBS. In this chapter, we will first introduce what is Mobile GIS and its core components. Then the technology stack of Mobile GIS and LBS will be presented. Several popular Mobile GIS and LBS applications will be reviewed after that. And finally we will summarize key points presented in this chapter and conclude this work.

2 Definition of Mobile GIS

A good science discipline starts with a good definition. However, this might not be the case for GIS since it tends to be an integrated domain and there are many variations for the definition of GIS or GIScience. Researchers have comprehensive thoughts and comments about this topic.

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Although it is not the focus of this chapter, it is worth for the readers who are interested in a holistic view of this domain to dive into more details through those references (Tomlinson 1987, 2007; Goodchild 1992, 2010; Mark 2003; Egenhofer et al. 2016).

According to the functionalities and usages, mobile geographic information systems (Mobile-GIS) extend traditional desktop-GIS beyond the offices and allow individuals and organizations to localize, collect, store, visualize and even analyze geospatial data in both field and office environments. Mobile GIS applications can either store collected datasets in the offline mode and then upload to a GIS server or a cluster later on, or directly update features to existing Web GIS services on the cloud server infrastructure in real time via mobile devices. Any user regardless of location and environment can have access to the geospatial data and GIS capabilities using the Web if the user has the Internet connection. Under such a mobile-cloud architecture, it is convenient to keep geospatial data distributed and synchronized across varying locations on the Earth (as shown in Figure 1), and enable the shareability of GIS data and geospatial resources through the Web and mobile devices among colleagues of the same group (i.e., enterprise cloud) or any users on the Internet (i.e., public cloud).

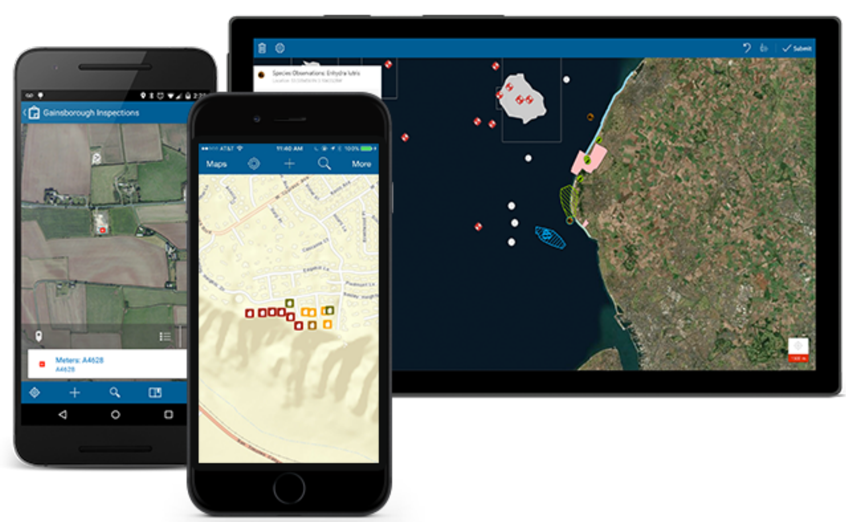

Figure 1. Screenshots of *Collector for ArcGIS* (Credit to Source: http://www.esri.com/products/collector-for-arcgis)

3 Key Components and Characteristics of Mobile GIS

In the section, we present some key components which mobile GIS should consist of. Geographic information scientists and GIS engineers might have different opinions on this topic. Here, we try our best to summarize important components based on both theoretical aspects and engineering practices.

- **Mobile device:** In general, it usually refers to personal digital assistants (PDAs), smartphones, tablets or even recently developed wearable devices like smart watches which have limited analysis or computing capability but would be sufficient for positioning, visualization and navigation purposes.
- **Apps:** Similar to GIS software on the desktop, mobile GIS applications (also known as "Apps") provide basic mapping functions and/or tools for collecting and storing geographic information. There are two types of apps: *Native* or *Web-browser apps*. Native ones are programmed for a specific mobile operating platform (such as Android or iOS) and can take advantage of mobile operating system features, while Web-browser apps are usually implemented using the HTML5 & Javascript framework and can be run in multiple operating platforms.
- **Data/Service Layers:** This is one of the most important and expensive components of mobile GIS. It usually consists of at least one basemap layer which provides the geographic background of current location of a mobile device and thematic layers which contain physical or socioeconomic properties, such as population, traffic, facilities, etc. The data layers shown in the mobile GIS environment can be retrieved from offline mobile databases, plain-text files or from online Web GIS services.

Mobile devices have limited memory, computational power, battery life, and screen size, as well as inconvenient input support (Virrantaus et al. 2001). These limitations imply that mobile GIS might need some new technologies to overcome the challenges. Compared with traditional desktop GIS, mobile GIS have several characteristics, including (but not limited to) web-based spatial data file formats, distributed spatial database, mobile geo-computing ability, and personalized visualization style.

- **Web-based spatial data file formats**

Because of the complexity of the spatial data, many spatial data file formats have been proposed and implemented in GIS to capture both geometric and topological information. Among these GIS data file formats, “Shapefile” which was developed by Esri Inc. is the most famous one and has been widely used and supported by almost all of mainstream GIS products. “DXF” (i.e., drawing interchange format, or drawing exchange format) is another popular spatial data file format which is developed by AutoCAD and has been widely used in urban planning and architecture design.

However, mobile GIS require frequent data exchange and communication between mobiles devices and remote servers. Web is the most popular user interface which has many advantages (Pundt and Brinkkötter-Runde 2000): 1) A graphic user interface (GUI) written in HTML and Javascript can simplify the user input tasks; 2) The WWW’s multimedia properties enable the visualization of spatial data in a graphically manner. All of the facts demonstrate that mobile GIS need a new spatial data format which can be easily transferred between mobile devices and servers, and can be easily read by Web GUI. Geography Markup Language (GML) is one of those data formats which satisfy these requirements. GML specified by the OpenGIS Consortium (Cox et al. 2001) is a kind of Extensible Markup Language (XML) which encoded geographic data. It is suitable for data exchange and supported by the Web. Nowadays, GML has been widely used in not only Mobile GIS but also many other Web-based geographic data services.

- **Distributed spatial database**

Mobile devices have relatively lower disk space than PC. It might be impossible to store all the spatial data on one small device. Even if several spatial data compression techniques have been proposed, it is widely accepted that only a small portion of the spatial data which are close to the user's current location can be stored in the mobile device temporarily using the caching technique or the dynamic data model strategy (Shi et al. 2009). The whole spatial database may be better stored in the servers while many mobile GIS also support offline storage mode (more details in the mobile database section). The spatial data can be stored in one server and can also be distributed among multiple servers and clusters.

- **Mobile/distributed geo-computing ability**

In traditional desktop GIS, geo-computing ability which involves in the data processing and spatial analyses only depends on the local machine which seems to be robust. But the low efficiency of traditional GIS has been criticized a lot when the volume of spatial datasets becomes so large. In contrast, because of the relative limited computing capability of mobile devices, mobile GIS advocate the idea of distributing the geo-computation tasks between mobile devices and servers. The greatest limitation in the distribution of geographic information over Internet is the difficulty in transferring and processing large sizes of spatial data. Mobile devices can only take care of some simple geo-computation tasks. When the user asks for a complex computation task, the mobile device will send a request to the backend server which has larger memory and higher computation ability. The serve will execute the geo-computation task and sent the result back to the device. In this way, a complex geo-computation task can be achieved by a reasonable time. In addition, a conceptual dynamic data model which considers the spatial, temporal and attribute constraints in a mobile environment has been proposed to increase mobile GIS performance, which can be measured by the response time of the database to a spatial query from a mobile GIS user (Shi et al. 2009).

- **Personalized visualization style**

The traditional desktop GIS often use a standardized visualization style. However, as for mobile visualization, a user may want to change the visualization style based on individual preferences to improve his/her understanding of information in mobile GIS. Adaptive mobile cartography has been proposed by Reichenbacher (2001) to take personal needs and context information into considerations for better mobile GIS assistance. Due to the variability of screen size, color setting, resolutions among different mobile derives, new concepts of the mobile interface design are also required. The full potential for efficient visualization of both spatial and non-spatial data on such small mobile screens may need to concern the load balancing between server and client, as well as enhanced mobile caching mechanisms.

4 Positioning and Tracking Technologies for Mobile GIS

Positioning is a key component to support mobile GIS development, mobility tracking studies, trajectory data mining and location-based applications. In this section, we present several important positioning technologies which have been developed in both outdoor and indoor environments.

4.1 Outdoor Positioning Technologies

Depending on the information technology infrastructures, popular outdoor positioning technologies include global navigation satellite system (GNSS), cellular networks, and wireless networks.

- **GNSS:** It provides the location (latitude/longitude) and time information in all weather conditions, anywhere on or near the Earth surface where there is an unobstructed line of sight to at least four or more global positioning satellites. Well-know GNSS infrastructures include GPS, the United States NAVSTAR Global Positioning System (GPS) and the Russian GLONASS, the Chinese BeiDou Navigation Satellite System, and the European Union's Galileo system. The most popular GNSS deployed on mobile devices on the current market share is the GPS. Many positioning techniques have been developed based on high-accuracy GPS chips, differential GPS, and assisted-GPS (Misra & Enge 2006).
- **Cellular networks:** Nowadays cellular network is one of the most important communication infrastructure among people and has almost a worldwide coverage. When a mobile call is made, the mobile phone signal is linked to the nearest cellphone tower or the base station with particular geographic coordinates. The location of the cellular tower can be used as an estimation of a mobile phone user when he or she makes a phone call communication. The spatial divisions of such cellular networks are divided into cells (regions) based on the Voronoi diagram in which for each cell tower location (as a center) there is a corresponding region consisting of all points closer to that center than to any others. That is, all phone calls within a given Voronoi polygon are closer to the corresponding cell tower than to any other cell towers. Generally, urban core areas have a higher density of mobile cells where the average distance

between mobile base stations is approximately one kilometer; the value of average separation depends on the size of the study area (Gao et al. 2013).

- **Wi-Fi:** The Institute of Electrical and Electronics Engineers (IEEE) 802.11 work group (2007) documents the standard use of Wi-Fi technology to enable wireless network connections in five distinct frequency ranges: 2.4 GHz, 3.6 GHz, 4.9 GHz, 5 GHz, and 5.9 GHz bands. The widely use of Wi-Fi access points for Internet connection in hotels, business buildings, coffee shops and many other fixed places makes Wi-Fi become an attractive technology for the positioning purpose. All of those Wi-Fi routers deployed in fixed places repeatedly broadcast wireless signals to the surrounding area. These signals typically travel several hundred meters in all directions such that they can form wireless signal surfaces; and one device could receive distinctive signals at different locations on the surface for localization. The accuracy of localization is then dependent on the separation distance among adjacent Wi-Fi reference points and the transmission range of these reference points (Bulusu et al. 2000).

Zandbergen (2009) systematically compare three dominant positioning technologies: Assisted-GPS, Wi-Fi, and Cellular positioning. Their pros and cons are discussed in terms of coverage, accuracy and reliability. It reports that Assisted-GPS obtains an average median error of 8m outdoors while Wi-Fi positioning only gets 74m of that and cellular positioning has about 600m median error in average and is least accurate. However, high-resolution GPS or Assisted-GPS positioning chipsets don't work well in indoor environments due to limited satellite visibility; and thus a number of indoor positioning technologies and systems have been designed and developed to increase the indoor positioning accuracy.

4.2 Indoor Positioning Technologies

In general, indoor positioning technologies can be classified into two broad categories: radio-frequency-based (RF) and non-radio-frequency-based (NRF) technologies. The RF group includes but not limited in *WLAN*, *Bluetooth*, and *RFID systems*, while the NRF group contains *ultrasound*, *magnetic fields*, and *vision-based systems*. Researchers have made great efforts in the field of indoor positioning using these sensors and technologies (Kaemarungsi & Krishnamurthy 2004, Ferris et al. 2007, Liu et al. 2007, Gu et al. 2009, Li et al. 2012, Liu et al. 2012, Kuo et al. 2014). The spatial coverage area and positioning accuracy of those different technologies have been reviewed by Mautz (2009). Here, we only briefly discuss the RF technologies that are most popular in the market share and have many challenging issues to investigate.

WLAN: Location positioning systems using wireless area local network (WLAN) infrastructure are considered as cost effective and practical solutions for indoor location estimation and tracking (Chang et al. 2010). The wireless networks are widely implemented in many types of indoor buildings in which wireless access points are usually fixed at certain positions. Those access points allow wireless devices (e.g., mobile phones, laptops and tablets) to connect to a wired network using Wi-Fi technology. And the relative distance between wireless devices and access points can be roughly estimated based on Wi-Fi signal strength using signal propagation models (Motley & Keenan 1988, Hidayab et al. 2009), which will be further discussed in the next subsection of methods. It is also well known that the accuracy of indoor position estimation based on Wi-Fi signal strength is affected by many environmental and behaviour factors, such as walls, doors, settings of access points, orientation of human body, etc. (Ferris et al. 2007, Wang et al. 2003). In practical applications, a good approximation of heterogeneous environmental signal surfaces could help to improve the indoor positioning accuracy. Spatial regression which is a widely used spatial-analysis method in finding spatial patterns of surfaces (de Smith et al. 2007) could potentially be a good candidate.

Bluetooth: Bluetooth technology that is designed for low power consumption allows multiple electronic devices to communicate with each other without cables by using the same 2.4 GHz radio-frequency band as Wi-Fi. The distance range within which Bluetooth positioning can work is about 10 meters. In the beaconing mode, Bluetooth permitted messages can be used to detect the physical proximity between two devices (Faragher & Harle, 2014). In an indoor environment equipped with equal or large than three Bluetooth low energy (BLE) beacons, the location of a target mobile device with Bluetooth can be determined using classic positioning approaches (see Section 2.2 in detail). In this way, location-dependent triggers, notifications and tracking activities can be enabled by employing multiple BLE beacons. There are several popular BLE beacon-positioning protocols and technology available online including *Apple iBeacon*[1]*, Google Eddystone*[2] *and Qualcomm Gimbal*[3], which guide developers to implement up-to-date indoor positioning and tracking applications.

Radio-frequency Identification (RFID): RFID is a general term used for a system that communicates using radio waves between a reader and an electronic tag attached to an object. Comparing with Bluetooth technology, RFID systems usually comprise of readers and tags that store relatively limited information about the object such as location and attribute information. Those tags can be activated and send out stored information if they receive the signal from RFID readers within certain distance thresholds, which can be used to estimate the reader's location

[1] https://developer.apple.com/ibeacon/

[2] https://developers.google.com/beacons/

[3] http://www.gimbal.com/

and to show relevant information. Currently RFID positioning and tracking systems are widely used for asset tracking, shipments tracking in supply chains, object positioning in retailing places and shopping malls.

Because of the sensor diversity and positioning challenges in various indoor environments, there is also an increasing trend towards combining and integrating different sensor networks to get a better spatial coverage and position accuracy than using single data source. For example, Evennou and Marx (2006) integrated Wi-Fi and inertial navigation systems to get performance close to meter by fusing pedestrian dead reckoning and WiFi signal strength measurements. Regalia et al. (2016) presented a novel crowdsensing framework and demonstrated that ambient sensors (e.g. temperature, pressure, humidity, magnetism, illuminance, and audio) available on mobile devices can help determine a location change in environments (e.g. moving from indoors to outdoors, or floor changes inside buildings) more accurately than typical positioning technologies (e.g. global navigation satellite system, Wi-Fi, etc.), and thus it might achieve higher positioning accuracy using multi-sensor positioning technology in the future.

4.3 Indoor Positioning Methods

The following methods usually work for both outdoor and indoor environments, but we want to emphasize the indoor case here. Note that those methods can be applied in most radio-frequency-based sensors, such as Wi-Fi, Bluetooth and so on.

4.3.1 Geometric Approaches

In geometry, trilateration is a method to determine the target location of a point by measurement of distances to three points at known locations using the geometry of circles, triangles, or spheres (Cayley 1841). This method has been widely used not only in positioning systems (Hofmann-Wellenhof et al. 1994, Doukhnitch et al. 2008), but also in robot localization, computer graphics, aeronautics, and so on (Thomas & Ros 2005). For the positioning purpose, if already knowing the coordinate (lat, lon) information of three fixed access points, it needs to convert the latitude and longitude of these locations on the Earth to axis values in the Cartesian coordinate system with some rules: (1) the x-axis goes through (0,0); (2) the y-axis goes through (0,90); (3) and the z-axis goes through the poles. The formulas of this conversion are expressed as follows:

$$x = R * \cos(lat) * \cos(lon) \qquad (1)$$

$$y = R * \cos(lat) * \sin(lon) \qquad (2)$$

$$z = R * \sin(lat) \qquad (3)$$

Where R is the approximate radius of earth (e.g. 6371km). Then we can try to find the solutions to trilateration equations to approximate the location of the target object by referring to three points with known locations (Hofmann-Wellenhof et al. 1994) (See Figure 2). The equations are nonlinear and it is not so easy to obtain an exact solution. Several iterative arithmetic methods have been proposed to find efficient solutions for trilateration-based localization (Manolakis 1996, Yang & Liu 2010).

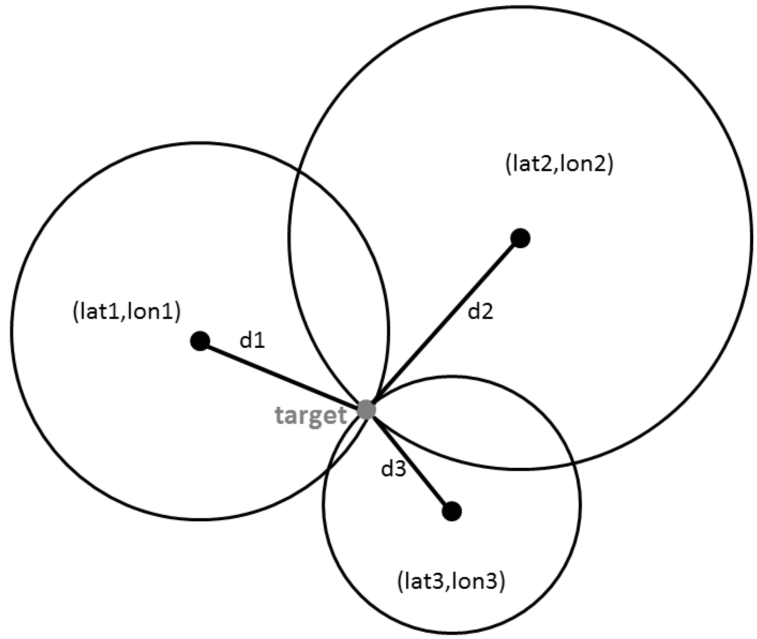

Figure 2. Determine the location of the target object by referring to three Wi-Fi access points with known coordinate information and the distances to them.

It is obvious that the distance between a wireless device and an access point is the key for Wi-Fi positioning using the trilateration method. The received signal strength doesn't directly lead to an estimated distance to a Wi-Fi access point. In general, it does follow a trend that the signal strength decreases with distance as is expected, but it is not a simple linear path loss model. The log-distance path loss model is one of the most simplistic radio-propagation models (Motley & Keenan 1988, Seybold 2005) that predicts the received signal strength at a certain distance inside a building or densely populated areas. It can be expressed as follows:

$$PL(d)[dB] = PL(d_0)[dB] - 10 * n * log_{10}\left(\frac{d}{d_0}\right) + X_g \qquad (4)$$

Where *PL(d)* is the received signal strength by a wireless device in decibel (dB) at a distance of *d* meters, $PL(d_0)$ is the received signal strength at a known reference distance d_0, *n* is a path-loss exponent factor, and X_g is a random that reflects the attenuation factors of complex environment. And we could solve this equation and approximate the distance to the wireless router if we get the empirical fits of the coefficients n and X_g, as well as a known received signal strength at a given distance d_0 and the signal strength at the unknown location.

However, in many practical situations, many factors underlying radio propagation can contribute to the reflection, refraction, absorption and scattering of signals. It is difficult to predict the received signal strength by a simplistic log-distance pass-loss model. Rather than creating a new pass-loss model, some researchers try to re-parameterize the classic log-distance model. For example, Bose and Foh (2007) found that at closer ranges (e.g., smaller than 5 meters) the n exponent factor of propagation model would take a higher value, and thus a dual-distance model has been proposed to adjust the propagation model at larger distances and to achieve a better positioning accuracy.

4.3.2 Fingerprinting Approaches

Although most Wi-Fi access points are located at the fixed locations of buildings, it is very hard to get their accurate coordinates and detailed digital floor maps because of privacy concerns. Fingerprinting approach is a popular wireless-network positioning technology in metropolitan areas since it doesn't need the exact position information of Wi-Fi access points and doesn't model the signal strength. Instead, it needs to construct an offline database that contains the signal strength distribution of Wi-Fi access points at known locations, i.e., the "radiomap". For a given location, it receives varying signal values from equal or less than the maximum number of available Wi-Fi access points. The set of access points and their signal strengths are distinctive and present a "fingerprint" to a unique location in the "radiomap". Thus, we can employ searching and comparison processes in the online positioning phase to find the most probable location.

Several fingerprinting matching and calculation methods have been developed to best estimate the location of the user based on received Wi-Fi signal strength (SS) values at known reference point (RP) locations (Kaemarungsi & Krishnamurthy 2004, Lin & Lin 2005, Mok & Retscher 2007, Gezici 2008). In its simplest form, it can be expressed mathematically as follows:

$$\underset{p\in(1,2,\ldots n)}{arcmin}\sqrt{\sum_{i=1}^{m}[SS_{RP}(i,p)-SS_{ME}(i)]^2} \qquad (5)$$

where $SS_{RP}(i,p)$ represents the received signal-strength value of access point i at a known reference point location p on the radiomap, and $SS_{ME}(i)$ is the measured signal-strength value of access point i at the current unknown location. The location p that has the minimum root-squared-differences of SS values for all available access points between reference points and the target location is considered as the most probable estimated location.

Machine-learning-based fingerprinting techniques have also been studied for improving the quality of location estimation in complex real environment, including Bayesian modelling, k-nearest-neighbour estimation, support vector machine, neural networks and so on (Bahl & Padmanabhan 2000, Roos et al. 2002, Youssef et al. 2003, Brunato & Battiti 2005, Lin & Lin 2005, Honkavirta et al. 2009).

4.3.3 Statistical Approaches

Commonly, wireless signal strength indicators used in positioning relate to power, direction and time of a received signal. Several characteristic indicators are widely used for position estimation purposes, such as time of arrival (TOA), angle of arrival (AOA), and time difference of arrival (TDOA). Gezici (2008) conducted a comprehensive survey on those wireless position estimation techniques. Statistical approaches are employed to formulate a generic framework for position estimation using one or multiple characteristic indicators, which can be expressed as:

$$Z_i = f_i(lat, lon) + \delta_i, \quad (i = 1,2, \ldots, N) \qquad (6)$$

where Z_i is the estimated i^{th} indicator value, $f_i(lat, lon)$ is the function for the i^{th} indicator value at a given location with coordinate *(lat, lon)*, δ_i is a noise parameter, and N represents the number of estimated indicators. The parameters can be estimated based on offline signal sampling data collected at different reference locations, which is similar to previously introduced fingerprinting approach. However, the main difference between fingerprinting and statistical approaches is whether to formulate a generic parameter-based theoretical framework that can be employed for online location estimation in the second step.

Depending on available information on the noise parameter or the indicator probability density function, we can choose *parametric statistical tests* relying on assumptions about the shape of the distribution (e.g., a Gaussian distribution) and about the form of parameters (e.g., mean, median, and standard deviations), or *nonparametric estimation methods* (e.g., least squares regression) relying on a fit to empirical data in the absence of any guidance or constraints from theory to estimate the target location.

5 Mobile Databases and Field Data Collection

5.1 Mobile Databases

Mobile database maintains all the spatial and non-spatial data for mobile GIS applications. Different mobile GIS applications usually have different mobile databases in terms of the size, content, schema, and network connection mode. Database schema, as the most important feature, defines how data are managed and organized in a given database. If two databases have heterogeneous schemata, it would be difficult to integrate them on one mapping layer and data conversion need to be processed and stored before mobile visualization.

Because of limited storage space of mobile devices, mobile databases are usually maintained in one or several servers rather than on mobile devices themselves. In this case, data which are held one the server will be queried, retrieved, transformed, and visualized in mobile clients through network connections. Therefore, frequent communication between clients and servers is necessary for a robust mobile GIS Web service. In fact, how to make the communication fast and stable is a hot research topic in the mobile computing field. Communication among different devices within a distributed system is a traditional goal for many network systems. However, a wireless network together with mobile clients has unique characters (Barbará 1999) compared to other networks because of its asymmetrical communication between clients and servers. It is asymmetry in communication means that the bandwidth in the servers-to-clients direction is much larger than that in the reverse direction. That makes data dissemination a hot topic in the early stage of mobile network communication. Data dissemination is the process to delivery data from servers to clients. How to deliver data to appropriate clients based on attributes of clients is very important and is still a hot research topic.

Data consistency is also an important area of research, especially when mobile databases have been maintains by multiple servers. On a field data collection process, a field worker can connect to one server of a distributed database and update the field survey data while another field worker may query the same part of data from another server of this system to do validation process simultaneously. If these two servers have not been synchronized, the second field worker will get out-of-date results and his/her validation work will be meaningless. Different methods and algorithms have been proposed to maintain the consistency of the database, such as session guarantees (Terry et al. 1994) which establish some rules on a sequence of I/O operations performed by a mobile client.

A fast response time for database query, especially spatial query, is a major objective for Mobile GIS. Shi et al. (2009) has proposed a specially designed dynamic database to accelerate the querying process. This dynamic database has been generated and continually updated based on spatial, temporal and thematic constraints which have been provided by users. This idea is similar to the caching technique which is used to obtain a small piece of data in which users are interested from the server database temporally. Location queries on mobile GIS depend on the real-time location of mobile clients. Caching technique works well in this process. The mobile clients "cache" both spatial and non-spatial data around the current location of users. Therefore, when users do a location dependent query, such as "nearby" information, the mobile GIS application will first search the data from local pre-cached database instead of sending a new request to the remote servers.

The most common way of storing and managing data on the mobile device is to use a cloud database and connects remotely in order to access its data. However, a mobile application needs an active and quite fast network connection. Embeddable databases which are lightweight self-contained libraries with no server component and limited resource requirements can provide offline data storage and retrieval capabilities. Popular ones among popular types of mobile operating systems in this category include BerkeleyDB, CouchbaseLite, SQLite, etc.. In order to store geospatial objects (points, polylines, polygons) and support spatial indexing, those databases usually extend with OGC Geometry Standard such as SpatiaLite (a geospatial extension of SQLite) and provide a powerful geospatial mobile database management systems.

5.2 Field Data Collection

According to the fact whether the mobile GIS services have data editing capabilities, mobile GIS can be classified into two major application areas: field-based GIS and location-based GIS (Tsou 2004). Field work is the first part of research tasks in many disciplines, e.g. survey mapping, environment monitoring. Traditional field mapping tasks with the help of desktop GIS software is time consuming and the quality of data collected by those traditional methods is difficult to control, let alone the semantic integrity of the field data. A good candidate to solve this problem would be integrating global position system, GIS and remote sensing capabilities into mobile GIS services with the help of semantic plausibility control which enables the field workers or scientists to edit, update and validate both spatial and non-spatial data.

One advantage of using mobile GIS devices for field data collection is real-time data updates and exchanges between centralized map servers and distributed mobile (Pundt 2002). Digital data editing capabilities and remote accessibilities to shared spatial datasets during data collection process can improve the cooperation among field workers and ensure the data agreement. Mobile GIS services with data editing abilities will improve the date collection process a lot in terms of efficiency and location quality. Moreover, prompt updates of geographic information such as road network connectivity and buildings are very important in disaster response and emergency management. Mobile GIS make use of many trending techniques and portable equipment which have been applied in an urban disaster management context (Montoya 2003).

In addition, the immediate access to shared geospatial data (georeferenced, topographic and cartographic information) while taking a field survey (Pundt and Brinkkötter-Runde 2000) gives the field workers more comprehensive understanding of the relationship between the real world features and digital features. By comparing the outdoor situations with the digital representation of features, field workers will have a better understand of the real world conditions. Thus it will reduce the errors in data collection process and thus improve the data quality. More advanced mobile GIS services, like knowledge-based diagnostic tools, automatic plausibility controls, can help to achieve semantic integrity of the mobile GIS database.

6 Location-Based Services and Applications

Location-based services (LBS), as a relatively new term compared with Mobile GIS which focus more on field data collection and mapping, can be defined as services utilizing the ability of real-time determination and transmitting the location of a mobile user with aim to help people geolocating themselves and guide them to the destination (Lemmens 2011; Abdalla 2016). By using the aforementioned outdoor/indoor positioning technologies, the location of the mobile user can be determined dynamically. Combined other geographic information, such as points of interest (POIs), transportation networks and traffic information, LBS applications can help users to do a variety of location related tasks. In the following, we will present some of those most popular LBS applications (Apps).

- **Google Maps**

A well-known example of LBS applications is the mobile version of Google Maps services (https://www.google.com/intl/en_us/mobile/maps/). It visualizes the current location of a mobile user on a basemap. The basemap helps the user to interpret his/her location by referring to the corresponding geographic background (e.g., road networks, POIs, buildings, landmarks, etc.). Google Maps reversely geocode the coordinates of a user's location on the Earth to a human readable address information. The most frequently used services are "NearBy" Service and

Navigation Service. As for the "NearBy" service, for instance, a user would like to find a "sports bar" nearby the stadium before the "Super Bowl" (Figure 3). The user can click on the "NearBy" button of the App. The App will search for bars close to the current location of user and visualize the location on the map. A list of these bars will also show up together with the attribute information, including address, open/close time, customers' reviews, rating, etc.. After getting this information, the user can easily choose one that he/she likes most. In addition, the Navigation service is another popular LBS service which has been widely used almost all over the world. A user can select an origin (current GPS location as the default) and a destination and the travelling mode (i.e., walking, public transportation, driving, and biking). After entering the "navigation" mode, the "shortest" path from the user's current location to the destination will be highlighted on the map. The basemap will also be rotated and zoomed into street-center views. Moreover, as more and more users begin to use Google Map Services, the App can get the location history and navigation trajectories, as well as real-time location of all users. By mining historical user logs and analyzing other information, Google Maps can derive insights about how users move and navigate the environment. It might be helpful to find better paths to avoid heavy traffic or traffic jam by integrating real-time information from traffic sensor networks and/or crowdsourced traffic reports.

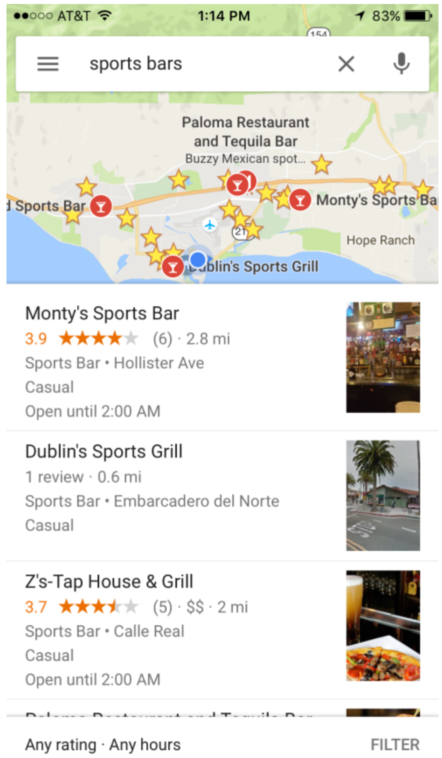

Figure 3. A screenshot of LBS using Google Maps App

- **Waze**

Waze is a community-based traffic and navigation app (https://www.waze.com), in which drivers or passengers share real-time traffic information to advise other drivers detour or find an alternative route for their trips on the road networks. This app falls into the category of volunteered geographic information (VGI) (Goodchild 2007), in which volunteers create and contribute geographical features or location descriptions to platforms where the entries are synthesized into databases. In the Waze app, users can report accidents, traffic jams, road work, speed limits, and police traps, as well as from the online map editor where users can update roads, landmarks, gas prices, and so on. Many users are engaged in the contributions since they can identify the cheapest fuel station nearby or navigate along a light-traffic route because of others' contributions. Such a sharing mode and gaming mechanism become more and more popular in many LBS Apps.

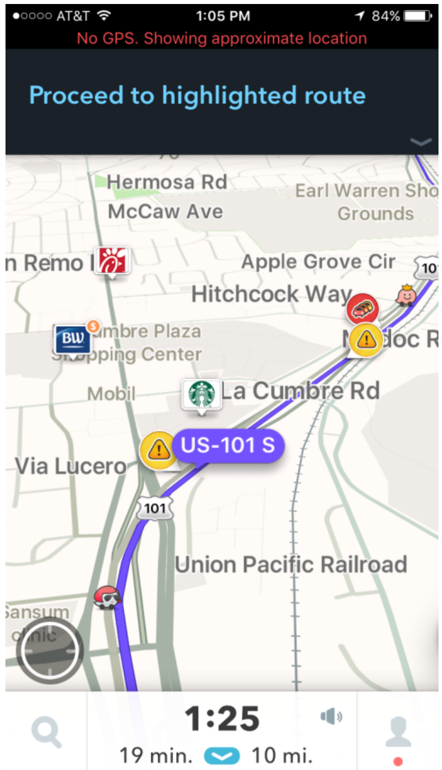

Figure 4. A screenshot of the Waze App

- **Yelp**

Yelp (https://www.yelp.com) is another popular LBS application which has been widely used in people's daily life. A user can find "nearby" restaurants with detailed business information (e.g., address, place type, open hours, contact phone number, food menu, etc.), and users' ratings and reviews (Figure 5). Compared with other LBSs, Yelp focuses more on services based on POIs, such as restaurants, shopping centers and etc.. Yelp owns a larger dataset of global POIs. After getting rich reviews from the users for many years, Yelp can be taken as a popularity reference or even "quality" evaluation source or POIs, which often help users to make a choice of food venue. The POI updating time cycle is a key factor that drives the changes in both spatial and non-spatial information in the database.

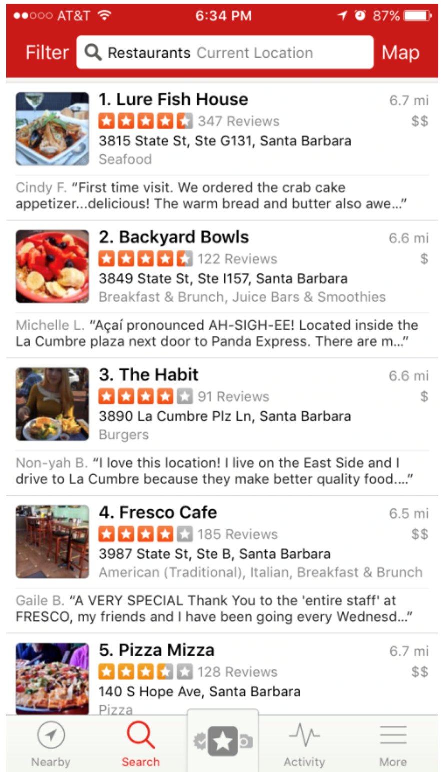

Figure 5. Search the nearby restaurants using the Yelp App

- **Foursquare & Swarm**

Foursquare (https://foursquare.com) and Swarm (https://www.swarmapp.com) are owned by the same company but with a different functionality focus on how people connect to places. Up to 2016, the Apps have generated an incredible amount of datasets – over 6 billion user check-ins, 300 million photos, 55 million tips, and hundreds of millions of edits of places. On one hand, the latest version of Foursquare app helps users discover new places nearby or search for places (restaurants, coffee shops, bars, parks, gyms, and so on) based on a user's current location. On the other hand, the Swarm app keeps the "check-in" feature and users can share their locations which they have been in or where they are currently styling and notify their friends or neighborhoods with enriching the location-based social networks (LBSNs).

(a) (b)

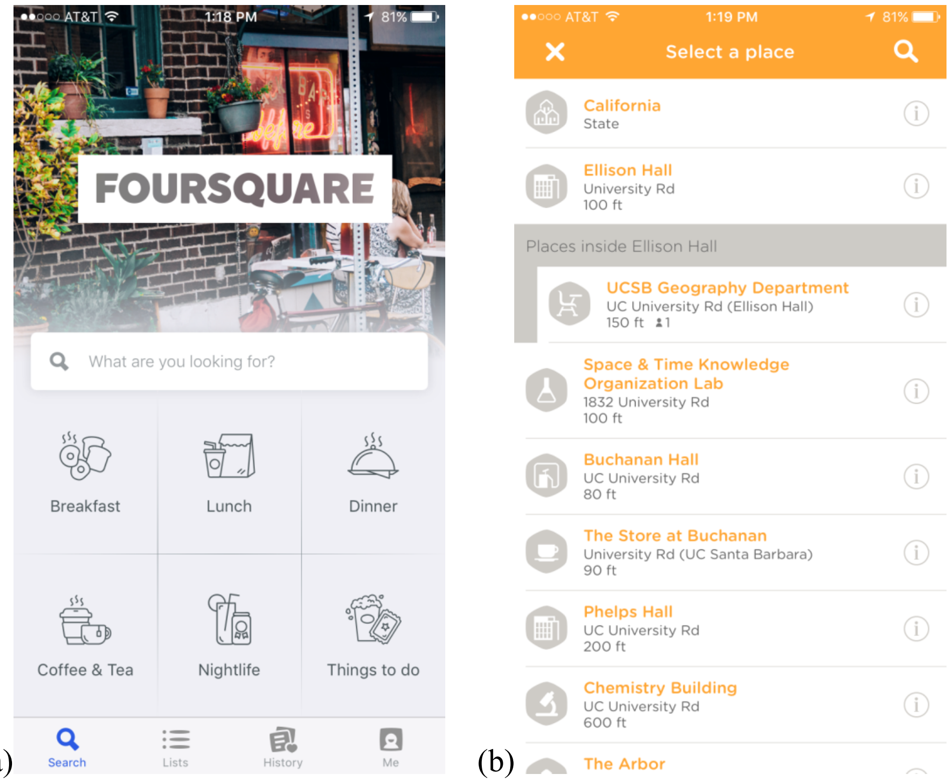

Figure 6. Screenshots of using the Apps (a)Foursquare; (b)Swarm

- **Uber**

Uber provides location-based real-time carpool sharing services (https://www.uber.com/). Uber aims at help the user to find a "near-by" Uber car according to both the passenger's and the driver's location. Uber are able to track all the registered Uber cars' locations (In fact, they are based on drivers' mobile phones which have been installed this App) on the server. Based on scalable carpool matching algorithms Uber can fast find the cars that are close to a passenger's request location and notify these car drivers. The Uber driver who accepts the request will drive the user to their destination. In their scenarios, it needs to manage large scale of spatiotemporal information for both the users and drivers and couple them dynamically.

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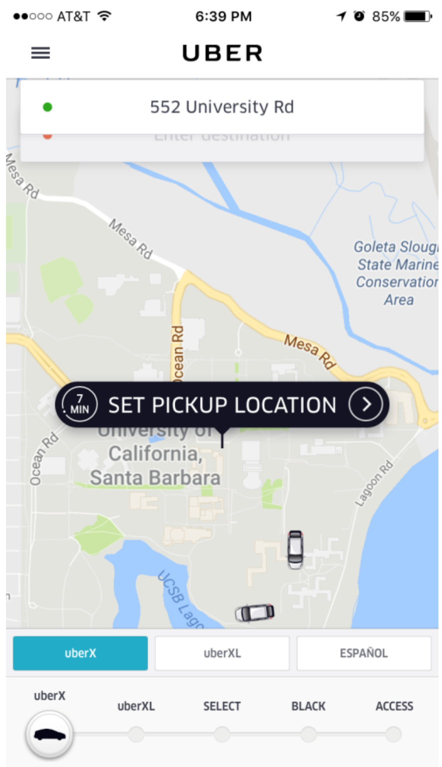

Figure 7. Screenshots of using the Apps (a)Foursquare; (b)Swarm

- **Nike Plus**

Nike Plus (http://www.nike.com/us/en_us/c/nike-plus/training-app) is another interesting sports application using mobile GIS technologies. It tracks users' locations when they are running, riding a bike, and so on. It automatically collects users' workout data, such as average speed, total distance, duration, and total burned calories. It enables users to share their workout data with their friends which will encourage them to work out regularly. It is actually very common for a LBS application to engage users' participation by connecting to the social network for sharing the user's activities. .

- **STRAVA**

Similar to Nike +, STRAVA is another application which helps people to manage their sports activity data (https://www.strava.com). But STRAVA is more popular for people who love to do exercise on terrains, such as mountain riding, hiking. Because STRAVA records not only the plane coordinates but also the elevation of a user's location. Based on the collected data from crowdsourced users, data engineers and geographic information researchers can perform advanced analysis to derive interesting geographic information such as accessibility and reliability of certain trails and roads on the terrain models in GIS.

7 Research Frontiers of Mobile GIS and LBS

There has been growing interest among researchers in studying human mobility patterns based on the data collected from location-awareness devices and social media, e.g., GPS-enabled devices (Zheng et al. 2008, Yue et al. 2014), cellular phones (Kang et al. 2010, Gao 2015, Xu et al. 2016, Zhao et al. 2016), and Bluetooth sensors (Nordström et al. 2007), as well as LBSNs such as Twitter, Foursquare and Jiepang (Cho et al. 2011, Scellato 2011, Cheng et al. 2011, Gao et al. 2014, Liu et al. 2014). All of those research areas offer new insights on complex human-environment interactions and how human behaviors and social connections captured by a variety of mobile applications, and thus can be taken as the frontiers of Mobile GIS and LBS.

Looking forward to the future, some areas may need further investigation and research as follows (but not limited to):

(1). Seamlessly integrated outdoor and indoor positioning and mobile tracking technologies. Positioning will still be the most important feature for enabling mobile GIS and LBS applications.

(2). Lightweight mobile geographic information databases. More and more users using mobile GIS need to have access to offline geospatial data and query information in field work or when navigating on the maps in a new environment. More efficient data compression and decompression technologies in lightweight mobile databases may help to storage large spatial coverage of data and response spatial search requests more quickly.

(3). Scalable and efficient mobile processing capability. The computation power of mobile devices is weaker than PC or computer servers. However, many geospatial queries and analytics do need complex computation. The development of scalable and efficient mobile processing technologies and approaches will advance mobile-based decision making and geospatial intelligence.

(4). For applications, mobile GIS and LBS will play an important role in community-driven locational data survey, disaster response and emergency management, public digital health and smart cities.

(5). Last but not least, with the fast development of information technologies, mobile GIS may also further integrate with cutting-edge technologies, such as artificial intelligence, augmented reality, internet of things, wearable devices, and so on.

8 Conclusions and Future Work

In this chapter, we present a comprehensive review of mobile GIS and LBS concepts, core components and characteristics, technology stack, a variety of applications, and research frontiers. This subject itself is also fast developing and advancing. We do hope this chapter not only educates the next-generation of geographic information systems/science major students with the abovementioned knowledge but also inspire them to dive into the challenging research areas and make their contributions in the future.

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