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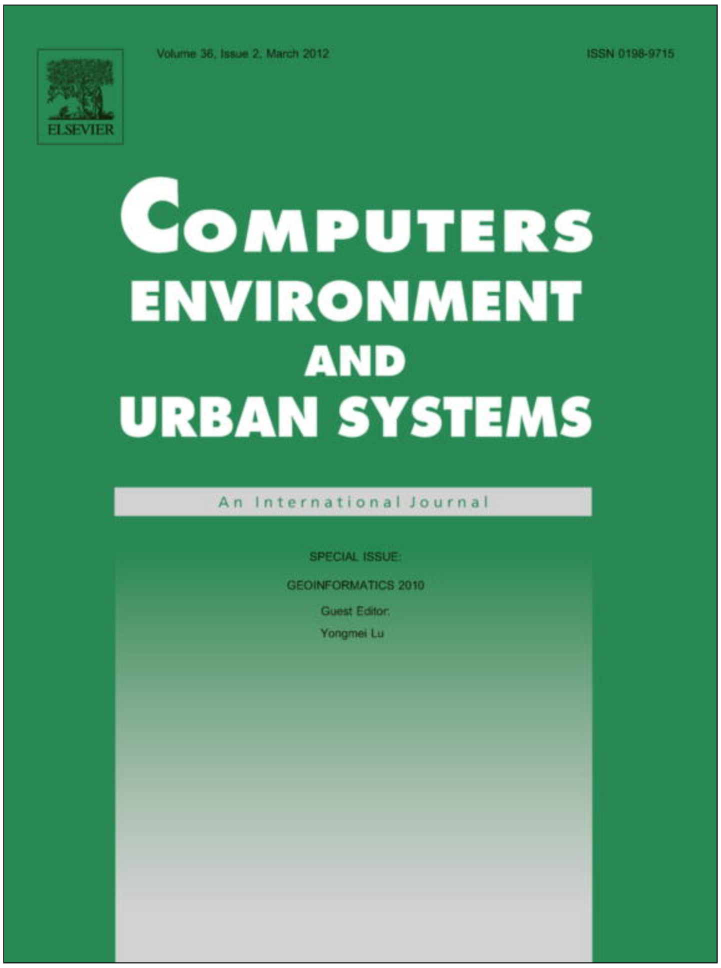
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# Pervasive location acquisition technologies: Opportunities and challenges for geospatial studies

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ABSTRACT

The rapid development and increasing availability of various location acquisition technologies provide geospatial studies with both opportunities and challenges. These opportunities and challenges are discussed in this paper focusing on the following three aspects: the massive acquisition of location data and data quality, the analysis of massive location data and pattern discovery, and privacy protection for massive location data. This paper examines the current status of and the potential opportunities for geospatial research in these three areas and notes the major challenges. Finally, the development of this special issue is described, and the four articles included in this special issue are presented.



## 1. Pervasive location acquisition technologies and recent research trends

With the accelerating development and commercialization of various location acquisition technologies, including Global Navigation Satellite Systems (GNSSs), mobile positioning systems, and indoor locationing systems, location data have become widely available. This occurrence has led to large-scale collection of location data at very fine spatial and temporal granularity, new opportunities to better describe and understand people's spatial and social behavior through data mining and knowledge discovery, and important challenges for appreciating and responding to the social implications of these data and technologies. The volume of literature since the beginning of the 21st century on many of these topics has undergone extensive growth. Studies on aspects of location data acquisition emphasize accurate, ubiquitous, timely, and affordable data collection, calibration, and integration. The research on data analysis and knowledge discovery typically attempts to discover, describe, and explain the patterns embedded in large geo-tagged datasets to better understand human beings' behavior as well as their interaction with each other and with the environment. Investigations into the social implications of pervasive location acquisition technologies are at a relatively early stage, especially as these relate to privacy and data security.

### 1.1. Location acquisition and positioning data accuracy

Location acquisition technologies nowadays can collect location data on an unprecedented scale, both spatially and temporally. Global Position System (GPS) and mobile positioning are the two most commonly used technologies. A GPS receiver can precisely log spatial coordinates of moving objects in real-time within several meters or less, making it optimal for small-scale and highly-precise investigations (Shoval, 2008). However, the multipath issue greatly limits the application of GPS technology in high-density and highly developed areas. In indoor environments, GPS generates either no location data or erroneous information. On the other hand, mobile positioning is free from these problems. It has the capability to access most locations as well as the majority of population due to its use of mobile phones (Praff, 2010). Thus, mobile positioning technology has the potential to support a broader spectrum of investigations that require large samples (e.g., Ahas, Aasa, Roose, Mark, & Silm, 2008; Ahas, Aasa, Silm, & Tiru, 2010; Ahas, Laineste, Aasa, & Mark, 2007; Ahas, Aasa et al., 2007; Bar-Gera, 2007; Caceres, Wideberg, & Benitez, 2007; Steenbruggen, Teresa, Nijkamp, & Scholten, 2011). However, mobile positioning does not have the same quality of location detection as GPS (Adams, Ashwell, & Baxter, 2003; Ahonen & Eskelinen, 2003), and its spatial accuracy depends on the density of mobile base stations. Its positioning error is approximately 300–600 m in urban areas and may be several kilometers in suburban areas (Ahas, Aasa et al., 2007; Ahas, Laineste et al., 2007).

Two groups of approaches in the recent literature aim at overcoming the limitations of these locationing technologies. One group seeks to improve location data acquisition and accuracy by

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adapting and integrating various sensors (e.g., Indulska & Sutton, 2003; Kealy, Roberts, & Retscher, 2010; Kealy, Winter, & Retscher, 2007; Yeung & Yum, 1995). The other group focuses on location fingerprinting technologies that utilize the spatial patterns of signal strength in radio-frequency networks, including WiFi (e.g., Borenovic & Neškovic, 2009; Brunato & Battiti, 2005; Swangmuang & Krishnamurthy, 2008). The major challenges in the coming years for pervasive location data acquisition and calibration are twofold. The first challenge is to continuously improve data quality by developing ubiquitous positioning technologies that work effectively in various environments, such as indoors and outdoors as well as in urban areas, rural areas, developed spaces, and open spaces. The second challenge is to continue to improve the accessibility and affordability of these technologies and data to various users and applications.

### 1.2. Analysis of massive location data and pattern discovery

Pervasive location acquisition technologies provide new datasets on a scale that was impossible in the past. Many recently published papers have reported on studies that were conducted based on these data. The first group of these studies adopts a data-driven approach by using data mining techniques to reveal the spatiotemporal patterns embedded in trajectory data and to detect a population's activity patterns with regard to their living and working environment (e.g., Ahas, Silm, Jarv, Saluveer, & Tiru, 2010; Ahas, Aasa et al., 2010; Bar-Gera, 2007; Calabrese, Lorenzo, Liu, & Ratti, 2011; Gonzalez, Hidalgo, & Barabási, 2008). The main contribution of these studies is to add to the empirical evidence of movement and trajectory patterns. Nonetheless, a number of important trends have emerged in the literature and merit discussion here. Several studies have attempted to describe population movement formally using mathematical models such as Lévy flights or truncated Lévy flights (e.g., Brockmann, Hufnagel, & Geisel, 2006; Gonzalez et al., 2008; Jiang, Yin, & Zhao, 2009; Kang, Ma, Tong, & Liu, 2012). Other studies applied advanced visualization techniques for pattern identification, such as the 3D space–time cube (Demšar & Virrantaus, 2010). A small number of studies explored the activity patterns of special population segments; the activity trajectories of these individuals are almost impossible to record without these pervasive location acquisition technologies. For example, Rossmo, Lu, and Fang (2011, chap. 3) analyzed parolees' GPS recorded trajectories with the goal of discerning crime-hunting behavior from non-criminal activities. One important challenge for the movement and trajectory analyses that are empowered by massive datasets is to further embrace the techniques and models that have been developed in and accepted by traditional studies. These techniques and models include methods for trajectory similarity analysis (Vlachos et al., 2002; Joh et al., 2002; Sinha & Mark, 2005), trajectory outlier detection (Ge et al., 2010; Lee, Han, & Li, 2008), and trajectory prediction (Liu & Karimi, 2006). In addition, there is the vector-based approach (Lu & Thill, 2003, 2008), which examines the trajectory displacement from trip origins to destinations, as well as the sequence alignment method (Joh et al., 2002; Shoval & Isaacson, 2007), which describes trajectories by sequencing geographical locations and their related semantic factors, if applicable. However, extending these techniques and models to movement and trajectory studies using newly available massive location datasets requires data quality control and data reduction processes (Lee & Krumm, 2011).

In addition to creating substantial data sources, the pervasive location acquisition technologies present an unprecedented opportunity for us to understand and respond to the dynamic and ephemeral person-to-person and person-to-environment interactions. The second group of the recent published papers addresses issues related to this aspect. As Silva and Frith (2010) noted, many types of location-aware equipment are built upon pervasive location acquisition technologies; these equipments can connect people to other people or to their environments based on their ever-changing physical locations. These connections form locative mobile networks (LMNs) with immense implications. As revealed by Liben-Nowell, Novak, Kumar, Raghavan, and Tomk (2005), two-thirds of the friendship relations in a large social network are related to geography. As a subject's spatial position changes, his/her social networks, positions in such networks, and service needs may or may not change (Silva & Frith, 2010; Zheng & Zhou, 2011). This presents a great challenge for location-based services and applications (LBSs). A few recent publications pioneered an attempt to reveal and depict dynamics of social networks from massive location datasets (Zheng, 2011; Zheng & Xie, 2011). These are early steps in addressing locative mobile social networks (LMSNs) to provide high-level LBS.

The third group of recent published studies that benefits greatly from the massive location data of large populations is urban study. A number of studies have been conducted using large volumes of spatiotemporal data collected in different cities (Shoval, 2008). Reades, Calabrese, and Ratti (2009) and Sun, Yuan, Wang, Si, and Shan (2011) explored the dynamic structure of human mobility as reflected by mobile phone usage, defining the city as a space of human flow. Other studies investigated patterns in the large datasets and linked them with urban space–time structures. For example, Ratti, Pulselli, Williams, and Frenchman (2006) found that mobile phone usage patterns in the metropolitan area of Milan are related to the city's urban commuting patterns. Jiang and Liu (2009) used GPS-recorded taxi movement data to interpret and predict traffic flow in a street network. Ahas, Aasa et al. (2010) revealed that suburban commuters' calling activities correlate with land use and infrastructure attraction. Similarly, Sevtsuk and Ratti (2010) estimated Rome's population distribution by call activity data; they found that land use patterns, economic characteristics, demographics and developed environments account for the call-volume patterns between mobile towers. Still other studies considered the patterns in large location datasets as indicators for the interaction between people and their city, i.e., the actual usage of, or demands for, city services and facilities, with the goal of achieving better urban planning, traffic management, and service delivery. Large spatiotemporal data were used to evaluate traffic conditions (Bar-Gera, 2007; Calabrese, Ratti, Colonna, Lovisolo, & Parata, 2011; Cayford & Johnson, 2003; de Fabritiis, Ragona, & Valenti, 2008; Herrera et al., 2010) and real-time accessibility (Li et al., 2011). Detailed mobile phone call data proved to be effective for traffic incident detection and management (Steenbruggen et al., 2011; Tong, Coifman, & Merr, 2009). Other research projects (Caceres et al., 2007; Calabrese, Lorenzo et al., 2011; Sohn & Kim, 2008) have used mobile phone data as probes for developing the traffic origin–destination (O–D) matrix, which was further used to simulate traffic flow.

### 1.3. Privacy protection of the massive location data

Discussions of privacy protection related to location data are not new in the literature (e.g., Armstrong, 2002; Curtis, Mills, & Leitner, 2006). The development of pervasive technologies has certainly intensified concerns over privacy and data protection (Ahas & Mark, 2005; Minch, 2004; Patterson, Muntz, & Pancake, 2003). Chow and Mokbel (2011) discussed the privacy issue at three levels: data privacy, location privacy, and trajectory privacy. These authors proposed different privacy protection strategies for processing massive location data to support LBS and trajectory studies. Recent studies have concluded that commonly used privacy protection approaches, such as anonymization (Ahas et al., 2008; Gonzalez et al., 2008; Markkula, 2001; Silm & Ahas, 2010) and authorization (Ahas, Aasa et al., 2010; Ahas, Silm et al., 2010; Piorkowski, 2009), are potentially effective for the new massive datasets. In particular, Rohini and Babu (2011) introduced the k-anonymity principle into the privacy protection of the LBS that responds to large datasets collected by pervasive location acquisition technologies. Ratti et al. (2006) and Calabrese, Ratti et al. (2011) found that data aggregation based on gender, age or geographical proximity is valid for data pre-processing to protect privacy. However, it is important to emphasize the special aspects of privacy protection for the collection of these massive spatiotemporal datasets and for the applications based upon these datasets. First, as location acquisition technologies have become easily available to both experts and the general public, well-developed techniques for data pre-processing before distribution, such as geomasking (Cassa, Grannis, Overhage, & Mandl, 2006; Kwan, Casas, & Schmitz, 2004; Lu, Yorke, & Zhan, 2012) are becoming harder to adopt. This is because (1) not all data producers have the training or expertise to pre-process massive location data and (2) data producers and data consumers (users) can be the same person(s) who may prefer accurate analysis over privacy protection and choose not to conduct proper data pre-processing. Second, data pre-processing for privacy protection may need to be conducted "on-the-fly" to reflect the dynamics of risk population and sampling subjects. Because data collection and distribution tend to be continuous, the definitions of risk population and sampling subjects are sometimes dynamic (Rohini & Babu, 2011). Data pre-processing techniques need to adapt to this dynamic nature. Finally, data pre-processing for privacy protection needs to be applied to the service provider side, but not necessarily to the service consumer side. Specifically, the challenge is that a service provider needs to provide updated LBS using the dynamically masked location data of a service consumer, who knows the exact locations as s/he moves around and sends in service requests.

## 2. Articles in this special issue

The articles in this special issue reflect some recent advances in the studies related to pervasive location acquisition technologies. The development of this special issue began at a series of special paper sessions organized for *The 18th International Conference on GeoInformatics* in Beijing in the summer of 2010. The *GeoInformatics Conference Series* was initiated by the *International Association of Chinese Professionals in Geographic Information Sciences (CPGIS)* in 1992 and has been held annually at different locations worldwide. This conference series has provided a unique forum for the exchange of ideas and knowledge on geographic information sciences and systems between GIS professionals from various backgrounds and with different areas of expertise. The initial response to the Call for Papers for this special issue generated a total of 13 manuscripts. Some of these papers were presented at the conference, while others were not, but all are nonetheless on relevant topics. After a peer-review process, including several rounds of revisions, it is our pleasure to finally have these four articles to present to the readers of *Computers, Environment and Urban Systems*. The studies reported in these articles were conducted at various locations across the world, including the US, China, and Australia. Their contributions are mostly concerned with the first two aspects of pervasive location acquisition technologies and the related geospatial analyses discussed earlier in this paper, namely location data collection and its calibration as well as massive spatiotemporal data analysis and how it is used to acquire knowledge.

The first article by Winter and Kealy (2012) seeks to improve the qualitative location description that is essential for location awareness and LBS. By integrating different positioning sensors that are not necessarily the most expensive ones available, this study illustrates an effective approach to derive a relatively accurate qualitative location description. The authors argue for a novel approach for improving location awareness using relatively inexpensive equipment for positioning data collection. The second article by Yuan, Raubal, and Liu (2012) adopts a data-driven approach in analyzing mobile phone call data in Harbin City of northeast China and investigates the relationship between phone calls and population mobility. This article concludes by noting that future research calls for a framework to define how natural and social factors impact the relationship between population mobility and information and communication technologies (ICT). The next two articles are both empirical in nature and report on research projects that use pervasive location acquisition technologies as surrogate data collection means to support urban studies. The article by Gong, Chen, Bialostozky, and Lawson (2012) reports the development of a GIS-based algorithm that can analyze GPS-recorded trajectory data to detect different travel modes. Applied to GPS trajectory data collected in New York City, the algorithm performed well enough to reasonably differentiate five common travel modes with a success rate between 92.4% for walking travel and 35.7% for commuter rail. Future research directions include improving the travel mode detection algorithm and the integration of other location acquisition technologies into data collection for underground travel. In the last article, Yue, Wang, Li, Li, and Yeh (2012) use GPS-recorded taxi trajectory data to approximate the patronage of shopping centers in Wuhan City in central China. Using the trajectory data for six shopping centers, the authors calibrated a spatial interaction model for the study area. The calibrated Huff model was used to predict the trading area for a 7th shopping center with satisfactory results. This study showcased the great potential of location acquisition technologies and the collected data for geographical, urban, transportation and marketing studies that traditionally reply on expansive survey data.

Although not directly reflected in these four articles, the third aspect of pervasive location acquisition technologies for geospatial studies are recognized by these studies. For example, Yuan and colleagues (2012) discuss how mobile phone call data were pre-processed before being made available for their research. While pre-processing was necessary for privacy protection, it reduced their capability to better connect mobility and phone calls with individual characteristics of the population. Similarly, Yue and others (2012) note that LBS' "check-in" functions may help accumulate a large dataset for a choice-based sample of shopping patronage, but the privacy issue was recognized as a major concern for the availability of such data for their study.

Overall, these articles are a sample of the many new studies that are enabled by pervasive location acquisition technologies or the data collected by such technologies. With the continuously improved accessibility of these technologies and data, geospatial studies are presented with opportunities as well as challenges to collect more and more accurate data at massive scales, to reveal patterns embedded in the data, and to use the data to empower the investigation and modeling of various topics related to human mobility. However, the potential advantages cannot be fully achieved without adequately handling of both data privacy and security issues.

## References

Adams, P. M., Ashwell, G. W. B., & Baxter, R. (2003). Location-based services – An overview of standards. *BT Technology Journal, 21*(1), 34–43.

Ahas, R., Aasa, A., Roose, A., Mark, Ü., & Silm, S. (2008). Evaluating passive mobile positioning data for tourism surveys: An Estonian case study. *Tourism Management, 29*(3), 469–486.

Ahas, R., Aasa, A., Silm, S., Aunap, R., Kalle, H., & Mark, Ü. (2007). Mobile positioning in space-time behaviour studies: Social Positioning Method experiments in Estonia. *Cartography and Geographic Information Science, 34*(4), 259–273.

Ahas, R., Aasa, A., Silm, S., & Tiru, M. (2010). Daily rhythms of suburban commuter's movements in the Tallinn metropolitan area: Case study with mobile positioning data. *Transportation Research Part C, 18*, 45–54.

Ahas, R., Laineste, J., Aasa, A., & Mark, Ü. (2007). The spatial accuracy of mobile positioning: Some experiences with geographical studies in Estonia. In G. Gartner, W. Cartwright, & M. P. Peterson (Eds.), *Location based services and telecartography, lecture notes in geoinformation and cartography* (pp. 122–146). Springer.

Ahas, R., & Mark, Ü. (2005). Location based services – New challenges for planning and public administration. *Futures, 37*, 547–561.

Ahas, R., Silm, S., Jarv, O., Saluveer, E., & Tiru, M. (2010). Using mobile positioning data to model locations meaningful to users of mobile phones. *Journal of Urban Technology, 17*(1), 3–27.

Ahonen, S., & Eskelinen, P. (2003). Mobile terminal location for UMTS. *IEEE Aerospace and Electronic Systems Magazine, 18*(2), 23–27.

Armstrong, M. P. (2002). Geographic information technologies and their potentially erosive effects on personal privacy. *Studies in the Social Sciences, 27*, 19–28.

Bar-Gera, H. (2007). Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: A case study from Israel. *Transportation Research Part C, 15*, 380–391.

Borenovic, M. N., & Neškovic, A. M. (2009). Positioning in WLAN environment by use of artificial neural networks and space partitioning. *Annals of Telecommunication, 64*, 665–676.

Brockmann, D., Hufnagel, L., & Geisel, T. (2006). The scaling laws of human travel. *Nature, 439*, 463–465.

Brunato, M., & Battiti, R. (2005). Statistical learning theory for location fingerprinting in wireless LANs. *Computer Network, 47*, 825–845.

Caceres, N., Wideberg, J. P., & Benitez, F. G. (2007). Deriving origin-destination data from a mobile phone network. *IET Intelligent Transport Systems, 1*(1), 15–26.

Calabrese, F., Lorenzo, G. D., Liu, L., & Ratti, C. (2011). Estimating origin-destination flows using mobile phone location data. *IEEE Pervasive Computing, 10*(4), 36–44.

Calabrese, F., Ratti, C., Colonna, M., Lovisolo, P., & Parata, D. (2011). Real-time urban monitoring using cell phones: A case study in Rome. *IEEE Transactions on Intelligent Transportation Systems, 12*(1), 141–151.

Cassa, C. A., Grannis, S. J., Overhage, J. M., & Mandl, K. D. (2006). A context-sensitive approach to anonymizing spatial surveillance data: Impact on outbreak detection. *Journal of the American Medical Informatics Association, 13*(2), 160–165.

Cayford, R., & Johnson, T. (2003). Operational parameters affecting use of anonymous cell phone tracking for generating traffic information. In *Paper presented at the 82nd TRB annual meeting*, Institute of Transportation Studies.

Chow, C., & Mokbel, M. F. (2011). Privacy of spatial trajectories. In Y. Zheng & Y. Zhou (Eds.), *Computing with spatial trajectories* (pp. 109–142). Springer.

Curtis, A., Mills, J. W., & Leitner, M. (2006). Keeping an eye on privacy issues with geospatial data. *Nature, 441*, 150.

de Fabritiis, C., Ragona, R., & Valenti, G. (2008). Traffic estimation and prediction based on real time floating car data. In *The proceedings of the 11th international IEEE conference on intelligent transportation systems*.

Demšar, U., & Virrantaus, K. (2010). Space-time density of trajectories: Exploring spatio-temporal patterns in movement data. *International Journal of Geographical Information Science, 24*(10), 1527–1542.

Ge, Y., Xiong, H., Zhou, Z. -H., Ozdemir, H., Yu, J., & Lee, K. C. (2010). TOP-EYE: Top-k evolving trajectory outlier detection. In *The proceedings of CIKM' 10*.

Gong, H., Chen, C., Bialostozky, E., & Lawson, C. (2012). A GPS/GIS method for travel model detection in New York City. *Computers, Environment and Urban Systems, 36*(2).

Gonzalez, M. C., Hidalgo, C. A., & Barabási, A.-L. (2008). Understanding individual human mobility patterns. *Nature, 453*, 779–782.

Herrera, J. C., Work, D., Ban, J., Herring, R., Jacobson, Q., Ban, J., et al. (2010). Evaluation of traffic data obtained via GPS-enabled mobile phones: The mobile century field experiment. *Transportation Research Part C, 18*, 568–583.

Indulska, J., & Sutton, P. (2003). Location management in pervasive systems. In *Proceedings of the Australian information security workshop conference on ACSW frontiers* (Vol. 21, pp. 141–151).

Jiang, B., & Liu, C. (2009). Street-based topological representations and analyses for predicting traffic flow in GIS. *International Journal of Geographical Information Science, 23*(9), 1119–1137.

Jiang, B., Yin, J., & Zhao, S. (2009). Characterizing the human mobility pattern in a large street network. *Physical Review E, 80*. 021136(1-11).

Joh, C-H., Arentze, T., Hofman, F., & Timmermans, H. (2002). Activity pattern similarity: a multidimensional sequence alignment method. *Transportation Research Part B, 36*(5), 385–403.

Kang, C., Ma, X., Tong, D., & Liu, Y. (2012). Intra-urban human mobility patterns: An urban morphology perspective. *Physica A, 391*(4), 1702–1717.

Kealy, A., Roberts, G., & Retscher, G. (2010). Evaluating the performance of low cost mems inertial sensors for seamless indoor/outdo or navigation. In *Position, location and navigation 2010, proceedings of IEEE and ION conference*, Palm Springs, CA.

Kealy, A., Winter, S., & Retscher, G. (2007). Intelligent location models for next generation location-based systems. *Journal of Location Based Services, 1*(4), 237–255.

Kwan, M., Casas, I., & Schmitz, B. (2004). Protection of geoprivacy and accuracy of spatial information: How effective are geographical masks? *Cartographica, 39*(2), 15–28.

Lee, J. -G., Han, J., & Li, X. (2008). Trajectory outlier detection: A partition-and-detect framework. In *The proceedings of IEEE 24th international conference on data engineering*.

Lee, W., & Krumm, J. (2011). Trajectory preprocessing. In Y. Zheng & Y. Zhou (Eds.), *Computing with spatial trajectories* (pp. 3–34). Springer.

Li, Q., Zhang, T., Wang, H., & Zeng, Z. (2011). Dynamic accessibility mapping using floating car data: A network-constrained density estimation approach. *Journal of Transport Geography, 19*(3), 379–393.

Liben-Nowell, D., Novak, J., Kumar, R., Raghavan, P., & Tomk, A. (2005). Geographic routing in social networks. *PNAS, 102*(33), 11623–11628.

Liu, X., & Karimi, H. A. (2006). Location awareness through trajectory prediction. *Computers, Environment and Urban Systems, 30*, 741–756.

Lu, Y., Yorke, C., & Zhan, F. B. (2011). Considering risk locations when defining perturbation zones for geomasking. *Cartographica*.

Lu, Y., & Thill, J.-C. (2003). Assessing the cluster correspondence between paired point locations. *Geographical Analysis, 35*(4), 290–309.

Lu, Y., & Thill, J.-C. (2008). Cross-scale analysis of cluster correspondence using different operational neighborhoods. *Journal of Geographical Systems, 10*(3), 241–262.

Markkula, J. (2001). Dynamic geographic personal data – New opportunity and challenge introduced by the location aware mobile networks. *Cluster Computing, 4*(4), 369–377.

Minch, R. P. (2004). Privacy issues in location-aware mobile devices. In *Proceedings of the 37th Hawaii international conference on system sciences* (pp. 1–10).

Patterson, C. A., Muntz, R. R., & Pancake, C. M. (2003). Challenges in location aware computing. *Pervasive Computing, 2*(2), 80–89.

Piorkowski, M. (2009). Sampling urban mobility through on-line repositories of GPS tracks. In *Proceedings of the 1st ACM international workshop on hot topics of planet-scale mobility measurements* (pp. 1–6).

Praff, J. (2010). Mobile phone geographies. *Geography Compass, 4*(10), 1433–1447.

Ratti, C., Pulselli, R. M., Williams, S., & Frenchman, D. (2006). Mobile landscapes: Using location data from cell phones for urban analysis. *Environment and Planning B: Planning and Design, 33*, 727–748.

Reades, J., Calabrese, F., & Ratti, C. (2009). Eigenplaces: Analysing cities using the space–time structure of the mobile phone network. *Environment and Planning B: Planning and Design, 36*, 824–836.

Rohini, B. R., & Babu, B. S. (2011). Modeling k-anonymity framework for the proximity-based privacy protection in context-aware LBS. In *Communications in computer and information science, proceedings of the 1st international conference on computational intelligence and information technology* (Vol. 250, pp. 187–193).

Rossmo, D. K., Lu, Y., & Fang, T. B. (2011). Spatial-temporal crime paths. In M. A. Andresen & J. B. Kinney (Eds.), *Patterns, prevention, and geometry of crime. Crime science series*. NY: Routledge.

Sevtsuk, A., & Ratti, C. (2010). Does urban mobility have a daily routine? Learning from the aggregate data of mobile networks. *Journal of Urban Technology, 17*, 41–60.

Shoval, N. (2008). Tracking technologies and urban analysis. *Cities, 25*, 21–28.

Shoval, N., & Isaacson, M. (2007). Sequence alignment as a method for human activity analysis in space and time. *Annals of the Association of American Geographers, 97*(2), 282–297.

Silm, S., & Ahas, R. (2010). The seasonal variability of population in Estonian municipalities. *Environment and Planning A, 42*(10), 2527–2546.

Silva, A. A. S., & Frith, J. (2010). Locative mobile social networks: Mapping communication and location in urban spaces. *Mobilities, 5*(4), 485–505.

Sinha, G., & Mark, D. M. (2005). Measuring similarity of geospatial lifelines in studies of environmental health. *Journal of Geographical Systems, 7*(1), 115–136.

Sohn, K., & Kim, D. (2008). Dynamic origin-destination flow estimation using cellular communication system. *IEEE Transactions on Vehicular Technology, 57*(5), 2703–2713.

Steenbruggen, J., Teresa, M., Nijkamp, P., & Scholten, H. (2011). Mobile phone data from GSM networks for traffic parameter and urban spatial pattern assessment: A review of applications and opportunities. *GeoJournal*. doi:10.1007/s10708-011-9413-y.

Sun, J., Yuan, J., Wang, Y., Si, H., & Shan, X. (2011). Exploring space–time structure of human mobility in urban space. *Physica A: Statistical Mechanics and its Applications, 390*, 929–942.

Swangmuang, N., & Krishnamurthy, P. (2008). An effective location fingerprint model for wireless indoor localization. *Pervasive and Mobile Computing, 4*(6), 836–850.

Tong, D., Coifman, B., & Merr, C. J. (2009). New perspectives on the use of GPS and GIS to support a highway performance study. *Transactions in GIS, 13*, 69–85.

Vlachos, M., Gunopulos, D., & Kollios, G. (2002). Robust similarity measures for mobile object trajectories. *Proceedings of the 13th International Wokshop on Database and Expert Systems Application*, 721–726.

Winter, S., & Kealy, A. (2012). An alternative view of positioning observations from ow cost sensors. *Computers, Environment and Urban Systems, 36*(2).

Yeung, K., & Yum, T. S. (1995). Call group decoupling analysis of a channel borrowing based dynamic channels assignment strategy in linear radio systems. *IEEE Transactions on Communications, 43*(2–4), 1289–1292.

Yuan, Y., Raubal, M., & Liu, Y. (2012). Correlating mobile phone usage and travel behavior – A case study of Harbin, China. *Computers, Environment and Urban Systems, 36*(2).

Yue, Y., Wang, H., Li, Q., Li, Y., & Yeh, A. (2012). Exploratory calibration of a spatial interaction model using taxi GPS trajectories. *Computers, Environment and Urban Systems, 36*(2).

Zheng, Y. (2011). Location-based social networks: Users. In Y. Zheng & Y. Zhou (Eds.), *Computing with spatial trajectories* (pp. 243–276). Springer.

Zheng, Y., & Xie, X. (2011). Location-based social networks: Locations. In Y. Zheng & Y. Zhou (Eds.), *Computing with spatial trajectories* (pp. 277–305). Springer.

Zheng, Y., & Zhou, X. (2011). *Computing with spatial trajectories*. Springer.