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Minireview

Traffic state estimation of urban road networks by multi-source data fusion: Review and new insights

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A B S T R A C T

Accurate traffic state (i.e., flow, speed, density, etc.) on an urban road network is important information for urban traffic control and management strategies. However, due to the limitation of detector installation cost, it is difficult to obtain accurate traffic states through detectors in the whole urban road network with limited detector equipment. In this paper, we review the studies that focus on the missing traffic state estimation problem, especially for the traffic state estimation on the segments without detectors. We provide a way to summarize for readers who have an interest in the different modelling and application of missing traffic state estimation. We first divide the existing studies into three categories: estimation under different missing scenarios, estimation with multi-source data, estimation by fusing different detector types. Then, we summary some existing challenges by the different missing scenarios, data applications, and methodologies. Finally, this work also discusses some future research directions.

Contents

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1. Introduction

Rapid urbanization and economic growth have enabled significant and continuous growth in traffic volume on urban road networks, in turn contributing to traffic congestion, traffic accidents, and pollution. Many forms of intelligent traffic management strategies have been developed and designed to alleviate urban traffic congestion through measures such as dynamic route guidance and responsive traffic signal control. An accurate estimation of traffic states (including traffic volume, density and speed) on roads is central to the successful operations of these intelligent traffic management strategies. Traditionally, information on traffic states is collected through fixed detectors installed throughout at road network, including ground loop detectors, microware sensors, and surveillance cameras [1].

Limited by the budgets for the detector equipment, it is not realistic to install detectors in each segment of a road network. Road segments without detector installation cannot be detected. On the other hand, due to malfunctions of hardware or software, network communication interruptions, power supply shortfalls, and facility maintenance, fixed detectors face random damage. Even on road segments with fixed detectors installed, some traffic data may be missed. Thus, estimating missing traffic states on urban networks has become a crucial component of urban traffic management [2]. As shown in Fig. 1, the unknown traffic state can be interpolated in the non-detection segments in central Bangkok, where detector equipment was not installed [3].

Recently, to address this urgently research issue, with the support from the academia, the industries (such as the companies of HERE, Gaode, TomTom, and Inrix) have published a number of mobile applications (APPs). All of them have their unique perspective on traffic analysis. HERE published an offline downloadable and small memory map APP, which provides accurate road information and also contains abundant geographical information. Gaode, as a traffic internet company, has a large market penetration in China. It obtains vehicle positioning data by providing route navigation and performs traffic state estimation. TomTom has a high-precision digital map that can be used for traffic state estimation in scenarios where require high accuracy, such as autonomous vehicle. Inrix is a comprehensive internet company that not only provides intelligent guidance, speed detection, but also long-term prediction of traffic states and even commercial property prices.

With the recent development of information and communication technology, a variety of traffic detectors have emerged. The application of these detectors in traffic state estimation, for example, mobile phone-based probe detectors, taxi GPS positioning-based detectors, and licence plate recognition detectors have given rise to emerging traffic internet company, such as Wejo, and StreetLights. Wejo takes the perspective of vehicles, provides real-time traffic states to all driving connected vehicles, and tries to implement user equilibrium in entire road network. StreetLights gives personalized travel options from the perspective of each traveller, combined with individual travel preferences.

However, compared with traditional detectors, emerging detectors have diverse characteristics in positioning accuracy, positioning interval, and market penetration rate. Each emerging detector data type has unique strengths and weaknesses and cannot be simply integrated due to data heterogeneity. There are some limitations for processing these emerging data by previous methods on traditional detectors. It is, therefore, necessary for researchers to consider the following two questions regarding urban traffic state estimation and imputation with missing data. (1) Is the previously proposed method feasible for different types of emerging detector data utilized for a variety of scenarios of missing traffic estimation? (2) How can the accuracy of traffic estimation be improved by integrating the advantages of multiple detector data?

Regarding question (1), most previous research focused on a review of traffic prediction; fewer reviews have addressed missing traffic state estimation. Only Toru et al. summarized traffic state estimation on highways [4]. However, traffic state estimation in the complex environment of urban road networks will become more difficult than in that of highways. This finding is especially true when it is applied to different types of traffic detector data in different missing scenarios. A summary of a review of papers on traffic estimation and prediction is shown in Table 1. In this paper, we collected nearly

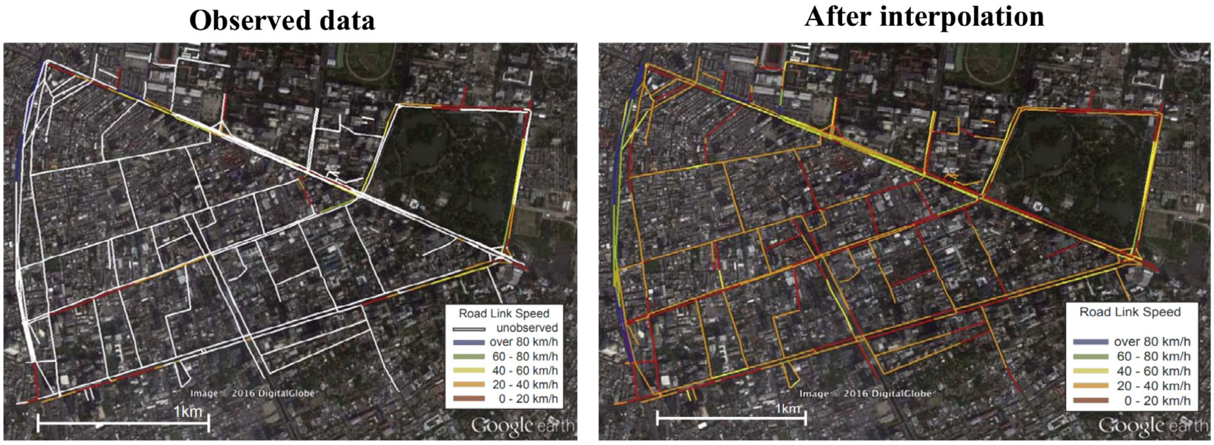

Fig. 1. Heat map of estimated traffic state in central Bangkok (14:00–14:05, Oct. 29, 2013). Hara et al. [3].

Table 1
The review of traffic estimation and prediction.

Transportation scenario	Estimation or prediction	Traffic information parameter	Key references
Highway & Urban link	Prediction	Traffic state	Eleni et al. [5] Shafiza et al. [6]
Highway & Urban link	Prediction	Traffic state	Nour et al. [7], Bahador et al. [8] Alireza et al. [9]
Highway & Urban link	Estimation & Prediction	Travel time	Usue et al. [10]
Highway	Estimation	Traffic state	Toru et al. [4]
Urban road network	Estimation	Traffic state	**This paper**

200 of the latest studies in the last 15 years; the research keywords are shown in Fig. 2. The research topics can be divided into three categories: estimation under different missing traffic scenarios, fusion by different types of detectors, and application by different data types. These studies could be viewed as a reference for current engineering applications, in which detector data and methodology are most appropriate for corresponding missing scenario applications.

To address question (2) and discuss insights for feasible future research directions, this study attempts to compare the differences among existing studies about missing traffic state estimation, and some challenges and emerging methodologies are also discussed. In addition, we analysed the influencing factors and limitations of missing traffic estimation as part of the exploration of different study areas and missing scenarios.

In summary, this paper is motivated by the increasingly promising potential of missing traffic estimation. The recently emerging development of missing traffic estimation modelling and analysis, was reviewed to explore the inherent application scenarios of missing traffic estimation and to identify their advantages and the current gaps to guide their further applications.

In the remainder of this paper, first, we introduce missing traffic estimation in different research scenarios and applications based on different data types, followed by the fusion of different detectors and methodologies in missing traffic estimation. Second, remarks and discussions are presented to intuitively demonstrate the analysis and application of missing traffic estimation. Last, conclusions are drawn.

2. Missing traffic state estimation in different scenarios

Missing traffic flow data can be classified by the missing information length. As shown in Fig. 3, we can divide missing data into three classes: point-wise missing data scenario, linear-wise missing data scenario, and panel-wise missing data scenario. In the point-wise data missing scenario, the traffic flow data on road segments are missing only at some time slots, and other data adjacent to the missing locations are intact. In the linear-wise missing data scenario, sequential missing values appear in consecutive periods for a road segment. In the panel-wise missing data scenario, it occurs when

Fig. 2. Keyword collection of relevant research papers in the past 15 years.

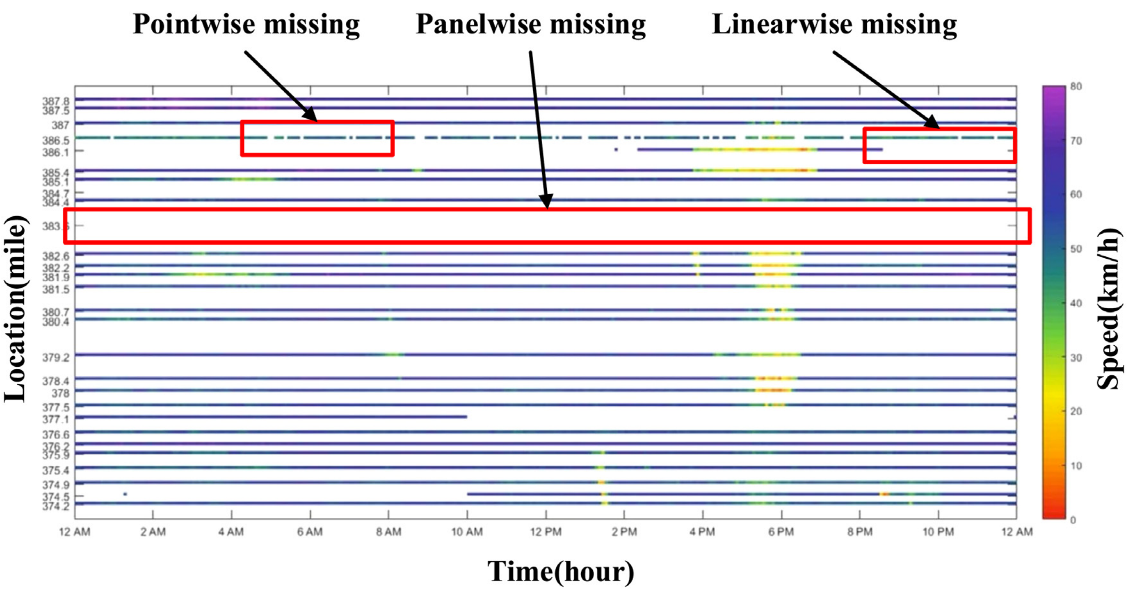

Fig. 3. Schematic of different missing traffic scenarios. Bumjoon et al. [11].

there is no detector installed on the research segment, which results in missing traffic volume on entire segment for all time periods. Over the last decade, many researchers have investigated the missing traffic flow estimation problem. In this section, we divide the literature review into two parts: data imputation on point-wise missing data scenario, and data imputation on linear-wise and panel-wise missing scenarios.

2.1. Traffic state estimation on point-wise and linear-wise missing scenarios

In general, models for point-wise missing traffic data imputation can be viewed as the input requirement for uninterrupted time series. Given the availability of a large dataset with few missing slots, simple techniques such as imputation by constant correlation values could enable the accurate performance of traffic missing conditions. For example, Henrickson et al. [12] introduced a statistical method and found that it performed satisfactorily with point-wise missing data. Furthermore, in machine learning methods for traffic data prediction or estimation, Haworth et al. [13] employed the K-nearest neighbour (KNN) to forecast missing values by combining correlative data information from neighbour segments. Zhong et al. [14] proposed artificial neural network (ANN) to realize missing data estimations with optimized genetic algorithms.

Similarly, for linear-wise missing traffic scenarios, feature extraction of spatio-temporal correlated data that come from similar segments and time periods, can be used to compensate for the continuous missing data problem, which is more complex than point-wise missing scenarios. Deep learning models are viewed as suitable for handling this problem. Wei et al. [15] applied a Stacked Denoising Autoencoder method to model the relationships between linear-wise missing data and other correlated data in the research area.

The tensor-based method is also available in point-wise and linear-wise interpolation problem, as it can be viewed as extract features from the perspective of three-dimensional spatiotemporal matrix space. For example, Tan et al. [16] analysed the multidimensional correlation from missing volume data and proposed tensor-based imputation for point-wise and linear-wise missing volume estimation. To consider multi-modal data distribution, Tang et al. [17] developed the Bayesian probabilistic tensor method for missing traffic imputation.

2.2. Traffic state estimation in panel-wise missing scenario

Panel-wise missing traffic data scenario mainly occurs when some road segments that sensors are missing. In such road segments, all traffic data are missing. This estimation method can be divided into statistical methods (e.g., linear regression model [18,19] and kriging-based model [20]) and machine learning methods (e.g., neural network model [21]).

In statistical methods for data imputation, the general method is to extract spatiotemporal features from segments with detector installed, and then impute the missing data by the model built from similar road segments. For example, Aslam et al. [22] evaluated the correlation from a set of road segments, which were selected based on the features of road facilities, and then utilized these segments to build a multiple linear regression (MLR) model to estimate the non-detection volume. Similarly, based on the MLR model, Liu et al. [23] revealed the hidden patterns in urban network and measured the segment correlations to estimate missing traffic statuses. Zou et al. [24] developed a kriging-based interpolation model, which was originally applied for geographical information weighting calculations, to estimate the missing traffic volume on non-detection segments. On this basis, Bae et al. [11] further introduced cokriging methods, which added temporal correlation analysis into the kriging method, to extend the diversity of missing research patterns.

In the application of machine learning methods, Zhan et al. [25] proposed a Bayesian network estimation model to build the feature graph from the fusion of taxi Global Positioning System (GPS) data and fixed detector data, thereby enabling the estimation of city-scale traffic volume. Following this study, Meng et al. [26] continued to develop a semi-supervised learning-based model for estimating these non-detection segments. Liu et al. [21] investigated a graph theory-based parallel computing model for missing state estimation, with the application of dynamic neural network.

In summary, we discover the aforementioned studies which focused on point-wise missing traffic scenario caused by detector network communication interruptions, power supply shortfalls, and panel-wise missing scenario caused by software in adverse weather or detector malfunction of hardware. But for linear-wise missing scenario, which are caused by detector equipment are not installed on some segments. There is only a small amount of research underway, but this issue is worth of further exploration.

3. Missing traffic state estimation with different types of detector fusion

3.1. Fixed detector-based traffic state estimation

Fixed detectors mainly refer to ground sensing coil detectors, infrared radar detectors, camera detectors, and radio frequency identification detectors, etc. This type of detector can be utilized for real-time acquisition of traffic volume, speed, travel time, and other traffic parameter data, and has unique stability and accuracy. Its detection principle is based on a record of the aggregation information when a vehicle passes the fixed detector point.

As traffic state data can be directly acquired from these detectors, previous traffic state estimation studies which based on fixed detector can be divided into missing traffic state imputation from missing points, or missing traffic state estimation from these non-detection segments.

Among the research of missing state imputation, Li et al. [27] discovered that spatial–temporal information from local and global variation could be employed to improve the accuracy of missing traffic imputation. Inspired by the multiview learning method, Li et al. [28] illustrated a hybrid spatiotemporal traffic state imputation model that integrated the time-series properties of the temporal part with the residual component of the spatial part.

In studies of missing state estimation for non-detection segments, missing data were interpolated by spatial–temporal correlation with adjacent road segments. Hara et al. [3] proposed a mixture Gaussian graphical model to solve the problem of hyperparameter estimation in the statistical interpolation model of each non-detection highway link. Considering the uncorrelation between different input detection segments and different object non-detection segments on a city-scale network, Zhang et al. [29] introduced a generative adversarial network (GAN) model to interpolate missing travel time.

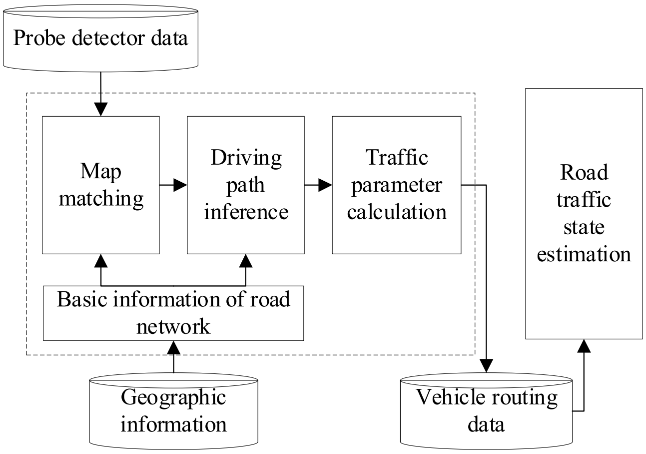

Fig. 4. Data collection and processing of probe detector.

Extended from the GAN model, a deep meta graph attention network structure was presented to address the challenges of complex spatiotemporal correlations [30].

In general, the application scenarios on fixed detector-based missing traffic state estimation focused on missing time slots caused by malfunction of fixed detector, or fixed detector not be installed. However, these methods are mainly based on a highway or a single segment. It was less used on whole urban road network, especially when rate of missing data on urban road networks is high or the distribution of fixed detectors is sparse.

3.2. *Probe detector-based traffic state estimation*

Among studies of various probe detectors that were performed for traffic state acquisition [31,32], probe detector data can obtain traffic flow information in a low-cost way but only obtain part of them. The collection and processing of probe detector data for traffic state acquisition are shown in Fig. 4.

With the rapid development of emerging positioning technologies, probe detector data can be directly applied for monitoring entire traffic volume or travel modes. Gao and Liu [33] discovered that mobile phone location data can be employed to identify traffic measures in proportional form, and that accurate traffic volume on a highway can be estimated by phone simulation data. Furthermore, this approach was further extended to urban arterial roads by a machine learning method with feature selection [34]. For the application of Wi-Fi and Bluetooth probe devices, Pu et al. [35] illustrated a public transit ridership volume monitoring system, in which can be implemented to provide real-time ridership flow and OD information. Furthermore, pedestrian traffic volume data were also acquired via simulation [36].

There are other classical, probe detector-based, traffic state estimation methods, which are original by the fundamental diagram (FD) theory of traffic flow. Due to the relationship among the three parameters (e.g., speed, density, and volume) of traffic flow in FD theory, the accurate traffic volume on each segment can be inferred by travel speed, and travel speed data can be easily obtained by probe detector, as first explored by [37].

Even though traffic volume or status can be monitored, as indicated in the aforementioned research. Compared with fixed detector-based data, there is less application for urban traffic state acquisition with high accuracy, the main reason is limited by the low marker penetration rate of these probe data.

3.3. *Traffic state estimation based on the fusion of fixed detector and probe detector*

Compared with methods using data from a single detector, data fusion methods extract information from multisource data, which can improve accuracy and more specific inferences [8]. The fusion framework of the probe detector and fixed detector is shown in Fig. 5. Generally, existing data fusion approaches in traffic state estimation can be categorized into data-level fusion methods and feature-level fusion methods, which are discussed in the following section.

With the development of information and sensing technology, a variety of data-level methods have been introduced and explored in traffic estimation and prediction. For homogeneous traffic detector data, proven traffic estimation methods have been applied, and it refer to statistical method [38], probabilistic method [39], and artificial intelligent method [40]. For heterogeneous traffic detector data, a sensitivity analysis experiments for influencing factors of fusion result should be organized first before data fusion in Zhu et al. [41]. Another similar study, in which both availability of cellular handoff probe data and microwave sensor data in a neural-network-based fusion model, were evaluated in [42].

Due to the difficulty in obtaining traffic data from all samples, missing traffic volume estimation is more complex than other traffic parameters estimation (i.e., traffic speed, travel time, and traffic state). Its estimation relies mainly

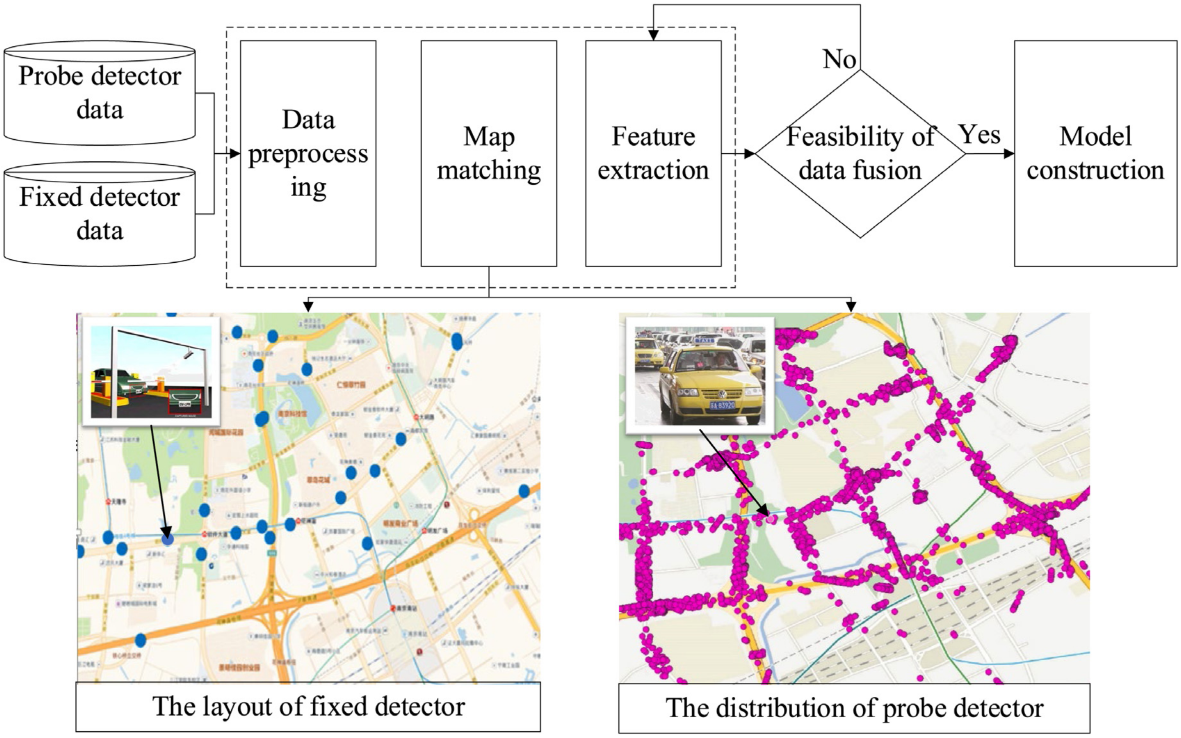

Fig. 5. Fusion framework of the probe detector and fixed detector.

on feature-level fusion approach. For example, fixed detector data were fused with probe detector data, which can fully utilize the merits of two kinds of detectors. The advantages include the characteristic of accurate volume acquisition from fixed detectors and the characteristic of full spatial–temporal coverage from probe detectors. Zhan et al. [25] investigated a hybrid traffic volume reinterpretation model on the non-detection segment, in which integrated Bayesian network theory with well-established traffic flow theory to estimate citywide traffic volume. A parallel study was conducted by Meng et al. [26]. Based on the similarities between non-detection segments and segments with loop detectors installed, the graph-based semi-supervised learning method was applied to estimate city-scale traffic volume based on the spatiotemporal features of taxi speed on whole segments and accurate traffic volume on part of segments obtained by fixed detectors. Cui et al. [43] discovered that the fusion of mobile signalling data and loop detector data could improve the accuracy of traffic volume estimation on highway by the Polaris-based compressive sensing model. Similar to a data application, Liu et al. [44] exploited an urban network volume estimation model by scanning the features of cellphone data and licence plate recognition data, which integrated a multi-grained ensemble learning model with a two-stage, zero-shot learner approach.

In general, the aforementioned studies were mainly applied to traffic volume estimation on general road networks. However, limited by the complex spatiotemporal correlation of urban traffic network, which includes the diversity in the deployment of fixed detectors on various network scenarios, and the influencing factors of probe vehicle travelling trajectory. Fusion-based methods do not work well on these road networks.

4. Missing traffic state estimation by different types of data

The aforementioned missing traffic scenarios could be estimated based on various detector types. However, even when the type of detector is the same, but the data types differ, the feasibility of application, methodology, and accuracy will completely different. For instance, mobile phone data and taxi GPS data are viewed as probe vehicle detector data. Although the two kinds of data positioning principles are similar, the market penetration rate, positioning accuracy, spatiotemporal coverage, data labels, and influencing factors of traffic facilities vary. As a result, the extracted traffic information and the applied technology are also different. Thus, to utilize and retrieve these merits and demerits from different types of data, the data heterogeneity from various data types should be considered before studies are conducted.

The development of emerging information and detection technologies provides unprecedented data type support for intelligent transportation. This section considered three kinds of novel traffic data as examples for the application of missing traffic estimation: mobile phone data, taxi GPS data, and licence plate recognition data. Table 2 shows the comparison of different data type.

Table 2
The comparison of different data type.

Data type	Detector type for data acquisition	Positioning accuracy	Market penetration rate	Traffic information
Taxi GPS data	Probe detector	High	Low	Only taxi volume data
Mobile phone data	Probe detector	Low	High	Vehicles with phones on board
Licence plate recognition data	Fixed detector	Location is fixed and accurate	Low	All vehicles that passed by

4.1. Application in mobile phone data detection

Mobile phone data comprise a derivative product that is used to provide the communication services; they always generate location data when information handoff occurs at the cell base station. The characteristics of the full spatiotemporal coverage and low-cost acquisition of these data have enabled a wide range of developments in the field of intelligent transportation in past decades [45–48]. Mobile phone data were first applied for traffic information acquisition by the University of Maryland [49] and the University of California, Berkeley [50] in the 2000s. This mobile phone data application was further extended for travel time estimation [51] and traffic speed monitoring [52] in Europe.

Based on the discrepancy of the mechanisms of cellular probe data generation, we can divide cellular positioning methods into active (handset-based) positioning method and passive (network-based) positioning method. The active positioning methods can be viewed as when a subscriber uses a mobile phone moves from one cell station service area to another, handover of information transmission occurs, the time and location information from the subscriber are actively recorded. When a cell phone user makes a call, send or receive messages, and use the Internet, etc., the positioning information is uploaded, which is called passive positioning method.

Due to the simplicity of the cellular communication technology for active positioning method, the mobile phone data generated is first applied in traffic surveillance. Fontaine et al. [53] summarized the impact of the design of wireless location technology (WLT) systems and the configuration in transport networks on the effectiveness of traffic information monitoring, and explored the relationship between the design of WLT systems and the accuracy of traffic parameters estimation [54]. Yang et al. [55] developed a simulation platform for evaluating cellular probe systems, in which can analyse the influence of cellular data sample size and potential factors (handover length and volume) on the accuracy of traffic parameter estimation. He et al. [56] analysed the effect of sample size of phone data on detection results by both simulation and field experiments. To improve the accuracy, Zhang et al. [57] fused the estimation results of cellular phone data and loop detector data. Hillel et al. [58] applied loop detection data to compare the reliability of cellular phone data in traffic speed and travel time detection. Keemin et al. [59] exploited cellular simulation data to estimate traffic OD volume. To enable traffic detection on urban road segments, Tama et al. [60] proposed a Tyson polygon approach to map matching base stations to road networks.

The active positioning data is generated only when the transmission handover of cell base station occurs, it has low penetration rate and small sample size. Furthermore, the positioning accuracy is determined by the size of the base station service area, and relatively low. Thus, it is suitable for application in macro traffic analysis of large areas. For example, Wang et al. [61] proposed a road network design approach based on active mobile phone data in Senegal, which is a developing country. It is also able to implement fast traffic congestion estimation provided that a reasonable method is proposed [62].

As for passive mobile phone positioning data, the positioning information can be generated when a mobile phone user interacts with an information centre. It can record the mobile phone user travel trajectory and behaviour information. The accuracy and sample size of passive mobile phone positioning data is higher than active positioning data. Thereafter, its applications can explore to traffic parameter extraction, traffic origin to destination (OD) estimation, urban commuting calculation, and traveller mobility analysis [52]. The passive mobile phone positioning data can be classified into two types by the difference of positioning events, it includes mobile call detail records (CDRs) and mobile cellular signalling data (CSD) [63].

CDRs were widely utilized from 2007 to 2015, starting with the rise of 2G communication systems and ending with the development of 3G and 4G communication systems. The research scenarios are focused on megacities or arterial highways, which do not need to consider the influence of low positioning accuracy, sparse location intervals, and long spatiotemporal distance [45]. CSD were developed with the internet communications handoff between mobile app-based phones and cell stations. This kind of handover generates more frequent positioning information, that can be applied more finely to traffic management. It can be further divided into traffic applications by micro perspective and macro perspective.

As for the micro perspective of traffic applications by CSD, Caceres et al. [63,64] applied cell phone signalling data to replace hardware sensors and experimented with real-time information monitoring and traffic flow estimation. Herrera [65] conducted an experiment to evaluate how much penetration rates of mobile data could reflect the actual traffic state by GPS-enabled phone data. The feasibility of traffic parameters was also tested with floating car measurements in Israel [58]. With the rise in the machine learning methods, the traffic state extraction based on mobile phone data has been illustrated by neural network model [42] and support vector machine model [62]. Combining the macroscopic fundamental diagrams (MFD) theory, more efficient traffic state estimation was proposed for urban congested networks [66].

With improvements in mobile phone positioning accuracy by location processing algorithms (e.g., time of arrival (TOA), time difference of arrival (TDOA)) [67], the study areas expanded from metropolitan areas and expressways [61] to high-density urban road networks [68], and the research objectives range from traffic parameters that are easily accessed to traffic flow estimation for specific travel modes [69,70]. To improve the accuracy of traffic estimation, some data fusion methods have been proposed for loop sensor data [71], licence plate recognition data [44], public transport data [41,72], etc.

As the number of mobile phone users driving on a road segment is not equal to the traffic volume in passenger car units (PCUs), it is essential to identify the travel mode of each mobile phone user. Gao et al. [33] introduced a clustering algorithm to detect similar travel modes, including drive alone, carpooling, and bus, by mobile phone simulation data on highways. Xing et al. [73] extended the application scenario to urban networks with high-precision cellular location data. Choudhury et al. [32] investigated the influencing factors for the travel mode choice of mobile phone users. Considering the noisy and irregular positioning intervals of cellular phone data, Huang et al. [47] summarized several research methods for different application scenarios.

As for the macro perspective of traffic applications by CSD, Jiang et al. [74] proposed a framework for analysing human travel mobility by cellular phone data in Singapore. Xiao et al. [75] analysed the travel distance of different traveller group by GPS mobile phone data. On the basis of the difference of mobile phone numbers which indicate coming from different areas, Yang et al. [76] compared the travel mobility between local mobile phone user and outside mobile phone user. With the rise of novel mobile phone users' website preference data, the travel destination of each traveller with labelled socioeconomic attributes was identified, and the application range was enriched by those mobile user portrait data [48]. Combining the point of interest (POI) data in study area, Chen et al. [77] analysed the influencing factors which effect the length of stay time and trip distance under different POI categories. In dealing with emergency application, mobile phone data could be used for the analysis of influencing factors on urban–rural mobility during the coronavirus disease 2019 (COVID-19) crisis [78], and Songhua et al. [79] proposed mobile phone data-driven framework, which could quantitatively assess travel mobility and policy effects during COVID-19.

The aforementioned research utilized the advantages of mobile phone data, but it also has some limitations, such as low positioning accuracy and small market penetration rate. These characteristics hinder its full utilization in traffic information estimation.

4.2. Application in GPS trajectory data detection

The GPS positioning system is mainly used to monitor real-time taxi driving trajectories, and maintain the normal operation of taxi services. In this process, taxis driving on urban road networks can provide their geolocation information, time stamp, and whether they have picked up passengers at a fixed time interval. These generated GPS trajectory data can be viewed as floating vehicle detector data, which can be applied to estimate real-time, urban network traffic states.

Among the applications of taxi GPS trajectory data in urban traffic network, they have the following three attributes: (1) high positioning accuracy, fixed positioning time interval; (2) the real-time location information updates of taxis can be transmitted to taxi service monitoring centres; and (3) the pick-up point and drop-off point for taxis passengers can be recorded. Due to these characteristics, the applications of taxi GPS trajectory data is classified into two lines of research.

The first line of studies regard taxi GPS data as a kind of floating vehicle data, which is used to traffic estimation or prediction. Kong et al. [80] proposed a fuzzy comprehensive evaluation method to estimate traffic congestion by floating trajectory data. With the development of deep learning technology, Ke et al. [81] developed a novel deep learning approach for taxi passenger demand prediction, which integrated multiple CNN (convolutional neural networks) and LSTM (long short-term memory) layers to better capture the spatiotemporal characteristics of explanatory variables. Following this study, Zhang et al. [82] improved this hybrid CNN-LSTM framework by a greedy algorithm for urban traffic flow prediction. Guo et al. [83] further extended the hybrid deep neural network framework by combining 3-dimensional convolution networks with the CNN-RNN (recurrent neural networks), which can consider the spatial dependencies and temporal evolutions of urban networks. Furthermore, Zhan et al. [84] applied taxi pick-up and drop-off data to estimate citywide travel time, which instead of other taxi GPS trajectory data.

The second line of studies take advantage of the high positioning accuracy and fixed positioning intervals of taxi GPS data, and the recorded travel trajectory is applied for route planning. Cui et al. [85] evaluated urban network accessibility by inferring taxi routes, and some low accessibility areas could be detected for the improvement of whole urban network. Li et al. [86] summarized studies of travel route planning based on taxi trajectory data. Previous studies focused on the effect of taxi travel frequency. Yang et al. [87] further considered the impact of taxi drivers' travel time, fare, and geolocation preference for route planning or pathfinding methods.

Besides taxi GPS trajectory data, there are still some other similar floating vehicle data, such as Inrix data, DiDi trajectories, etc. They can be used for traffic state (traffic flow, queue length) estimation or prediction on arterial road segments.

In a study that apply trajectory data to estimate queuing status at intersections, Park et al. [88] proposed a Bayesian structural equation model to identify congestion patterns on road segments and intersections using INRIX data. Qin et al. [89] developed a traffic flow estimation model to judge traffic congestion by GPS trajectories. Luo et al. [90] exploited traffic flow estimation method on urban arterials road based on connected vehicle trajectories collected by vehicle-to-cloud communication. Unlike existing single-intersection models, the model considered traffic states and traffic signal coordination between adjacent intersections to capture the delay and queue length of arterials road by the shock wave theory. In conducting a study on perimeter control strategies for macroscopic fundamental diagram (MFD), Tsubota et al. [91] illustrated the application of GPS trajectories to compensate for the impact of fixed detector-based data in analysing the queuing overflow phenomenon at intersections.

In the study of some emerging artificial intelligence methods, based on travel time data provided by INRIX, Zhang et al. [92] proposed a gradient-enhanced regression tree approach to quantify the effects of different parameters on the performance of arterial traffic prediction model. In traffic prediction based on DIDI trajectories, Fafoutellis et al. [93] proposed a dilated LSTM networks model, which effectively avoided the exploding or disappearing gradients and improved the accuracy. Based on this, Xia et al. [94] proposed a spatio-temporally weighted k-nearest neighbour model in MapReduce framework for distributed modelling on Hadoop platform. Based on the spatio-temporal correlation of DiDi trajectories in urban road networks, Zhang et al. [95] proposed a trip information maximization generation adversarial network model to approximate the trip time distribution in each road segment.

In the study of fusion with other fixed detector data, Lovisari et al. [96] fused fixed detector data and INRIX data, which in turn improved the accuracy of traffic density estimation in the road network. Wang et al. [97] developed a data-driven method for estimating traffic flow under a relatively sparse road network with licence plate recognition (LPR) detector deployment by fusing LPR data with GPS trajectory data.

Although GPS trajectory data have some advantages (accurate positioning, fixed interval, and real-time traffic state monitoring), the applications of GPS trajectory data is still hindered by the random traffic demand effected by passenger, sparse trajectory density, and complexity of spatial–temporal coverage. Furthermore, the market penetration rate in several underdeveloped suburban district is low that cannot be disregarded.

4.3. Application in licence plate recognition data detection

Licence plate recognition (LPR) equipment is a kind of detector installed at an urban road intersection or arterial road segment. This detector is mainly installed for red-light violation enforcement, vehicle monitoring, and access control. When a vehicle passes this detection equipment, it records the licence plate number information, passing timestamps, and occupied lanes. Due to the limitation of LPR detector technology and the number of detector layouts, in the 20th century, LPR was only employed for travel time detection on highway [98] and for OD estimation between two cities [99]. With the increasing number of LPR detectors installed in recent years, the application of LPR data is extended to calculate queue length at an intersection, infer vehicle driving paths, and estimate traffic status and vehicle emissions [100]. In this section, based on the size of the study area in the process of LPR data application, we divided related studies on the application of LPR data into micro and macro perspectives.

From the micro perspective of LPR applications for traffic state estimation, the advantage of recording high coverage of vehicle trajectory information from LPR detectors was utilized at intersections or road segments. Based on the vehicle arrival and departure (VAD) curves described by the LPR detector at an intersection, Zhan et al. [101] proposed a Gaussian interpolation model to estimate part of the missing VAD curves, and then calculated the intersection queuing time. Based on the same VAD curves, Mo et al. [102] developed a kind of vehicle car-following model, which is used to capture speed profiles on research segments by inferred missing LPR detection information. Since the efficiency of the queue estimation model decreases in the context of a sparse floating vehicle trajectory, with high coverage of LPR data at upstream and downstream intersections, An et al. [103] illustrated a piecewise probability model to estimate the average vehicle arrival rate of each lane at the downstream intersection. Tan et al. [104] further exploited the characteristics of this high coverage rate, fused LPR data and floating vehicle trajectory data, and estimated the intersection traffic state under saturated and unsaturated conditions by Bayesian theory.

For queue length prediction, Luo et al. [105] calculated the queue length of last signal cycle to analyse trajectory of single vehicle, and then predict the queue length in next signal cycle. To view the LPR detector at intersection still as research object, Zhan et al. [106] proposed a method to estimate segment traffic state by queue length at intersection, in which avoid the need to collect excessive traffic data on road segment. For missing traffic state interpolation in citywide, Shao et al. [107] proposed a tensor model to estimate traffic state on non-detection segment with the fusion of LPR data and POI data.

From the macro perspective of LPR application, as the LPR detector can record licence plate information, the travel trajectory of a recorded vehicle can be referred to citywide. In the early stage, the possibility of traffic estimation was discussed by using simulated LPR data [108]. However, the development of such an application is limited by the impact of LPR detector coverage. Zhou et al. [109] developed a multi-objective optimization method that combined user equilibrium (UE) theory for traffic estimation. Based on the model of Zhou et al. [110] further extended the two-step, least squares algorithm to relax the assumption of UE, and employed the proposed Bayesian model to reconstruct vehicle trajectory. On this basis, Rao et al. [111] proposed a particle swarm optimization algorithm to reconstruct a vehicle trajectory by the vehicle ID of the LPR data label, which can be used for traffic estimation. Furthermore, some studies also focus on exploring how to modify or optimize the deployment of the LPR detector [112].

As taxi can be identified by plate information of LPR detection, Li et al. [113] evaluated the impact of taxi emission on the overall urban emissions. Based on the difference of travel pattern summarized by LPR data information, the vehicles identified can be divided into commuter travel and leisure travel [114]. As LPR detector can record unique vehicle plate ID information, different vehicle types can be identified. Sheida et al. [115] compared the driving and stopping states of passenger and freight vehicles, which used to better understand urban traffic operation. As the travel time for all vehicle can be recorded by LPR detector, the distribution of path travel time can also be inferred [116].

Although the LPR detector can obtain accurate vehicle information, it still has the disadvantages of a small number of detector allocations, spare and uneven deployment, low density of detector layout, and inability to obtain accurate OD information of vehicles. In extreme weather conditions, data missing scenarios will occur.

5. Missing traffic state estimation by different research methods

In this section, we review previous methods for estimating traffic states and give a little mathematical background of them, as well as the comparison about the estimation efficiency under three computational forms.

5.1. Methodologies in traffic estimation

In the study of missing traffic state estimation problem, the methods can be classified as model-based and data-driven methods [4]. The standard for judging model-based or data-driven is that whether the implementation of traffic state estimation is based on model or data.

In the model-based studies, some models used in physical field are gradually explored to describe the traffic dynamics in transport scenario. For example, the autoregressive integrated moving average (ARIMA) is illustrated to handle with short-term traffic prediction and estimation in 1970s [117]. Model-based methods have been extensively developed after that. Currently, Model-based methods can be divided into three categories, i.e., microscopic, macroscopic and mesoscopic. Microscopic models mainly show the detail of each driving vehicle [117], such as travelling trajectory [118], and instantaneous speed [119]. The details of an individual vehicle movement are used to modelling entire road traffic state. Furthermore, macroscopic models, refer to the aggregated vehicle movements, which are based on the relationship between speed and volume. They can be directly used to infer traffic volume by speed or density, and have highly computational efficiency and low accuracy. For example, Cheng et al. [120] recently proposed a novel s-shaped three-parameter fundamental diagram model, which connects the macroscopic model to a consistent microscopic car-following model, and also gives the analytical formula for link capacity, which is a function of the free flow speed, critical density, and speed at critical density. Thus, they are appropriate for real-time traffic estimation and management, such as the cell transmission model [121], kriging-based model [11]. Mesoscopic models are hybrids of microscopic models and macroscopic models with the description of various levels of traffic details [122]. Under the assumption that models can be used to describe traffic dynamics, the estimation results are reliable. Although a number of models have been proposed, there is still no general model for all traffic scenarios. This limits the application of model-based methods.

Differ with model-based methods which is originated from physical models, the data-driven methods only require traffic data detected by sensors, which are applied for finding the inherent dependencies of data and then based on these extracted features for further prediction. The data-driven methods are constructed based on machine learning models and a litter bit of statistical models. Recently, deep learning methods also have been exploited in transport topics. With the successful application of a deep stacked autoencoder (SAE) to traffic prediction in Lv et al. [123], a lot of researchers have focused on deep learning methods for traffic prediction and estimation. Nevertheless, deep learning methods still suffer from computational complexity during the model training phase. Also, these methods heavily rely on the data preparation or pre-processing procedures, which influence the real-time application. Furthermore, Bayesian optimization method is another data-driven models that can be suitable for dealing with complex nonlinear relationships [124]. Both of them have their unique pros and cons, and their opportunities and challenges are discussed in Section 6.3.1.

Based on the different application scenarios in traffic state estimation, we can further divide these data-driven methods into micro-level (segment based) methods and macro-level (network based) methods. They are determined by whether an individual segment or entire network is organized for traffic state estimation. Micro-level methods include state-space neural networks [125], recurrent neural networks [126], zero-shot learning [44], scalable deep learning [127], multimodal deep learning [128] and adaptive transfer learning models that consider multiple data distribution forms [129]. Macro-level methods include the Bayesian network method [25], tensor decomposition theory [130], the deep meta-learning method [30], the spatial–temporal attention-based learning model [131], the hybrid deep learning model [132,133], and the graph-based learning model [21]. Furthermore, due to the characteristics of stochastic noises, uncertainties and nonlinearities from collected traffic flow data, particle filtering (PF) frameworks have been another prevailing macro-level methods for state estimation, which have the unique advantages in handling the stochastic noises, uncertainties and nonlinearities from collected traffic flow [134]. For example, the PF approach can be modularity of traffic estimation when faced with heterogeneous data fusion [135,136], vehicles with distinct driving behaviours [137], and simultaneous estimation of traffic states and incidents [138].

Table 3
Summary of traffic state estimation methods.

Study	Methodology	Estimation approach	Missing scenario	Detector fusion	Input data
Javed et al. [22]	Model-based method	Spatial weight regression	Panel-wise and linear-wise missing	Fixed & Probe detector	Taxi GPS data and loop data
Bae et al. [11]	Model-based method	Co-kriging correlation	Point-wise and linear-wise missing	Fixed & Probe detector	Traffic speed data
Daganzo et al. [121]	Model-based method	Cell transmission model	Panel-wise missing	Probe detector	Highway traffic flow
Mihaylova et al. [134]	Data-driven method	Particle filtering framework	Panel-wise missing	Fixed detector	Highway traffic flow
Tan et al. [16]	Data-driven method	Multi-linear rank tensor completion	Point-wise missing	Fixed detector	Highway volume data
Zhan et al. [25]	Data-driven method	Traffic flow theory and Bayesian network	Panel-wise missing	Fixed & Probe detector	Taxi GPS data & LPR data
Meng et al. [26]	Data-driven method	Spatio-temporal weight correlation	Panel-wise missing	Fixed & Probe detector	Taxi GPS data & LPR data
Liu et al. [21]	Data-driven method	Parallel computing in graph regression	Panel-wise missing	Probe detector	Taxi GPS data
Liu et al. [44]	Data-driven method	Zero-Shot Learning	Panel-wise missing	Fixed & Probe detector	Mobile phone data & LPR data

Table 3 summarizes existing traffic state estimation studies with model-based and data-driven methods in different missing scenario and input data.

Furthermore, to understand the aforementioned methods well in the application of traffic estimation, the mathematical background behind the key described methods are introduced, such as tensor decomposition method, Bayesian optimization method, and stacked autoencoders method.

(1) Tensor decomposition method

Tensor completion approaches have been widely used for missing data imputation in many fields of science. The tensor decomposition-based method involves converting tensor decomposition into low-rank approximation when parts of tensor entries are observed [139]. Among the typical tensor decomposition methods, there are two main types: CANDECOMP/PARADAC (CP) [140] decomposition and Tucker decomposition [141].

For simplicity, let us take the three-order weighted optimization tensor for an example. Let A be original missing traffic volume, denoted by a real-valued three-order tensor of size $I_1 \times I_2 \times I_3$. A non-negative weight tensor W of the same size as A is used to indicate where missing data happen. The imputation model based on Tucker decomposition for missing traffic data can be formulated as:

$$\mathsf{F}(\mathsf{S}, X, Y, Z) \equiv \arg min \frac{1}{2} \|\mathsf{W} * (\mathsf{A} - \mathsf{S}_{\times 1} X_{\times 2} Y_{\times 3} Z)\|_F^2 , \tag{1}$$

where $X \in \mathbb{R}^{I_1 \times R_1}$, $Y \in \mathbb{R}^{I_2 \times R_2}$, $Z \in \mathbb{R}^{I_3 \times R_3}$ are factor matrices and can be viewed as the principal components in each mode. The subscript F refers to Frobenius norm. The tensor $\mathsf{S} \in \mathbb{R}^{R_1 \times R_2 \times R_3}$ is called the core tensor [130].

(2) Bayesian optimization method

The Bayesian optimization approach to traffic state estimation evaluates the posterior distribution of the system state given a prior state estimate and measurement data. The traffic state of the system $\mathbf{x}^k$ at time k is defined as:

$$\mathbf{x}^k = [p_1^k, \ldots, p_i^k]^T \tag{2}$$

where p_i is the traffic state in road segment of i.

The state propagation is:

$$\mathbf{x}^k = f(\mathbf{x}^{k-1}, \boldsymbol{\theta}) + \mathbf{w}^k \tag{3}$$

where f is the traffic state estimation model, and it propagates the traffic state to the next time step, with the input parameter vector $\boldsymbol{\theta}$. The terms $\mathbf{w}^k \sim \mathsf{N}(0, Q)$ denote the additive unbiased process at time k with assumed covariance matrices Q.

The state estimation problem can be viewed as sequentially evaluating the prior state distribution $p(\mathbf{x}^k \left| \boldsymbol{Y}^{k-1} \right.)$ and the posterior state distribution $p(\mathbf{x}^k \left| \boldsymbol{Y}^k \right.)$ given measurements $\boldsymbol{Y}^k = [\boldsymbol{y}^1, \boldsymbol{y}^2, \ldots, \boldsymbol{y}^k]$, according to:

$$p(\mathbf{x}^k \left| \mathbf{Y}^{k-1} \right.) = \int p(\mathbf{x}^k \left| \mathbf{x}^{k-1} \right.) p(\mathbf{x}^{k-1} \left| \mathbf{Y}^{k-1} \right.) d\mathbf{x}^{k-1} \tag{4}$$

$$p(\mathbf{x}^k \left| \boldsymbol{Y}^k \right.) = \frac{p(\boldsymbol{y}^k \left| \mathbf{x}^k \right.) p(\mathbf{x}^k \left| \boldsymbol{Y}^{k-1} \right.)}{p(\boldsymbol{y}^k \left| \boldsymbol{Y}^{k-1} \right.)} \tag{5}$$

On the basis of this approach, the particle filter [134] and enhanced particle filter [137], Kalman filter [142–144] and Bayesian network [25] have been applied and extended in traffic state estimation.

(3) Stacked autoencoders (SAEs) method

The SAE model is a stack of autoencoders, which is a famous deep learning model. It uses autoencoders as building blocks to create a deep network [123]. An autoencoder is a neural network that attempts to reproduce its input, i.e., the target output is the input of the model. Given a set of training samples $\left\{x^{(1)}, x^{(2)}, x^{(3)}, \ldots\right\}$, where $x^{(i)} \in R^d$, an autoencoder first encodes an input $x^{(i)}$ to a hidden representation $y(x^{(i)})$, and then it decodes representation $z(x^{(i)})$, respectively.

By minimizing reconstruction error $L(X, Z)$, we can obtain the model parameters, which are here denoted as θ, as

$$\theta = \arg\min_{\theta} L(X, Z) = \arg\min_{\theta} \frac{1}{2} \sum_{i=1}^{N} \left\| x^{(i)} - z(x^{(i)}) \right\|^2 \tag{6}$$

To achieve the sparse representation, we will minimize the reconstruction error (RE) with a sparsity constraint as

$$RE = L(X, Z) + \gamma \sum_{j=1}^{H_D} KL(p \left\| \hat{p}_j \right.) \tag{7}$$

5.2. Computational implementations in traffic estimation

In the studies of traffic state estimation in transport network, not only the choice of appropriate traffic state estimation method, but also the computational efficiency, should be considered. Even if the proposed estimation model can produce accurate results, it is still not properly used when the computational efficiency is slow. The usual computational methods mainly include centralized algorithms, parallel algorithms, and distributed algorithms.

Centralized computing is to calculate a task as a computing unit, while parallel computing is to divide the task into multiple subtasks to calculate in parallel. Parallel computing contains shared memory computing and distributed memory computing. Shared memory computing refers to that multiple CPUs of a single computer share a piece of memory to compute, and distributed memory computing is that the CPUs of multiple computers (clusters) are used on their own memory to assist in computing within a local area network. Currently, the prevailing data computing platforms include Hadoop, Spark, and Storm.

In general, centralized architecture algorithms face challenges due to high communication demands. Decentralized or distributed algorithms can give timely feedback and faster computation in traffic state estimation and control of large-scale networks since they can be computed separately at each local control centre and do not require information to be transmitted back to the general control centre for computation. Calculation of traffic state estimation in urban road networks, which can later be converted from a large urban road network into individual smaller sub-networks with MapReduce framework [145]. Decentralized or distributed computing is suitable for large-scale urban road networks, but it needs to divide the subnetwork effectively. For example, deep 3D convolution network [146] and graph convolution network [147] were proposed in traffic flow prediction by the spatio-temporal correlation of each segment in subnetwork. Furthermore, in data fusion based for urban traffic state estimation, the decentralized gaussian process method enables fusion of individual floating vehicle state data, and implement active sensing for real-time spatiotemporal traffic state [148].

Parallel computing is a form of computation that can be implemented after determining decentralized or distributed frameworks. The parallelized architecture could reduce the computational time and provide high estimation accuracy by simultaneous computing in up-loading, processing, and back-loading phases when dealing with massive data problems. A parallel implementation is valuable for researchers to quickly examine the interactions of vehicular flow and analyse the complex traffic phenomena on a larger scale [149]. It also helps to improve on-line traffic state estimation and prediction. Particularly, it is appropriate to utilize parallel computing approaches in the process of traffic state estimation in large-scale transport networks with a large number of iterative training steps, such as deep learning. We generally applied the MapReduce framework of distributed modelling on a Hadoop platform which is the hardware that provides computing resources for parallel computing in short-term traffic flow estimation [150]. Furthermore, Spark platform also could provide parallel computing resources for some hybrid improved deep learning algorithms [151].

In early studies, parallel computing techniques have been applied in several transportation simulation systems, Cetin et al. [152] studied the parallelization of microscopic transportation simulation based on TRANSIMS (Transportation Analysis and Simulation System) using another sophisticated graph partition algorithm. Potuzak et al. [153] reported a distributed microscopic discrete time-stepped simulator DUTS (Distributed Urban Traffic Simulator) and performed road traffic simulation on a cluster of computers with multi-core processors. In the field of traffic assignment, Florian et al. [154] offered a good review on parallel computing approaches for performing the shortest path algorithms. Liu et al. [155] demonstrated a solid effort for accelerating the Monte Carlo simulation method for solving probit based stochastic user equilibrium problems using a distributed computing system.

Although the centralized algorithm has the disadvantage of lower computational efficiency when dealing with large-scale road networks, it also has its unique advantages in dealing with traffic estimation scenarios. For example, when the deployment of fixed detectors in the urban road network is relatively uneven, there is not enough similar segments that could be used to provide input sample data for modelling in each sub-network. The entire transport network should be considered to find the similar segment, and it is appropriate for the centralized algorithm [137].

6. Challenges and discussions

The aforementioned overview focused on the development of urban traffic state estimation, and most of the effort occurs under different missing state scenarios, different detector categories, different data type applications, and different methodologies. However, there are still some research deficiencies, which create an unprecedented opportunity to expand horizons and direct work in three challenging directions: challenges in changing missing research scenarios, the process of data fusion, and methodology application. These challenges are introduced in the following section.

6.1. Challenge 1: variations in different missing scenarios

6.1.1. Effect of different missing lengths and missing rates

Different missing lengths and missing rates of traffic volume constitute different traffic estimation scenarios, as aforementioned in Section 2.

With an increase in missing traffic volume length, the method of missing volume imputation will be more complicated. For example, the longer traffic missing data length would cause the larger missing information of traffic dynamic fluctuation. Especially when the traffic volume on entire road segments are unknown, this estimation of traffic dynamic fluctuation based in time series presents a great challenge [22]. This missing volume estimation problem is equivalent to a long-term multi-step traffic flow forecasting problem [156]. Furthermore, the estimation difficulty will increase when missing rate rises, particularly in which missing states occur at multiple locations on a road segment.

To address the difficulties caused by the different missing volume scenarios, two specific approaches have been proposed among the formulations of missing value estimation methods. First, when some road segments are missing point-wise and linear-wise volume, the missing volume can be interpolated based on neighbouring data or historical data which are correlated with missing object data. Some imputation methods can be employed to realize this goal by feature extraction [157]. Therefore, this kind of imputation method can be divided into statistical learning based methods (e.g., linear regression [22], weighted regression method [158], matrix decomposition [159], compressive sensing [23]), and the machine learning based method (e.g., ensemble learning theory [160], neural network [125], and Bayesian optimization [161]). Each approach has its advantages and shortcomings. To improve the estimation accuracy, conducting scenario analysis and data pre-processing is crucial before determining the research method.

Second, when the whole road segment lack traffic volume data, we need to estimate the missing volume by the correlation between the non-detection segment and other detection segments on the whole network. The general method is to view these road segments as nodes, where nodes are connected by edges, and the correlations between segments are regarded as the weights of the edges. This kind of method mainly includes semi-supervised learning [26], generative adversarial networks [162], autoencoder networks [163], etc. As the missing volume information is attributed to non-detection, the traffic volume estimation method for all missing scenarios is unsupervised learning. In the evaluation of the proposed methods, we usually assumed that the detection segments are non-detection segments to be verified.

Although some validated methods have been introduced, there are still some scenarios that are not covered but are worthy of future research. For the research method selection, some estimation methods involve a combination of multiple missing lengths and missing rates can be considered. In the aspect of different data type applications, the feasibility of realizing traffic estimation based on emerging data and how to fuse these data to improve the estimation efficiency should be discussed, respectively. In terms of the research object, combined with the actual missing length and missing rate, some discussions about the impact of random missing data and non-random missing data on the traffic estimation results can be conducted.

(a) The whole road network. (b) Downtown area.

Fig. 6. Traffic estimation with different transport network sizes. Liu et al. [21].

6.1.2. Effect of the size and internal composition of transport networks

In the feature extraction process of transport network volume estimation modelling, different transport network sizes and internal road segment compositions will affect the estimated accuracy and algorithm efficiency [21]. As shown in Fig. 6, choosing city-scale and downtown areas for modelling validation, the same estimation model with different transport network sizes will produce different results. The aforementioned two kinds of scalability challenges in transport networks should be considered. First, the larger the size of the selected transport network is, the larger the number of road segments that can be used to extract the training dataset, and the better the applicability of the estimation model. For example, Zhan et al. [25] trained the taxi trajectory data of all detection segments among city-scale areas, and the proposed traffic volume estimation model based on FD theory of traffic flow can be applied for any remaining non-detection segments. Liu et al. [21] dynamically selected the detection segments that are correlated with object segments from the entire city-scale areas, and sufficient correlated segments were extracted to improve the accuracy. However, as traffic volume estimating algorithms are generally data-driven approaches, and consequently limited by the computational efficiency of massive training data extracted from all segments at the city-scale, the solution of the model algorithm is time-consuming.

Second, the same estimation model in different internal segment composition scenarios would produce different estimated volume results. For example, as an effect of the built environment (i.e., point of interest, population density) and traffic facilities, the traffic complexity of the road network in the city centre is much higher than that in the suburbs [164]. Several studies have systematically reviewed the impact of built environment heterogeneity on traffic demand [72,165,166]. Thus, the validity of the missing traffic estimation algorithm has some limitations. In most cases, when the missing traffic estimation model established in one transport network is applied to another transport network, the effectiveness of the model may be poor. Furthermore, the compositions of different grades of road segments in transport networks also causes the diversity of the estimated results. Critical consideration should be given to the effectiveness of the volume estimation technologies concerning different road segment grades (arterial road, secondary trunk road, and branch road).

Combining the characteristics of "5V" in big data, some other challenges in transport network should also not be ignored. In terms of "volume", innovations in information sensing technology have led to continuous improvements in traffic data positioning intervals and location precision. The data applied for analysing traffic state of transport network, has evolved from the original ground loop data, to cell phone data, and to the emerging radar data [167]. The data positioning interval becomes smaller, and the accuracy of data becomes higher. For example, the positioning interval of some floating vehicle detector data have grown from a few minutes to a few seconds. The previous nearly discrete traffic data have now evolved into nearly continuous traffic data. This brings the challenges of increasing data size to state estimation in transport network. In respect of "velocity", to enable online traffic state estimation and real-time traffic signal optimization as much as possible, the computational efficiency in the selected transport network is crucial. When the scale of selected transport network is large, it is time-consuming to realize the traffic state estimation of entire networks, and do not have much extra time to give feedback to traveller. To improve computational efficiency, the general approach is to split transport network into individual sub-networks and use distributed or parallel computing methods to process each sub-task [168]. However, due to the sparse deployment of fixed detectors and the structural variability in some transport networks, it is challenging task to divide the transport network effectively [169]. In challenge of "variety", it is mainly posed by vehicles with distinct driving behaviours, different traffic incidents, the diverse internal structure and data categories in transport network. During the process of traffic state estimation, we will suffer difficulty from the diversity of the density, the length, and the curvature of road segments in transport network, and the number of intersections. Furthermore, effected by the heterogeneous data, the traffic parameters that can be obtained are also different. This can be a barrier to data fusion. In the issue of "veracity", with the development of autonomous driving technology and connected vehicle (CV) technology, the requirement for the accuracy of traffic state estimation is further increasing [170]. The emerging CV technologies can potentially reduce such dependencies on conventional fixed and probe detectors with the vehicle-to-cloud (V2C) CV data. The improvement of accuracy will affect the computational efficiency to a certain extent [171]. Therefore, it is also a challenge to choose the appropriate estimation accuracy according to different scenarios.

To address these challenges, some improvements can be tried. To improve the calculation efficiency of the algorithm and reduce the running time, the road network can be partitioned and the set of road sections similar to the target road segment can be dynamically selected. Parallel computation technology can be employed to estimate the missing volume on these non-detection segments. To select road network size, it is also necessary to comprehensively analyse the influencing factors of road environment and traffic facilities where the road network is located. The composition of different grades of roads in the road network also determine the study size of the road network. In particular, avoiding the uneven distribution of road segments of different grades in road networks is crucial. For example, the number of detectors on the arterial road is less than that of the secondary trunk road.

6.1.3. Effect of the deployment of fixed detectors

The deployment of the fixed detector in road networks has a crucial impact on missing volume estimation in urban networks. The estimation accuracy of non-detection volume segments in the road network is influenced by whether these detectors are too sparse or installed at key positions. The number of fixed detectors installed on the segment and the layout planning of the fixed detectors are two main factors that affect the accuracy of estimation by the deployment of the fixed detectors.

First, the number of segments with fixed detectors installed is valuable for missing volume estimation on road networks, and could provide sufficient training data during the modelling process [25]. When the number of fixed detectors in a study area is relatively small, it will be difficult to identify a similar road segment on which a fixed detector is installed. This similar information is used for feature extraction while building a missing volume estimation model on the remaining road segment on which fixed detector are not installed. In reality, limited by the high cost of fixed detector installation, fixed detectors were initially installed on well-developed road networks. For example, the number of fixed detector installations in city centres with more complex traffic conditions is higher than that in suburban areas. Hence, the application of a network-level estimation model will not obtain the desired results in this scenario.

Second, researchers also explored how the layout planning of fixed detectors affected missing traffic information estimation [172]. When a detector is not placed in some valuable locations, the role of this detector for traffic information estimation is limited. The multi-objective integer programming model [173] and data-driven model [174] are usually employed to optimize the deployment of fixed detectors for traffic flow parameter estimation. As the fluctuation information and distribution of the traffic volume for different grades of road segments are usually diverse, it is necessary to install these fixed detectors on road segments with different grades, which ensures that the number of detector installation on road segments with different grade is as balanced as possible. However, as different types of fixed detectors have different main applications, the detector location layout is also different [21]. For example, some fixed detectors (i.e., ground coil detectors, and microwave detectors) are mainly installed on arterial roads for traffic volume detection. Other fixed detectors (i.e., licence plate recognition detectors, and radio frequency identification detectors) are mainly installed near the intersections for traffic trajectory recognition and traffic safety monitoring. Hence, the layout planning of fixed detectors is not reasonable in some study road networks.

Generally, there are two potential ways to address the above-mentioned problems. The first method is to make some improvements before the deployment of detector installation. Based on user equilibrium theory [71,155,175], the detector layout is optimized in the initial stage [176]. The optimal detector layout is carried out by considering missing traffic volume estimation. Some core segments for traffic estimation are identified, and priority is given to ensuring the installation of detectors on these segments [177]. The number of fixed detectors can be increased by fusing different types of fixed detectors. By reasonably using the data of the emerging probe detector, some features are extracted for modelling estimation.

The second method is to propose methods that consider the heterogeneous distribution of traffic volume from different grades of segments, such as adaptive transfer learning [178]. Furthermore, when the number of detectors is small in some road networks, some temporary detectors can be added at some moments.

6.2. Challenge 2: homogeneity and heterogeneity in data fusion

In the modelling of traffic state estimation on urban road networks, the applied traffic detector data are often utilized as an input feature for model training, the data quality has a great impact on the efficiency of the traffic estimation model. Among the fusion of different types of detector data for improving the accuracy of missing volume estimation, the challenge introduced by the homogeneity and heterogeneity in the process of data fusion should not be disregarded.

6.2.1. Data homogeneity

Previous studies usually applied historical data or adjacent spatiotemporal data that are correlated with missing traffic data as input to estimate or predict traffic flow information [81]. This data correlation, which is also known as data homogeneity, is an important reference for evaluating the feasibility of the model. For example, Javed et al. [22] analysed the correlation of traffic facilities and taxi flow between detection segments and non-detection segments, extracted the detection segments that are similar to the target non-detection segment, and then used a simple linear regression model to estimate traffic volume on the non-detection segments. Tan et al. [16] applied both adjacent spatiotemporal data and historical data that correlated with missing data for traffic estimation by the tensor-based method. Hence, data homogeneity can be divided into spatiotemporal data correlation, correlation of different data categories, and correlation in different time granularities.

First, due to the interconnection between each segment of the road network, there are some correlations between different spatiotemporal traffic data. This spatiotemporal correlation can be applied to estimate or predict missing traffic data. As aforementioned in three kinds of missing estimation in Section 2.1. Generally, each road segment in a road network is regarded as a point, and the relationship between each road segment is viewed as an edge composed of weights. Thus, missing volume estimation can be realized based on graph theory [21].

Second, the correlation among different data types can also be employed for traffic state estimation. As there are few segments with fixed detectors installed in road networks, floating car data have completed spatiotemporal coverage. The correlation between probe data and fixed detector data can be utilized to evaluate whether probe data can be used to reflect real traffic states that are similar to fixed detector data. The fixed detector data represent the actual traffic volume, while the probe data represent the part of traffic volume. The correlation between two types of data is the basis of data fusion modelling [160].

Third, the data correlation in different levels of time granularity aggregation also differs. For example, when the aggregation level is high, due to the elimination of the variance of traffic volume data in time series, the data correlation will increase, and vice versa. The input traffic data under different time granularities also have a different impact on the volume estimation results.

Data homogeneity analysis has been applied by previous researchers as an important index to evaluate data quality, which is mainly based on the Pearson correlation analysis method. However, this method judges the correlation by measuring the distance between two vectors, and the traffic volume is vector data in time series, so the Pearson analysis method cannot adequately describe the correlation of traffic data. We need to combine the fluctuation information of real-time traffic volume and the distribution difference among volume data from different road segments to describe the similarity. To address these problems, Zhan et al. [25] proposed a similarity analysis method based on the Jensen–Shannon (JS) divergence method, which adds the consideration of the distribution variance of different types of traffic detector datasets. For the influence of time series fluctuation on traffic volume data, Liu et al. [44] developed a similarity analysis method based on warping distance.

In future research on data homogeneity analysis, the following directions should also be discussed: (1) Expanding the selection range of correlation analysis by increasing the data categories used for missing traffic volume estimation; (2) Exploring some correlation analysis methods that consider both data distribution variance [179] and time fluctuation differences; and (3) Based on different missing volume scenarios, reasonable correlation judgement criteria should be developed.

6.2.2. Data heterogeneity

With the development of information technology, many emerging data can be applied to estimate the missing traffic volume of urban road networks, such as radar data, mobile data, probe GPS data [180], online hailing data, and licence plate recognition data. The data application is introduced in the aforementioned section. Because of the heterogeneity of these emerging data, different data in the modelling process will produce large variances in estimation results. For example, comparing mobile phone data with taxi GPS data, both of them are viewed as probe detector data that are fused to other fixed detector data, taxi GPS data have more accurate positioning information than mobile phone data, and more accurate travel speed data can be obtained. However, due to the effect of the variance of travel demand from different areas, some areas with low travel demand rarely have taxi passing by, and the driving trajectory in these segments is sparse. Mobile phone data compensate the shortcomings of the sparse distribution of taxi data, and can have whole spatiotemporal coverage. However, limited by the influence of positioning accuracy and irregular positioning intervals, the accuracies of travel speed parameters from mobile phones are poor. Due to the differences in location accuracies and positioning intervals, the application of proposed estimation methods for different data types will not be consistent, and it is necessary to fully utilize of these unique data characteristics in the process of developing a volume estimation model.

Generally, the problem of data heterogeneity is mainly considered from three aspects: data structure, data parameters, and data distribution. For different data structures, with the different market penetration rates of sample data, we need to calculate the minimum sample size by speed distribution. For the characteristic of the sparse distribution of trajectory data, it is necessary to consider fusion with other points of interest (POI) data. For different data parameters, we need to establish an integrated model for inferring other valuable traffic parameters by microscopic traffic flow diagrams [181] and fundamental network diagrams [182,183]. Furthermore, due to the difficulty of different data distributions, the adaptive transfer learning theory can be applied to address this problem [184,185].

In future traffic estimation studies for data heterogeneity, we also need to consider the following research directions: (1) with the continuous improvement of data positioning accuracy, multiple data types can be considered for fusion; (2) some methods in the field of gear fault detection can be employed as reference in the study of missing volume estimation, which have sufficiently considered the different data distributions and data heterogeneity [186]; and (3) the advantages of differences in heterogeneous data from the perspective of spatial and temporal should be fully utilized.

6.3. Challenge 3: methodology for traffic state estimation

6.3.1. Pros and cons of different models

Since each method has its unique features, in this section, the pros and cons of two types of prevailing traffic state estimation methods, which are deep learning methods and Gaussian process methods, have been compared.

Deep learning (DL), which is a type of machine learning method, is evolved from the artificial neural network. It uses the activation function as a perceptron, which constitutes a network structure model by input layer, hidden layer, and output layer. Based on error backpropagation form, the optimal value can be reached. DL algorithms could use multiple-layer architectures or deep architectures to learn inherent complex features in high-level data from the lowest level to the highest level [123].

As a data-driven model, it can learn the model well only with training data, providing sufficient amount of data. There is no need to consider complex backgrounds, and the method has a wide range of applications. For example, in the application of traffic state estimation or prediction, to improve the accuracy of model in the process of feature extraction, DL models can learn complex features from multiple categories of datasets, such as tweets, and weather datasets [133]. To improve feature learning efficiency, a hybrid deep learning model can be proposed to filter redundant features [132]. To provide sufficient datasets, DL also can change the scalability of the road network [127].

But when sufficient data is not available, the model is not better than the general model. to reflect actual scenarios, and also suffers from high consumption of computational resources. In the hyperparameters solution process, limited by the number of hyperparameters, it tends to fall into the local optimal solution. When the gradient vanishing problem occurs, it will be overfitting phenomenon.

Nevertheless, it suffers from the long training time when used for online real-time traffic prediction and control due to computational complexity of deep learning models. Also, these methods heavily rely on the data preparation or pre-processing procedures, the presence of noisy data have an impact in model learning, and it is generally applicable to simple structure of traffic data [124].

Gaussian process (GP) models are a kind of nonparametric model to explore implicit relationships between a set of variables, and it cleverly constructs the prior and posterior distributions of the data by means of variance and mean. A surrogate model can be built for describing the relationship between variables and objective. Although it is also a heuristic algorithm, it does not fall into the case of a locally optimal solution when targeting non-convex problems. In particular, it is best-suited for the optimization problem over continuous domains of less than 20 dimensions, and tolerates stochastic noise in function evaluations [187].

GP is a data-driven approach, also known as a kernel-based learning algorithm. GP have been demonstrated to be powerful in understanding the implicit relationship between data to give estimates for unseen points [127]. Based on GP framework, Bayesian inference and particle filter are further developed. For example, due to the uncertainties and nonlinearities of traffic flow data, Mihaylova et al. [134] proposed a particle filtering framework for real-time traffic state estimation on highway networks, which can track multi-modal distributions of well. Moreover, the enhanced particle filters has also been used to explore the traffic state estimation problem for heterogeneous traffic (vehicles with distinct driving behaviours), such as overtaking and creeping behaviours [136,137]. While performing traffic state estimation, particle filtering methods can also be used for accident detection [138].

Compared to DL based methods, GP based methods are able to (1) deal with massive amounts of heterogeneous data from different types of detectors, (2) provide robustness in sparse deployment of detector in urban network, (3) incorporate different models that can deal with various traffic regimes (i.e. different vehicle behaviours, different traffic events), and (4) cope with multimodal conditional probability density functions for traffic states [134].

However, GP still suffers from the cubic time complexity in the size of training data [124]. Furthermore, GP based method (particle filtering framework) would spent lots of computational time for processing units in terms of communications when the number of particles is high [149]. Generally, the parallelized particle filtering is usually used to reduce computational complexity and communication time. The structure of the PF fits well to the compositional traffic networks, and it allows for parallelization for different segments.

In the aspect of traffic state estimation, GP can handle more complex traffic flow scenarios while avoiding noise interference. Based on sparse traffic volume and speed data, a GP-based particle filter method is introduced for traffic density estimation with traditional traffic flow theory [134]. Furthermore, it has an unique advantage in handling highly heterogeneous traffic scenarios, which is composed of different vehicle sizes [136]. The experiments are designed under creeping traffic flow and overtaking traffic flow, respectively, which is used to show the effectiveness of particle filter method [138] and enhanced particle filters method [137]. Limited by slower calculation time, Mihaylova et al. [149] proposed a parallelized gaussian method to provide the possibilities to decrease the computational complexity in the whole traffic network estimation problem.

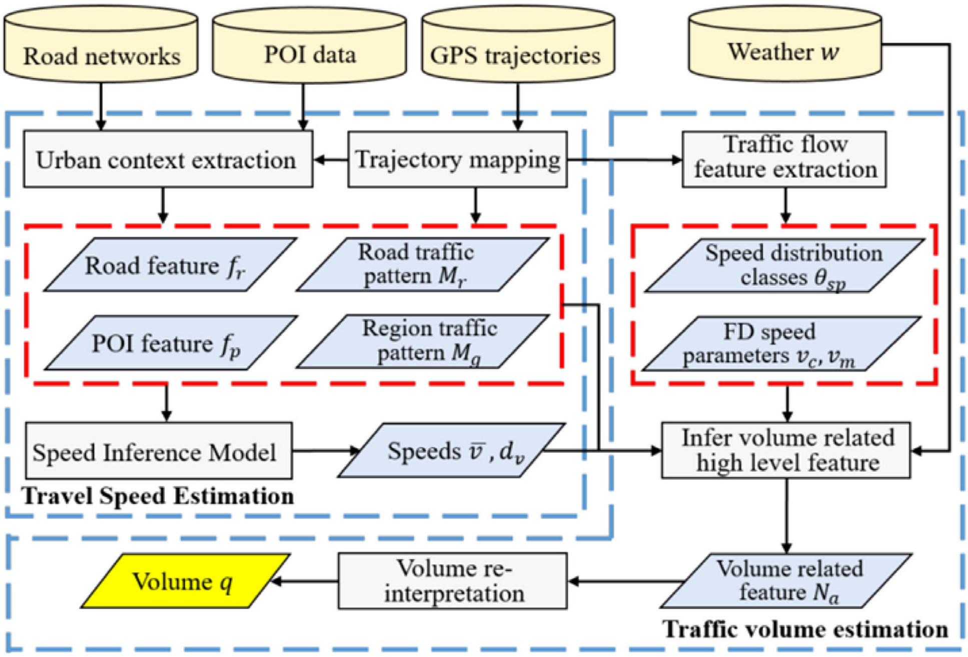

Fig. 7. Research framework of traffic volume estimation by data fusion. Zhan et al. [25].

In future research, we can take advantage of the GPs in solving hyperparameters and combine deep learning with GPs to perform traffic state estimation. For example, when determining the number of training layers of a deep learning network and the number of nodes in each layer, using Bayesian optimization can be faster and more accurate to obtain the optimal combination.

6.3.2. Model applicability challenges

Different research methods should be determined when dealing with different types of data. With the increase in the complexity of the network structure and size of the road network, it is necessary to evaluate the proposed method in terms of computational efficiency and estimation performance. Generally, we usually evaluate them by comparison with other baseline methods. However, the following problems in the summary of traffic estimation methods should not be discarded: (1) As traffic volume in urban networks would also be affected by complex road environmental factors, there are no distinct criteria to judge whether extracted traffic feature information for the specific missing volume scenarios is valuable in the field of urban traffic estimation; (2) Most of the existing data fusion models usually integrate the same traffic parameters, such as traffic speed estimated by other detected speed that is extracted from another kind of detector. However, few studies address the fusion of different types of traffic parameters. (3) Due to the variance of road facilities and travel mode composition, such as the number of accommodation lanes [188–190], the proportion of carpooling [191], and network traffic control to traffic assignment [192], the detected traffic volume has great differences in different spatiotemporal ranges. This cause that the robustness of the data fusion method in different scenarios needs further verification. One of the research frameworks of traffic volume estimation by data fusion is shown in Fig. 7.

Furthermore, the following research direction for method determination can be considered: (1) the calculation efficiency should be improved by parallel computing and distributed computing; (2) during the similar segment selection in whole road network, the emerging information entropy methods can integrate the two previous methods to improve efficiency.

7. Conclusion

This paper consists of a literature review of missing traffic state estimation based on multi-source data fusion on urban road networks. Previous research on this topic, which is classified based on different missing scenarios, different application data categories, and different fusion modes has been reviewed and summarized. In summary, among the actual engineering applications of missing state estimation on urban networks, we can choose the appropriate methods published in previous papers to carry out practical application with accuracy requirements of projects and data resources. This research has a certain reference value in improving the accuracy of estimation results and optimizing the deployment of fixed detectors.

Furthermore, this paper also discussed the challenges and opportunities of urban road network volume estimation from the perspective of different missing scenarios, different data structures, and different fusion methods. By summarizing and classifying existing problems, and investigating existing advanced methods and limitations, this paper discussed feasible, future research directions. With the advent of the digital twin era and the continuous development of detector technology (such as parallel computing applications [171]), we can obtain better data quality and provide better computing resources. Hence, we can explore more complex missing traffic volume scenarios, and improve the accuracy of traffic volume estimation after calculating the minimum number of fixed detectors. In addition, this research provides more precise traffic control and intelligent guidance for the future urban traffic environment of automatic driving [193] and the Internet of Vehicles [194].

CRediT authorship contribution statement

Jiping Xing: Methodology, Formal analysis, Writing – original draft, Visualization. **Wei Wu:** Conceptualization, Writing – review & editing. **Qixiu Cheng:** Conceptualization, Investigation, Writing – review & editing. **Ronghui Liu:** Resources, Supervision, Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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