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Intelligent Technologies for Urban Traffic Congestion Management

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Abstract. With continuous urbanisation and the increase in the number of cars, traffic jams in cities have become worse and are affecting people's lives, the economy, and the environment. Recently, the development of intelligent technology has offered a new path for alleviating traffic congestion through enhanced traffic perception, prediction and control. This paper reviews previous research and representative cases to explore the application of intelligent technology in the three areas of traffic condition monitoring and congestion detection, traffic flow prediction and congestion warning, and intelligent control for congestion mitigation. Multi-source traffic sensing enhances traffic data collection. Machine learning and deep learning methods are employed for short-term traffic flow prediction, while intelligent control technology can adapt to changing traffic conditions. However, in practice, there are still problems of data quality, information sharing, model adaptability and system integration. Further improvements are needed in utilising multi-source data, enhancing the robustness and coordination of sensing-prediction-control systems, etc., to effectively promote the application of intelligent technology in urban traffic congestion control.

Keywords: urban traffic congestion, intelligent transportation systems, traffic sensing, traffic flow prediction, intelligent control

1. Introduction

The rapid development of cities has led to problems with traffic congestion. With the continuous development of urbanisation and the increase in the number of motor vehicles, the demand for traffic has gradually exceeded the capacity of roads. Traffic congestion increases the time and expenses for residents to travel, raises energy consumption, emits more greenhouse gases from transport, and reduces the efficiency of urban traffic and environmental quality. Therefore, prompt observation of road conditions and precise forecasts of traffic jams must be conducted to help manage traffic in cities more effectively.

In recent years, many intelligent technologies such as multi-source traffic sensing, big data analysis, machine learning, deep learning and intelligent control have been gradually applied to urban traffic management. Multiple sources of data, such as video and Light Detection and Ranging (LiDAR), can be integrated to reduce the spread of local congestion in surrounding areas by synchronising signals at several adjacent intersections [1]. At the same time, machine learning and

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deep learning methods have been used to analyse the temporal characteristics and spatial relationships of traffic flow for short-term traffic prediction and congestion warning systems [2, 3]. With the increase in the availability of real-time traffic information, adaptive signal control and coordinated speed-signal control strategies have also been developed for intersections and road networks [4, 5]. Most of the previous research has either focused on a single technology or a specific application. The roles, actual effects and deficiencies of various intelligent technologies for managing traffic congestion in cities need to be studied.

This paper studies urban road traffic congestion management and analyses the application of intelligent technologies in three areas: traffic condition monitoring and congestion detection; traffic flow prediction and congestion warning; and intelligent control for congestion mitigation. Based on the analysis of previous studies and representative cases, this paper will introduce the main functions and attributes of various technologies for traffic congestion control, as well as discuss problems in data quality, model adaptability, system integration, and practical application.

2. Background of urban traffic congestion and intelligent technologies

2.1. Characteristics and causes of urban traffic congestion

Urban traffic congestion refers to a situation where, due to high demand and insufficient road capacity, vehicles are slowed down, long queues form, and travel time increases. Based on the patterns of occurrence and main reasons, urban traffic congestion can be divided into recurring congestion and episodic congestion. Generally, recurring congestion occurs during the morning and evening rush hours, or in areas with high road demand due to factors such as insufficient road capacity, bottlenecked intersections, and concentrated commuter trips; it has a regular cycle and is relatively predictable. Episodic congestion, on the other hand, is often caused by traffic accidents, bad weather, major events or other temporary traffic disruptions, and it has a sudden onset and high uncertainty, so its timing and location are difficult to predict in advance.

There are many reasons for the occurrence of urban traffic congestion; it is caused by a combination of factors such as increased travel demand, poor road conditions and inadequate traffic management. At peak hours, a large amount of travel demand is concentrated on some roads and intersections, and this local demand often exceeds the road capacity. Insufficient road space, low intersection throughput and a mismatch between signal timing and actual traffic conditions can further reduce the efficiency of road resource utilisation. At the same time, traffic accidents and bad weather can quickly change the operating conditions of the roads, spread the vehicle queue to adjacent sections, and turn local congestion into large-scale traffic disruption.

Different kinds of traffic jams have different problems for urban traffic management. For recurrent congestion patterns with a certain trend, historical traffic data can be used to identify high-risk periods and roads in advance, and preventive adjustments to traffic organisation and signal control plans should be made. Episodic congestion, on the other hand, occurs suddenly; thus, timely traffic monitoring must be employed to quickly detect abnormal conditions and ascertain the location and extent of damage to traffic flow. Therefore, current traffic congestion management requires the collection of basic data, such as traffic volume, travel speed, road occupancy and queue length, and needs to be able to analyse changes in traffic conditions and predict short-term congestion trends.

Therefore, urban traffic management has evolved from a purely reactive response to a system characterised by real-time perception, proactive prediction and dynamic regulation. Considering changes in network conditions, traffic authorities need to adjust signal timing and traffic

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organisation promptly, divert vehicles and provide travel information to reduce the mismatch between traffic demand and road capacity. Therefore, it is necessary to improve the timeliness of traffic data collection and accuracy of traffic condition assessment and enhance the adaptability of management measures in response to changes in urban traffic.

2.2. Intelligent technologies for traffic congestion management

With the development of intelligent transportation systems, multi-source traffic sensing, big data analysis, artificial intelligence and intelligent traffic control technologies have been applied to urban traffic congestion management to some extent. Based on their main functions, these technologies fall into three types: traffic detection, data analysis and prediction, and intelligent control. The three types correspond to the three stages of acquisition, analysis and application of traffic condition data and traffic information, and together they form the basic technology for intelligent traffic management.

Traffic-sensing technology is used to continuously acquire data on the situation of road traffic. Some typical data sources are road-mounted cameras, radar, inductive loop detectors, floating car data based on the Global Positioning System (GPS), mobile phone location information, and vehicle-to-everything (V2X) communication. Fixed-type detection devices can collect information such as traffic volume, speed and road occupancy at specific road sections or intersections; video surveillance, in combination with image-processing technology, can count vehicles, determine queue length and track the movement path of vehicles, and floating car and mobile positioning data can provide broader views on the movement patterns of vehicles or travellers. Different sensing modalities have different characteristics in terms of spatial coverage, temporal resolution, data accuracy and environmental adaptability; thus, integrated use of multi-source traffic data has gradually become a key direction for the development of traffic-state monitoring.

Based on the continuous accumulation of traffic data, big data analysis and artificial intelligence technology are used to identify traffic flow patterns and predict future traffic situations. Earlier studies used only time-series analysis of historical traffic data and were not suitable for fluctuating traffic conditions. Machine learning can also be used to identify non-linear relationships between traffic conditions and various other factors, such as weather, time of day and road conditions. In recent years, deep learning has improved both the modelling capacity for the temporal changes in traffic flow and spatial correlations among road networks and is gradually being applied to problems such as traffic state recognition, short-term traffic flow prediction, and congestion early warning [2]. These methods can extend traffic management from the evaluation of present conditions to predictions of future traffic-operation states.

Intelligent traffic control technology adjusts traffic management measures according to the actual or predicted situation of traffic. Adaptive signal control adjusts the signal timing dynamically based on changes in traffic volume and queue length at the intersection; area-wide coordinated control coordinates the signals of multiple adjacent intersections to improve the overall efficiency of the road network. Route guidance provides travellers with the latest route information based on real-time road conditions, and dynamic traffic organisation can adjust lane usage, speed limits and traffic control measures according to changes in demand. These technologies no longer rely on fixed management modes; instead, they can promptly adjust control strategies according to changes in traffic conditions and thus provide greater flexibility and adaptability in traffic management [6]. Traffic perception, data analysis and prediction, and intelligent control are generally linked in the management of traffic congestion. Traffic perception provides the basic data; data analysis and

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forecasting identify the current situation and predict future changes; intelligent control applies the results of analysis to manage traffic.

3. Applications of intelligent technologies in urban traffic congestion management

3.1. Traffic condition monitoring and congestion detection

Accurate observation of road traffic conditions is necessary for effective congestion control. Traditionally, only a few fixed detection devices were used to collect traffic volume and speed data at various points along the road. With the expansion of the sources for traffic data, video surveillance, floating car trajectories, radar and mobile positioning data are increasingly employed to achieve more continuous and all-weather traffic-state monitoring. By analysing the speed of vehicles, road occupancy, queue length and vehicle trajectory, the operating status of the road can be determined and abnormalities can be found, such as abnormal traffic flow, vehicle queues and localised congestion. Multi-source data fusion can leverage the strengths of multiple data sources in terms of spatial coverage, temporal resolution and measurement accuracy, etc., to improve the situation awareness of complex traffic conditions.

Most of the previous studies have focused on traffic condition detection and traffic congestion identification using video analysis, vehicle trajectory analysis, and multi-source data fusion. Computer vision technology is used on video data to count vehicles, measure their speed and queue length, and floating-car data are employed to understand the condition of roads over a larger area. Since single-source data often have issues of insufficient coverage or low accuracy, multi-source data fusion is employed to obtain data from various sensors and improve the robustness of traffic-state estimation. For example, in queue-length detection at intersections, video data and LiDAR point cloud data can be combined to improve vehicle recognition and queue-length estimation in complex traffic conditions [1].

In light of the problem of queue-length perception in urban signalised intersections, Wang proposed a queue-length perception model based on multimodal data fusion [1]. LiDAR point-cloud data and road-monitoring videos are combined in this study to achieve spatiotemporal alignment and information fusion of the two data sources for vehicle position and queue tail identification. According to the results of the above experiments, the detection module can work normally in an 80 m environment, and when the queue length exceeds 60 m, the mean error rate is 4.3%. Therefore, multi-modal data fusion can improve the observation capacity of traffic conditions under extended queueing [1]. To address the deficiencies in both coverage and recognition accuracy of single sensors, multi-sensor traffic detection can be carried out. However, the actual operating conditions will also affect the results of sensor placement and data quality.

3.2. Traffic flow prediction and congestion warning

Traffic state monitoring generally observes the current situation of road traffic, while congestion early warning needs to anticipate future fluctuations in this traffic. Most short-term traffic flow forecasts are based on historical and current data of traffic volume, vehicle speed and road occupancy, and often include external factors such as weather, holidays and other unforeseen circumstances in the prediction model. Accurate short-term forecasts will give traffic management authorities sufficient time to respond and change the mode of congestion control from reactive to proactive warning and mitigation.

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Traffic flow prediction methods have shifted from traditional statistical models to machine learning and deep learning. The Autoregressive Integrated Moving Average (ARIMA) statistical model is commonly applied to investigate the time-series characteristics of traffic flow and has a simple structure that is relatively easy to interpret [7]. Machine learning can be applied to find more complex non-linear relationships among weather, road conditions and traffic data [8]. Recently, deep learning methods such as Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN) and Transformer have been increasingly used to address the problem of short-term traffic flow forecasting by extracting temporal dependencies and spatial correlations in traffic data [2]. Given the prominent spatial connectivity of urban road networks, where congestion often spreads from one segment to adjacent ones, at present, research has begun to explore how to combine both time-varying elements and the spatial structure of the road network in traffic flow prediction.

Wang used historical traffic volume, vehicle speed and road topology data to study the spatiotemporal correlation among different road sections and built a graph convolution-based prediction model to address the problem of short-term urban traffic congestion forecasting [3]. Urban road networks are modelled as graphs in this study, with nodes and edges, and spatiotemporal graph convolution techniques are used to forecast traffic conditions over a short period. The model's performance has been compared with that of the historical mean method and other GCN models. The results show that the model can effectively capture the dynamic patterns of traffic flow on weekdays, weekends and holidays, and has better prediction performance than some traditional methods [3]. In summary, both the spatial connection of roads and temporal changes in traffic flow can be included in the model to improve the accuracy of short-term traffic-state prediction for complex urban road networks and provide useful support for congestion early warning and subsequent traffic management decisions.

3.3. Intelligent control and congestion mitigation

Traffic condition monitoring and congestion forecasting can provide support for traffic management, and in response to congestion, practical control measures need to be implemented. At present, the main ways are adaptive signal control, area-wide coordinated control, route guidance and dynamic traffic organisation. Adaptive signal control adjusts the cycle length and green light duration according to changes in the number of vehicles and queue length at the intersection. Area-wide coordinated control can reduce the problem of localised congestion spreading to adjacent roads by synchronising traffic lights at several neighbouring intersections. Route guidance and dynamic traffic organisation generally adjust the route or road-use pattern of vehicles based on real-time road conditions to avoid excessive congestion in certain sections of the network.

Most previous research has focused on adaptive signal control and coordinated vehicle speed-signal control. The original fixed-time signal plan assumes of ideal traffic flow and has a slow response speed to a sudden increase in traffic volume. Based on real-time data of traffic volume, vehicle speed and queue length, signal parameters can be dynamically adjusted according to the current traffic situation [4]. In a mixed-traffic area, coordinated vehicle speed-signal control adds intersection signal information to vehicle dynamics and forms a cooperative system of vehicle-level control and signal timing [5]. Although the above methods can increase the adaptability of traffic control systems to changes in traffic conditions, their actual performance depends on factors such as the structure of traffic, data quality and the range of coverage for control [9].

Relevant research has also aimed to integrate short-term traffic flow forecasting with adaptive signal control by using the prediction results to optimise intersection signal timing. Adaptive signal control under multi-modal traffic conditions is a typical example of such studies, which consider the

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traffic demands of motor vehicles, non-motorised vehicles and pedestrians simultaneously, and adjust the signal control strategy according to short-term traffic flow forecasts [10]. Adaptive control can improve the allocation of green light time and reduce vehicle delay and queue length significantly compared with the traditional control method [11]. This case shows that by incorporating real-time traffic conditions and short-term forecast results, the adaptability of signal control strategies to changes in traffic patterns can be improved. Nevertheless, the effectiveness of the above measures in different traffic conditions has not been confirmed by other field trials.

4. Challenges and future directions

Applications of intelligent technology in urban traffic congestion control are still limited by problems with data quality, model construction and practical implementation. The various types of collected traffic data differ in accuracy, time resolution, spatial coverage and data format, which makes them difficult to align and share. To forecast traffic flow, deep learning and graph convolutional networks are often used to address the problem of complex spatio-temporal correlations; however, these models generally need a large amount of training data and high-performance computing resources, and their predictive accuracy can differ under various road conditions and traffic circumstances. In addition, the internal structure of some complicated models is not easy to understand; thus, the application of their predictions in actual traffic management is limited. At present, a stable integration mechanism for traffic monitoring, forecasting and control in the control stage has not been established; most of the approaches have been verified only in simulation or on limited road networks, and their long-term effectiveness in complex urban road networks has yet to be confirmed.

In the future, more effort will be made to coordinate the use of multi-source traffic data and improve data interoperability among devices and systems to provide a more stable data basis for assessing traffic conditions and forecasting. In addition to improving the accuracy of predictions, traffic flow forecasting models need to be adaptable to changes in road conditions and traffic circumstances, and also reduce the data and computational costs of real-world application. The coordination of real-time monitoring, short-term forecasting and signal control in traffic regulation should be further strengthened, and forecast results should be directly applied to adjust signal timing, route guidance and changes in traffic organisation. At the same time, extended field trials in real-world road environments are required to test the stability and practical effectiveness of intelligent traffic management approaches under various traffic conditions.

5. Conclusion

Intelligent technology provides new ways to monitor, predict and manage traffic congestion in cities. Multiple sources of traffic data improve the collection of road-condition information and support congestion detection. Machine learning and deep learning methods exploit the temporal characteristics of traffic flow and spatial relationships among road segments to improve short-term traffic prediction and congestion warning. At the same time, adaptive signal control, coordinated control and route guidance can be implemented based on real-time or predicted traffic conditions. Case studies have shown that different intelligent technologies are used for various stages of congestion control; however, their actual application in real-world road networks is still limited by data quality, model adaptability, cross-system information integration, and deployment conditions. In the future, improvements will be made to multi-source data utilisation, the robustness of models in various traffic scenarios, and coordination among traffic sensing, prediction and control.

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Specifically, this study finds that multi-modal data fusion can significantly improve the accuracy of state detection in long-queue scenarios, and spatiotemporal graph convolutional models can effectively capture topological correlations of road networks to optimise short-term early warning. At present, the problems of heterogeneous data compatibility and weak generalisation ability for deep learning models still need to be addressed. In the future, a standard data-sharing platform will be established, a small-footprint adaptive algorithm that reduces deployment costs will be developed, and cross-stage closed-loop collaborative validation will be promoted to improve the efficiency of congestion control in complex urban areas. With the application of more advanced intelligent technologies in urban transportation, stable technical support will be provided to tackle traffic jams and an all-encompassing data system for decision-makers will be constructed.

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