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Overview

Smarter and more connected: Future intelligent transportation system

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ABSTRACT

Emerging technologies toward a connected vehicle-infrastructure-pedestrian environment and big data have made it easier and cheaper to collect, store, analyze, use, and disseminate multi-source data. The connected environment also introduces new approaches to flexible control and management of transportation systems in real time to improve overall system performance. Given the benefits of a connected environment, it is crucial that we understand how the current intelligent transportation system could be adapted to the connected environment.

1. Introduction

Analysis and understanding of transportation issues are often constrained by domain-dependent data sources. Recent emerging technologies toward a connected vehicle-infrastructure-pedestrian (VIP) environment and big data have made it easier and cheaper to collect, store, analyze, use, and disseminate multi-source data. A connected VIP environment also makes the system more flexible so that real-time management and control measures can be implemented to improve system performance. With a connected environment, vehicles, infrastructure, and pedestrians can exchange information, either through a peer-to-peer connectivity protocol or a centralized system via a 4G or more advanced telecommunication network (VIP environment). Such technology is regarded as one of the most potentially disruptive technologies for the urban eco-system. The interaction and exchange of information can occur vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), pedestrian-to-infrastructure (P2I), or vehicle-to-pedestrian (V2P). Given the benefits of a connected environment, and considering its unique characteristics, it is crucial to understand how current intelligent transportation systems could be adapted to work with the connected environment. This paper aims to: (1) review current trends in intelligent transportation systems (ITSs) and smart cities; and (2) offer insights on the introduction of connected VIP environment into these systems.

The paper is organized as follows. The next section is a review of the current trends in intelligent transportation systems. In Section 3, we discuss smart cities and related artificial intelligence (AI) techniques. The concept of a connected environment is described in Section 4. Finally, Section 5 offers insights into future ITSs and smart cities.

2. Current trends in intelligent transportation systems (ITSs)

Congestion, accidents, and pollution issues due to transportation are becoming more severe as a result of the tremendous increase in various travel demands, including vehicular traffic, public transportation, freight, and even pedestrian traffic. To resolve such issues, ITSs have been developed that are able to integrate a broad range of systems, including sensing, communication, information dissemination, and traffic control. Three essential components are necessary for any ITS to perform its function(s): data collection, data analysis, and data/information transmission.

Data-collection components gather all observable information from the transportation system (e.g., traffic flow at a particular point of the road network, average travel time for a particular road section, number of passengers boarding a transit line, etc.) for further analysis of the current traffic conditions. Traditionally, inductive loop detectors [1,2], which detect the presence of vehicles based on the induced current in the loop with passing vehicles, and pneumatic tubes [3], which detect the presence of vehicles based on pressure changes in the tube, have been used to collect basic traffic information such as traffic volume and spot speed. However, because of their high implementation cost and impact on traffic during implementation, these methods are becoming less popular, especially in congested areas.

Due to advances in sensing and imaging technology, video cameras and radio-frequency identification (RFID) scanners are increasingly being considered for use in traffic data collection. Cameras can be installed at different locations in the network to collect traffic videos. The videos are then analyzed using specifically designed image

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processing software (e.g., Autoscope) to determine information such as traffic flow, speed, vehicle types, etc. [4,5]. In this context, automatic license plate recognition [6,7] is one crucial area of research, as through the recognition and matching of license plates, it can provide additional information such as selected paths and travel times. On the other hand, radio-frequency identification data (RFID) can commonly be obtained at locations that accept contactless payment (e.g., Autotoll and Octopus systems in Hong Kong), or for freight transport. Through the matching of unique RFID, different traffic-related information, such as path choice and travel time, can be extracted [8,9].

Recently, due to increasing penetration of smartphones and advanced communication technologies, Global Positioning System (GPS) data [10,11], media access control (MAC) addresses from Bluetooth and WiFi components [12,13], and mobile phone data [14,15] are becoming available for the analysis of traffic conditions or even travel behavior. Compared to the data sources listed above, these new types of data are more at the level of the individual, as such devices are usually personalized, and capable of continuous tracking (e.g., GPS and mobile phone data). With such characteristics, more detailed and/or behavioral-related analysis could be conducted.

Data analysis components of ITSs aim to provide various information and management/control measures, using the traffic data collected from the various sources discussed (e.g., inductive loop detectors, GPS, etc.). Traditionally, predefined and pre-calibrated models, such as traffic equilibrium models [16,17], flow models [18,19], and various models for signalized intersection [20,21], have been adopted to evaluate traffic conditions and provide the necessary response. Recent improvements in computation power and the need for more detailed evaluation have led to the development of micro-simulation and agent-based models in data analysis components [22,23]. Due to the introduction of new sources of data, these models have been extended to effectively use the new data to improve the accuracy and detail of evaluations [8,13,14,24].

The data/information transmission components of ITSs help communicate the collected data to operation centers for evaluation and disseminate information, and/or management/control measures, to travelers and infrastructures. Methods for transmitting collected data have evolved from wires to optical fibers to wireless networks (e.g., 3G/4G, WiFi, etc.) with cloud platforms. For the dissemination of information and control/management strategies, methods have evolved from traditional traffic signs and radio broadcasting to variable message signs [25], mobile applications [26], and in-vehicle information [27] by taking advantage of improved communication technologies.

With these basic components, ITSs can be categorized into one of two categories based on their functionalities. These are Advanced Traveler Information Systems (ATIS) and Advanced Management Systems (AMS). The details of each are presented below.

Advanced Traveler Information Systems – ATISs aim to help travelers make travel decisions (e.g., mode choice, route choice, departure time choice, etc.) by providing various types of information (e.g., travel time, wait time, available parking). Of the various implementations, travel time estimation/prediction [8,10,28], and route guidance systems [29,30] are the most commonly studied areas as they can affect travelers' choices directly, especially route choice. With the advancement of the data-collection methods and communication technologies described above, travel time and route guidance information provided can be in a more accurate and real-time manner. With the additional sources of data (e.g., GPS data, mobile phone data, etc.), other real-time information is also available to travelers. For example, analysis of road-condition images from drivers taken automatically from smartphone applications can be used to determine available roadside parking in real time [31]. Another example is the prediction of bus arrival time from information transmitted by bus passengers through mobile phone signals across different cell towers [32].

Advanced Management Systems – AMSs aim to control or manage different infrastructures and operators within the transportation system under different situations to ensure the efficiency and safety of the transportation system. In the literature, such control/management methods are applied to arterials [33], freeways [34], freight transport [35], transit services [36], and incident/emergency situations [37]. With enriched data sources, improved data resolution, and enhanced information dissemination methods, more real-time and detailed management is possible. For example, Fu and Yang [36] proposed bus-holding control strategies based on real-time bus location information to regulate bus headway at specific stops. Although these researchers have only validated their models in simulation experiments, they provide good insight into how new sources of information could be used in transit management. Kurkcu et al. [37] provide another example by using open data sources and social media data for incident detection, which is the crucial first step of incident-management procedures.

3. Reviews of smart cities and related artificial intelligence techniques

The ITSs introduced in the previous section aim to solve transportation-related issues and improve the overall efficiency of transportation systems. These ITSs fall under the category of smart mobility within the framework of smart cities, which is gaining its concerns in the recent decades. In the literature, there is not yet consensus as to what constitutes a smart city, and there are diverse definitions [38,39]. For example, Hall [40] suggested that a smart city would monitor its components (e.g., roads, buildings, etc.) to better optimize its resources, plan preventive maintenance activities, and monitor security, while maximizing services to its citizens. Lombardi et al. [41], on the other hand, proposed that smart cities are those that use information and communication technology (ICT) on human capital, social and relational capital, and environmental issues. The definitions also depend on the background of stakeholders and the focus of the government [42]. For instance, academia considers improving quality of life to be the major goal of a smart city, while stakeholders in a private company might opt for efficiency as the primary goal [42]. Despite this diversity of definitions, using advanced electronic/digital technology (e.g., ICT), embedding ICT or other electronic hardware into city infrastructure, and improving stakeholders' interests in different aspects of the system are the three common characteristics or dimensions of the smart city.

Concerning functionalities, smart cities can be divided into six different components [39,41,43,44]: smart governance, smart economy, smart human/social capital, smart environment, smart living, and smart mobility. *Smart Governance* aims to use ICTs to enhance the efficiency and transparency of public sector organizations in the management of public resources, and to encourage public participation in decision-making. The goal of a *Smart Economy* is to employ ICT and related technologies to improve productivity in the manufacturing chain and to enhance and fortify online transactions for the promotion of e-commerce. *Smart Human/Social Capital* aims to improve the education level and active public participation of citizens through the provision of enriched information generated from the other components of the smart city. The goal is also to collect individual views and attitudes, as these data are some of the best information any government can obtain. The objective of a *Smart Environment* is to reduce pollution and resolve other environmental issues with the ultimate goal of improving urban/city sustainability through the use of technology. *Smart Living* seeks to improve quality of life (e.g., security, housing quality, social cohesion, etc.) through the implementation of advanced technologies within cities and infrastructures. *Smart Mobility*, sometimes considered under the rubric of smart living due to the focus on the efficient transport of people, attempts to use advanced ICT to optimize logistics and transportation systems and provide efficient, safe, and environmentally friendly services for passengers and freight. Based on these components, various indicators (e.g., local accessibility, productivity, emissions, etc.) have been designed [41,45] to evaluate the performance of smart cities and help decision makers design policies that pave the way toward even smarter cities.

In the context of smart mobility and ITS, various estimations, predictions, and management and control methods must be carried out in real time based on available information from sensors and stakeholders. Transportation-related problems are characterized by a large number of variables with parametric relationships that are not well-understood, large volumes of incomplete data, and unclear goals and constraints [46]. Recently, AI-related techniques, with their unique strength in knowledge building, have been adopted in smart mobility and ITS. AI is the intelligent demonstrated by machine in rationally perceived the environment (analyzing data from various types of sensors), and to make rational decisions that maximize the chance of achieving a goal [47]. The commonly adopted AI approach for transportation problems involves artificial neural networks, support vector machines, and Bayesian networks.

Artificial neural networks (ANN), with the ability to perform non-linear mapping between inputs and outputs through the consideration of hidden layers and sufficient training, are suitable for addressing transportation problems in which the parametric relationships among variables are not well-understood. In the literature, ANNs are commonly adopted in state estimation/forecasting [48,49], incident detection [50], traffic/infrastructure control [51], and behavior analysis [52]. Similar to ANN, *support vector machines* (SVM) are supervised learning models that analyze input data, but are more focused on the classification of stages/scenarios. As a result, although SVMs have been applied to other transport-related problems [53,54], they are mainly used for problems like incident detection [55,56] and accident prediction [57,58] in the context of ITS. Unlike ANN and SVM, which are solely data-driven, Bayesian networks are a type of statistical model that considers the probabilities and conditional dependencies of the control variables. In the ITS literature, Bayesian networks have been used for various transportation problems [59,60], but are mainly used when the focus is traffic forecasting [61,62] and incident/accident-related issues [63,64].

4. A connected environment for smart mobility

Due to the substantial advancements in ICT and related sensing technologies, the current trend is toward installing and using Vehicle Automation and Communication Systems (VACS) in vehicles. VACS have been shown capable of improving individual safety, comfort, and convenience, as well as emissions in connected vehicles [65]. It is also expected that VACS could develop the potential to promote global traffic efficiency through traffic control [66–69]. The number of connected automated vehicles (CAVs) equipped with VACS will rapidly increase in the coming decade. Meanwhile, regular human-piloted vehicles (RHVs) will continue to play a major role in the market in the short term [70,71]. Thus, the road will soon be shared by CAVs and RHVs.

The penetration of CAVs and VACS into the market may lead to improvements in freeway network performance and traffic-flow efficiency. It will also make it possible to implement control schemes, such as individual vehicle speed and lane-change advice that are not available with RHVs. As stated in Diakaki et al. [65], VACS that respond to traffic flow conditions, i.e., adaptive cruise control systems (ACC) and cooperative adaptive cruise control systems (CACC), create changes in the characteristics of macroscopic traffic flow. In addition, reduced reaction time due to CAVs can improve traffic flow efficiency via smaller inter-vehicle headway [70,72,73]. In mixed-autonomy single-lane ring road experiments (consisting of 22 RHVs on a 230-m ring track), Stern et al. [74] demonstrated over 40% fuel consumption savings by the insertion of a CAV in the traffic to dampen ring instability. However, research to address the implications of emerging VACS on the flow characteristics of traffic mixed with CAVs and RHVs, as well as their potential for improving traffic flow operations, has been limited [65,75].

Compared with in-vehicle travelers, pedestrians are the most vulnerable road users. Pedestrians contribute to a significant proportion of total road traffic fatalities and injuries (e.g., there were 273,000 pedestrian fatalities in 2010). Current efforts concentrate on developing advanced driver assistance systems-based pedestrian protection systems. The performance of such systems is vulnerable under complex urban environments because of various obstacles and insufficient time for drivers to react. Vehicle-to-pedestrian (V2P) communication technology attempts to solve problematic pedestrian and traffic collisions to improve pedestrian safety.

Owing to the advancement of ICT and increasing penetration of smart devices, the idea of a connected environment in the transportation-related context has been extended and now crosses the physical boundary. In the literature, traffic networks are usually modeled as directed graphs for transport infrastructure only. However, traffic networks should consist of human, physical infrastructure, perceptual road marking, and multimodal transport systems. Thus, it is more reasonable to consider the complete network in cyber, social (human behavior) and physical (CSP) spaces. There is increasing discussion about the construction of a flexible hierarchical traffic network model that integrates physical, semantic, logical and perceptual networks in the digital reconstruction of CSP spaces [76].

5. Future of intelligent transportation systems and smart cities

From the reviews in the previous section, it may be seen that the future of ITS falls within the multiple layers of the connected environment (i.e., cyber, social and physical). Given this understanding, this section aims to provide some insights into the development of future ITSs and smart cities that include: analysis of information from cyber sources, CSP network modeling, and flow models in a connected environment.

5.1. Analyzing public attitudes and perceptions from cyber sources

Apart from the physical data that could be collected by various sensors, public attitudes and perceptions gathered from cyber sources (e.g., social networks) are the other promising sources of data for understanding a city's status and the performance of its transportation system. Thus, future ITSs should use these data sources to monitor and manage the systems. To extract useful and meaningful information from social network data sources (e.g., public comments on Twitter), a natural-language processing (NLP)-based algorithm that adopts predefined semantic structures is suggested for data analysis. The NLP algorithm should be able to detect social events and/or public comments that could lead to potential traffic issues (e.g., congestion after a football match), or reveal public attitudes toward and perceptions of the transport system/current policy. In addition, with temporally and spatially tagged social network data, the extent and seriousness of traffic issues (e.g., comments on the delay of train service after an 8 AM train disruption) could also be estimated.

5.2. CSP traffic network modeling

To better incorporate the data from the CSP spaces and other emerging multi-source data, a CSP model should be developed to allow for the association and fusion of data. In the future, a hierarchical traffic network model that integrates physical, semantic, logical and perceptual networks in the digital reconstruction of CSP spaces should be considered. A cross-layered (i.e., between the cyber, social, and physical layers) network connection could be enabled by cognitive computing and/or probabilistic inference models to depict network connectivity. The association rule of cross-domain data could be investigated using statistics and NLP. For instance, the spatiotemporal association rule could be set between Bluetooth intensity and traffic volume, or building energy usage and pedestrian flow. In formulating this hierarchical traffic network model, due to the abundance of available traffic information, it will be crucial to identify and define the types and amounts (in terms of temporal and spatial resolution) of information that will be sufficient to implement various services effectively.

5.3. Flow models under connected environments

With the increasing popularity of VACS, it is certain that future ITSs will be applied in connected environments with mixed CAVs and RHVs. As the behavior/characteristics of CAVs are substantially different from those of RHVs, it is critical to understand the flow characteristics of such mixed-vehicle environments for use in ITS. Extended vehicular flow models will be necessary at both the microscopic and macroscopic level. At the microscopic level, new car-following (CF) models will be considered with the intention of incorporating the CAV-related characteristics (e.g., unreliable vehicular communications, communication delay, platooning driving protocols, penetration rate of CAVs, etc.). Such CF model could then be used in the design of link-based control in ITS. In contrast, at the macroscopic level, the CAV-related characteristics should be considered in the development of the network-level flow model to help in regional monitoring and planning (e.g., monitoring the congestion level of a district, designing cordon-based road pricing scheme, etc.).

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