Machine-Learning-Based Positioning: A Survey and Future Directions

Ziwei Li, Ke Xu, Haiyang Wang, Yi Zhao, Xiaoliang Wang, and Meng Shen

Abstract

Widespread use of mobile intelligent terminals has greatly boosted the application of location-based services over the past decade. However, it is known that traditional location-based services have certain limitations such as high input of manpower/material resources, unsatisfactory positioning accuracy, and complex system usage. To mitigate these issues, machine-learning-based location services are currently receiving a substantial amount of attention from both academia and industry. In this article, we provide a retrospective view of the research results, with a focus on machine-learning-based positioning. In particular, we describe the basic taxonomy of location-based services and summarize the major issues associated with the design of the related systems. Moreover, we outline the key challenges as well as the open issues in this field. These observations then shed light on the possible avenues for future directions.

Introduction

During the past decade, with the rapid development and spread of the Internet of Things (IoT), cloud computing, mobile computing, and intelligent terminals, the application of location-based services (LBS) has attracted wide attention from both academia and industry. Based on users' location information, LBS providers can offer richer, faster, and more accurate services.

New technologies have spawned many new applications, as shown in Fig. 1. In the outdoor environment, satellite-based positioning technologies can provide convenient location services for people, such as Global Positioning System (GPS)-based vehicle navigation and cargo tracking. LBS can also provide nearby living entertainment information and intelligent path navigation services for individual users. When encountering an emergency, based on people location information, the public service department can provide emergency counseling and medical assistance services.

However, in the indoor environment, due to serious object occlusion and multipath effects of signal propagation, satellite-based positioning technologies face great challenges and cannot meet people's daily demands. Since the 1990s, indoor location technology has been the focus of academic and industrial research, leading to a lot of achievements. Eight typical indoor scenarios are described in Fig. 1, including hospital, mall, exhibition center, prison, transportation hub, community, school, and factory. In different indoor scenarios, the demands for different LBS-based applications are also different. For example, hospital administrators need to track dangerous goods and special patients in real time, and provide navigation services for patients. In a mall, individuals need to find where their cars are parked and the location of their intended stores. Furthermore, shopping center managers need to obtain customer flow analysis data and direct them to precision advertising and marketing. In order to ensure safety, an LBS system in prisons and schools can set up electronic fences to prevent special persons from walking out of designated areas. Applications of LBS have been widely used in transportation hubs. The system can automatically identify arriving passengers and push traffic information. Nowadays, the rapidly developing LBS and smart home technology provide people with more comfortable and convenient living environments. In a lighting system, a lamp can turn on when a person enters but turn off when he/she leaves. When people are on their way home, the smart home service system can intelligently adjust the temperature control system in the home according to their location information and daily habits. In a factory, people can use the LBS system to monitor and track people or assets, such as automatic check-in and patrol recorder. LBS have been applied to all aspects of human life, and they also have their own characteristics in different application areas.

Although the LBS system brings great convenience to people, there are still some disadvantages that restrict its promotion and popularization, including the large initial infrastructure investment of the LBS system, complex system usage, insufficient positioning accuracy, and so on. Currently, the most urgent issue to be solved is how to tune the problem of large data collection and computing, and high manpower and material resources cost. Artificial intelligence (AI) and machine learning (ML) have developed rapidly in recent years, and have been employed by many researchers to improve LBS systems. We have noticed that some related research on deep learning and transfer learning concentrate on optimizing location technology, demonstrating that the ML technology provides a new opportunity to address these challenges [1].

In this article, we present a survey and future directions of ML-based positioning. We present the main localization technologies and outline the solutions currently available. Then, in a later

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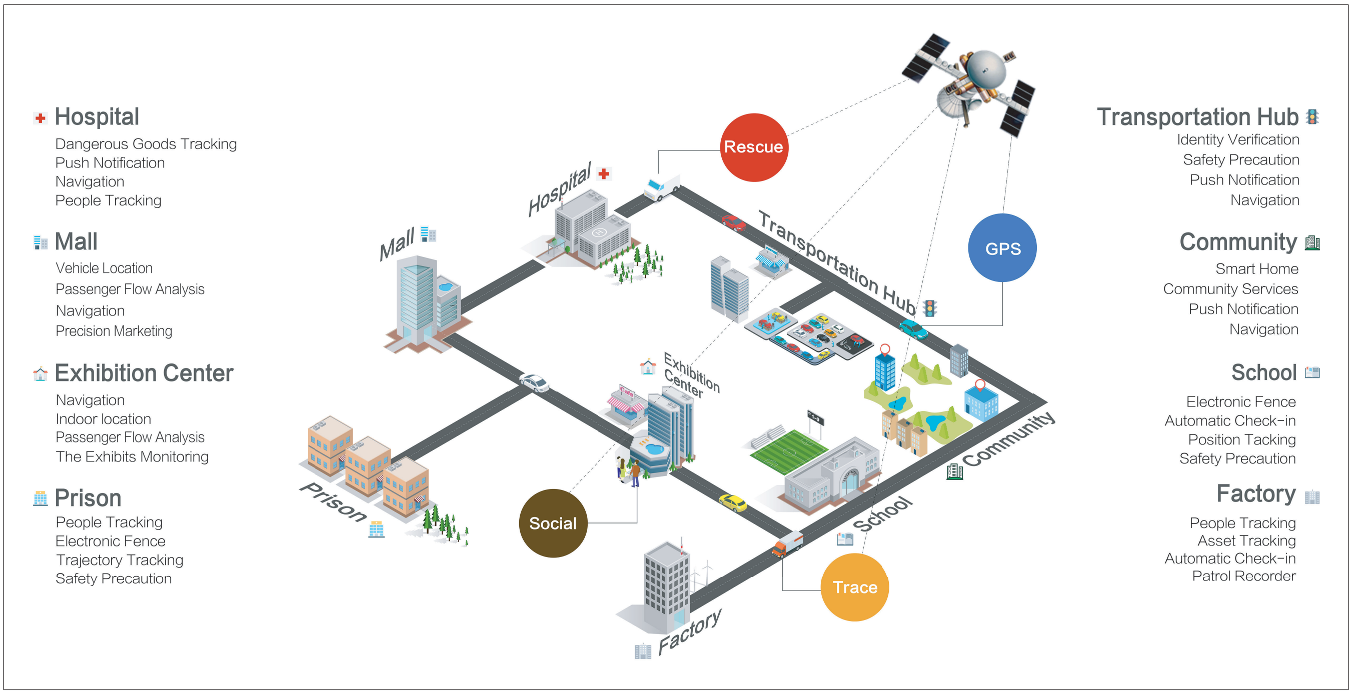

FIGURE 1. An overview of LBS, including both indoor and outdoor positioning scenarios.

section, we dwell on the newly developed deep learning and transfer learning research, with a special focus on the applications of positioning technology. Finally, we point out possible directions and challenges of future studies.

Localization

In this part, we overview existing localization technologies, which can be divided into two directions: outdoor localization and indoor localization.

Outdoor Localization

With the rapid development of the satellite positioning technology, outdoor LBS have gradually penetrated into every aspect of people's lives, bringing great convenience to people. The mainstream satellite positioning systems mainly include GPS, the Global Navigation Satellite System (GLONASS), BeiDou Navigation Satellite System (BDS), and Galileo satellite navigation system (GALILEO). First of all, GPS is a radio navigation and positioning system developed on the United States Navy navigation satellite system. It can provide users with geographical location on the Earth as well as time information. Another example is GLONASS, which is a second-generation military satellite navigation system independently developed and controlled by the former Soviet Ministry of Defense. It is the second global satellite navigation system after GPS, and consists of three parts: satellite, ground monitoring station, and user equipment. In terms of technology, GLONASS has better anti-interference ability than GPS, but its single point positioning accuracy is not as good as GPS. BDS is a new global satellite navigation system developed in China. It is composed of a space terminal, a ground terminal, and a user terminal. BDS has been applied in many fields, including surveying, telecommunications, emergency management, and so on. In Europe, GALILEO is more popular, which consists of two ground control centers and 30 satellites. For these 30 satellites, the number of working satellites is 27, and the rest are spare satellites.

Indoor Localization

Outdoor positioning technology has brought great convenience to human life. However, the accuracy of outdoor positioning still needs to be improved. Especially in the indoor environment, due to occlusion, uncertainty, and complicated structure, existing outdoor positioning technologies cannot meet the indoor positioning requirements. Therefore, a large number of researchers have begun to focus on indoor positioning technologies.

Existing indoor positioning technologies are based on different signals, such as ultrasonic, ultra-wideband (UWB), radio frequency identification (RFID), Bluetooth, and WiFi.

Ultrasonic-based positioning technology mainly uses reflective ranging, that is, transmitting ultrasonic waves and receiving echoes generated by the measured object, and then calculating the distance between them according to the time difference, and finally determining the position of the measured object. Ultrasonic-based positioning has high positioning accuracy, but it cannot penetrate walls and some obstacles. The ultrasonic-based localization system faces the multipath effect, and it requires a large amount of investment in the underlying hardware facilities. Kim *et al.* [3] proposed an ultrasonic reflections-based positioning system that exploits time difference of arrival (TDoA) technology in location estimation. Although it can achieve high positioning accuracy with errors smaller than 35 cm, it deployed 20 beacons in the $620 \times 980\ cm^2$ room. UWB transmits data by sending and receiving nanosecond ultra-narrow pulses. It has the advantages of strong penetrating power, high safety, and low system complexity. However, it is difficult to

	Deep learning	Transfer learning
Outdoor localization	High scene stability Less labeled data	High scene stability Fewer similar scenes
Indoor localization	Large amount of labeled data Low scene stability	Multiple similar scenes Low scene stability

TABLE 1. Advantages and disadvantages of deep learning and transfer learning for positioning.

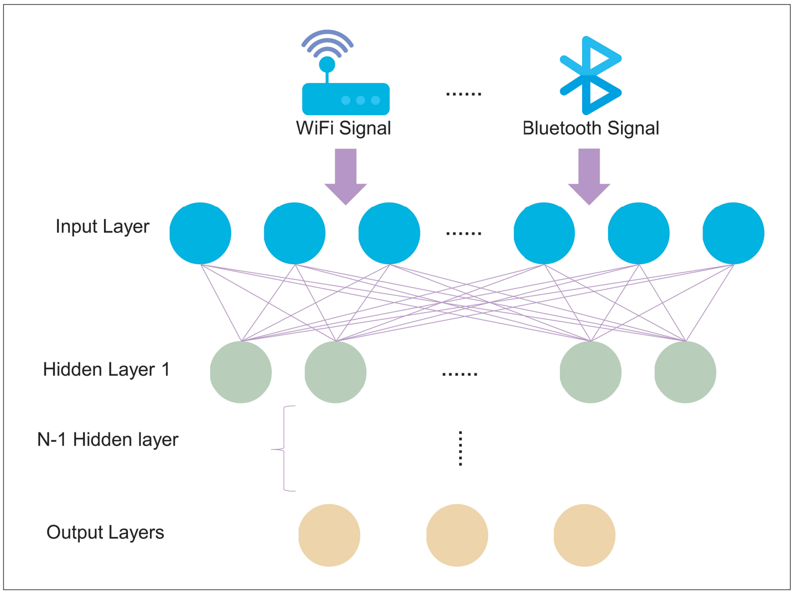

FIGURE 2. Deep learning for positioning.

achieve large-scale indoor coverage with UWB, and higher system construction costs limit the development of UWB-based positioning system.

RFID can automatically recognize a target object through RF signal and acquires relevant non-contact data. In general, RFID-based positioning technology has advantages of non-contact operation and non-line-of-sight transmission of signals, while it requires the deployment of separate devices, usually including reader, tag, host, and so on. Huang *et al*. [3] proposed a real-time RFID indoor positioning system based on Kalman filter (KF) drift removal and Heron bilateration location estimation. It implemented an active RFID tag, a portable RFID indoor positioning device, and a terminal for localization and orientation indications. Bluetooth-based positioning was performed by measuring Bluetooth signal strength or fingerprinting methods. The Bluetooth chip has the advantages of small size, low power consumption, and easy integration and deployment of the device. However, in a complex environment, the Bluetooth signal is susceptible to interference from external noise signals.

WiFi, as the most widely deployed indoor wireless network infrastructure, has covered most public places including shopping malls, museums, airports, railway stations, libraries, and so on. Indoor positioning technologies based on received signal strength of WiFi signal have received the most extensive attention and achieved successful application. This localization system was divided into two stages from the algorithm aspect, that is, the offline data acquisition stage and online positioning stage. In the offline stage, the researcher needs to obtain a certain amount of WiFi signal strength information at the sampling points specified in the area to be located, forming the WiFi fingerprints in this area. Then, in the second stage, matching the WiFi fingerprint collected by the intelligent terminal in real time with the offline fingerprint database takes place to determine the user's current actual location. Current research in this stage mainly focuses on algorithm optimization, such as fingerprint matching method, reduction sampling frequency, and other auxiliary positioning technologies. At the same time, in the offline stage, matters such as the specific methods of selecting fingerprints, sampling point selection, and prediction sample value of wave function have also received extensive attention.

Machine Learning for LBS

In recent years, with the rapid development of ML, ML-based positioning technologies are also very popular and have achieved good results. In these ML-based positioning technologies, deep learning and transfer learning are more practical due to the complexity and diversity of the positioning environment. As shown in Table 1, we summarize advantages and disadvantages of deep learning and transfer learning for positioning. In this part, we also summarize some typical work related to deep learning and transfer learning.

Deep Learning for Positioning

Deep learning is a branch of ML. The motivation is to build and simulate a neural network for human brain analysis and learning. It mimics the mechanism of the human brain to interpret data. The concept of deep learning stems from the research on artificial neural networks. The multi-layer perceptron with multiple hidden layers is a deep learning structure. Deep learning combines low-level features to form more abstract high-level representation attribute categories or features to discover distributed feature representations of data. Deep learning has a wide range of applications in many areas, including computer vision, speech recognition, natural language processing, search engines, finance, online advertising, and more [4, 5].

As shown in Fig. 2, in recent years, deep learning has also been attempted in wireless-signal-based localization algorithms to improve localization accuracy and reduce labor costs [6, 7]. Wang *et al*. [8] proposed a deep-learning-based indoor fingerprinting system for indoor positioning named DeepFi, using channel state information (CSI). This system is similar to the usual indoor fingerprinting system, which includes an offline training phase and an online localization phase. Deep learning is used to train all weights of a deep network as fingerprints in the offline training phase. In order to reduce the system complexity, it used a greedy learning algorithm. And then, in the online localization phase, to obtain accurate position prediction, it employed a probabilistic method based on the radial basis function.

Based on deep autoencoder, Khatab *et al*. [9] proposed a new method to obtain high-level extracted features. It solved the shortcomings of traditional methods that could not describe the high-dimensional features of data. Furthermore, taking into account the dynamic nature of the environment, it can incrementally learn and continuously use new data to make the method more stable and more accurate.

Transfer Learning for LBS

Transfer learning is another kind of ML method. It is an optimization method for people to learn things in new fields by comparing what they have learned. In other words, transfer learning is more suitable for new scenarios without much data. In terms of data scarcity, there is deep reinforcement learning [1]. The difference is that deep reinforcement learning is suitable for gradually generating data through interaction, and gradually finding the optimal solution. For example, when we learn the backstroke, it is easy to learn freestyle. Running skills can be applied to race walking. As shown in Fig. 3, transfer learning effectively reduces the initial training cost and reapplies the training model from one task to another related task.

At present, supervised learning has been widely used in business. However, supervised learning needs to be based on massive training datasets. Through the correspondence between the existing input data and the output data, a mapping function model is generated by training, and the unknown data samples are predicted with the known model. This requires sufficient training samples, and the training samples and test samples are distributed independently. In some scenarios, the cost of obtaining data samples is very high, or it is impossible to obtain enough data samples at all.

In recent years, transfer learning has been widely studied in the field of ML. The advantage of transfer learning is that we can apply the model to similar problems and get good results by making minor adjustments to a trained model. For example, in the user evaluation of some new systems, the data available for training in the target domain is very little, which is usually unlabeled text. We need to analyze the emotional categories of user evaluation through natural language processing. It is difficult to deal with these texts using the traditional ML method. By using transfer learning, it can analyze the user evaluation historical data of existing similar systems, build the evaluation emotional analysis model, and then apply the model to the user evaluation analysis of the new system. Transfer learning can transfer models suitable for large amounts of data to small amounts of data through deep mining of common features of problems. It is similar to label-less learning [10], which fundamentally solves the problem of ML with a small amount of labeled sample data.

Typically, for an LBS system the amount of data in the source domain is sufficient, whereas the amount of data in the target domain is small. This scenario is very suitable for transfer learning. When we want to provide indoor LBS for one new area, the fingerprint data is usually seriously insufficient, while there is a large amount of relevant fingerprint data available for training. There are some characteristic distribution difference between training data and implementing data, including spatial distribution, wireless signal hotspot layout, and so on. In this case, if a suitable transfer learning method is adopted, the wireless signal fingerprint accumulated in the source domain will transfer to a new space. It will greatly

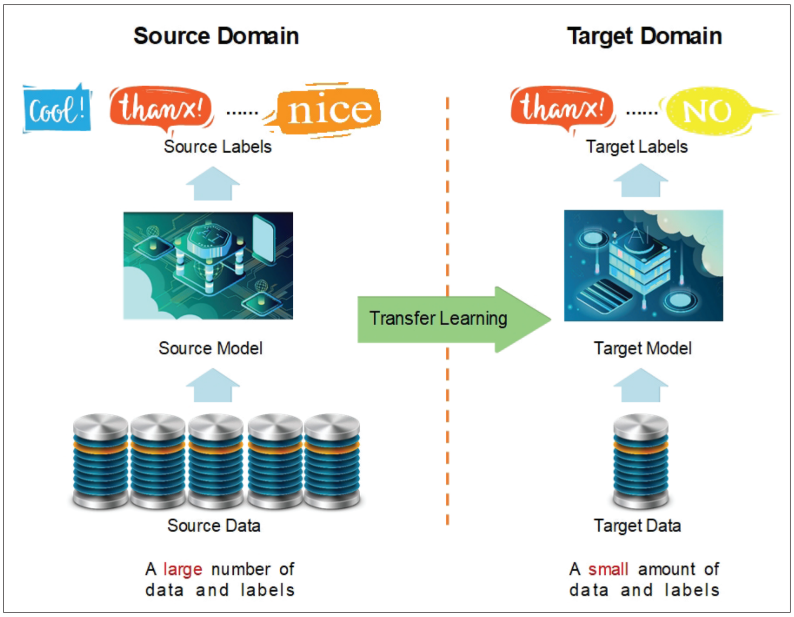

FIGURE 3. Transfer learning for LBS.

reduce the need for fingerprint collection work, significantly improving the positioning accuracy under the support of a small number of test sets. It is conceivable that the main obstacle hindering the large-scale promotion of LBS could be solved with the support of transfer learning technology. At present, many studies have achieved corresponding results in this respect.

Chang *et al*. [11] proposed FitLoc, a fine-grained and low-cost device-free localization (DfL) approach that can localize multiple targets in various areas. This research is based on compressive sensing theory, using transfer learning to unify the radio map over various areas. FitLoc clearly reduces the deployment cost. Compared to other ways of using the Radio Topology Imagine model, FitLoc uses an innovative transfer learning scheme during the localization phase. In order to reuse the radio map of one area in various areas, FitLoc projects the received signal strength (RSS) into a subspace where the distribution distances over different areas are minimized.

Chang's study is based on the isomorphic localization system. Compared to the former, Zheng *et al*. [12] researched the cold-start heterogeneous device localization problem. in their paper, they trained the localization model from the data of the gauge device and tested it using the data from the heterogeneous target device. In order to start the positioning system in a cold-start environment, they wanted to find a robust representation of the feature. A new high-order pairwise (HOP) feature representation and a novel constrained restricted Boltzmann machine (RBM) model were proposed in this paper. To gain more discriminative HOP characteristics and implement local deployment, this system combines the robust feature learning with localized model training.

A Possible Vision and Challenges

The rapid development of LBS has facilitated people's work and lives. Both public and business users have a wide range of demands for location information and LBS. However, existing outdoor

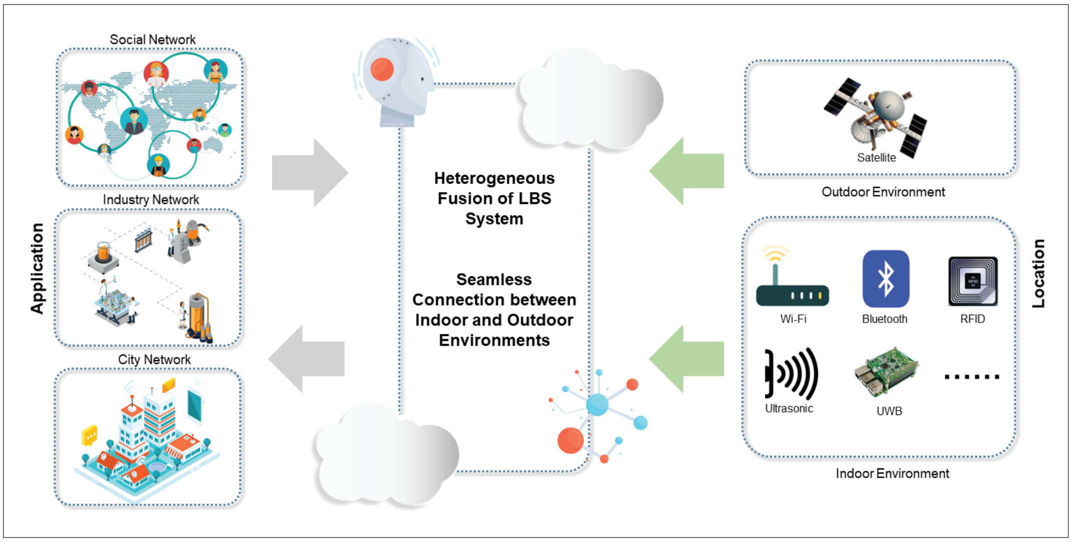

FIGURE 4. A possible vision for an LBS system.

and indoor LBS systems lack uniform standards. Different operators have different system architectures and cannot achieve seamless connection. Technology is always evolving rapidly with demand in order to provide better LBS for people, which requires not only in-depth academic research, but also the combined development of industry.

A Possible Vision

Many researchers, engineers, and enterprises have been committed to the research and development of LBS, and people hold different opinions on future visions. In this article, we describe a possible vision of the future, integration of heterogeneous LBS systems and seamless connection between indoor and outdoor environments, as a possible development direction.

In Fig. 4, the right panel demonstrates a variety of heterogeneous LBS systems that are suitable for indoor and outdoor environments. In our daily lives, we often need to navigate from a location in a large indoor environment to an outdoor destination. For example, in an underground transportation hub, if we want to take a taxi to an exhibition center, the current systems require us to use the indoor LBS system of the transportation hub when navigating to the taxi station, and then manually switch to the outdoor positioning system when navigating to the destination.

In the future development of LBS systems, we need to study not only the intercommunication between multiple scenes, but also the interconnection between multiple heterogeneous LBS systems. There are many kinds of positioning technologies, which have different advantages and disadvantages. Based on the ML method, optimizing and intergrating multiple heterogeneous LBS systems can effectively improve the positioning accuracy and system robustness, and reduce the overall investment in LBS system solutions. Furthermore, more in-depth and accurate LBS need to integrate with a variety of networks, such as social networks, industrial networks, and smart city networks. In addition, edge cognitive computing can be used to save energy consumption[13]. People not only desire location-based information, but also need the semantic information of different locations in different scenarios, as well as the situational information when people request the LBS.

Challenges

From a long-term perspective, we identify the following challenges.

How to Improve the Effect of Machine Learning Effectiveness under RSSI Changes: As we all know, received signal strength indication (RSSI) is greatly affected by changes in the surrounding environment, different population densities, room temperatures, humidity, and temporary large obstructions. How to represent the RSS fluctuation caused by environment change affects the positioning accuracy and the algorithm validity. Moreover, it is impossible to ensure that the RSSI is collected in different physical spaces completed by the same equipment in practical application. This inevitably leads to the requirement of normalization between existing fingerprint data in different scenarios. Otherwise, the measurement error between different devices may reduce the positioning accuracy directly. The above two problems are important to LBS system development, and should be solved effectively before large-scale commercial applications.

How to Avoid Negative Transfer: When RSS fingerprint data from a given region is transferred to a new unmeasured region, it is important to select the appropriate feature values and transfer objects. Due to differences in spatial layout and wireless signal access point distribution among regions, improper feature selection and transfer mode may bring serious negative transfer effects, resulting obviously decreasing positioning accuracy. How can we avoid negative transfer effectively? There are two research directions. One is to design an effective evaluation mechanism for transfer, judging the correlation between different regions and providing appropriate feature selection that ensures the effectiveness of fingerprint feature transfer. Second, a negative transfer discovery and correction algorithm should be designed to evaluate the transfer effect in real time, and improve by modifying or replacing the feature mode to achieve satisfactory positioning accuracy. It is believed that this problem will be one important research direction of LBS technology in the future.

How to Collect, Transfer, and Store a Massive Amount of Location Data: ML-based positioning needs large-scale high-accuracy location data as support. In the LBS scenario, location data is generated with high frequency and large amounts. Therefore, the collection, transmission, and storage of a massive amount of location data face great challenges. In the research on location data collection, many researchers obtain location data by crowd sourcing, but there are certain errors between different signal data acquisition devices. Moreover, much data transmission and storage face problems such as high energy consumption, high latency, and poor reliability. In order to promote the rapid development of positioning technology, it is necessary to solve the above problems in the future.

How to Ensure User Privacy and Facilitate Data Sharing: Location information can reflect the user behavior and thus be utilized in advertising and recommendation systems [14]. But the user behavior data contains personal sensitive information [15], which may bring potential risks to the user if the data is hacked by an attacker. Therefore, users have a skeptical attitude toward existing LBS systems, which inhibits the promotion and development of LBS to some extent. In addition, LBS providers need users' accurate location data to provide richer, convenient, and accurate LBS support. As the existing user location privacy protection and data sharing model cannot solve the problem, a service model is urgently needed, which can not only effectively protect user location privacy, but also encourage users to share their non-sensitive location information.

Conclusion

In this article, we present a survey and future directions of the LBS and positioning technologies, especially from an ML perspective. Some positioning technologies based on different signals, such as satellite, ultrasonic, UWB, RFID, Bluetooth, and WiFi, are summarized. We then present the new research achievements and applications of ML-based positioning. We believe that possible directions of positioning technology are integration of heterogeneous LBS systems and seamless connection between indoor and outdoor environments. There are still many challenges that can be further explored in the future. LBS applications have great potential and broad prospects, and ML will play an important role.

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