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Editorial

Special Issue on Future Intelligent Transportation System (ITS) for Tomorrow and Beyond

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1. Introduction

Intelligent Transportation System (ITS) has evolved into a system for provision of traffic information and traffic control with the help of advanced IT technologies. Congestion and safety issues arise when the number of vehicles on the road increases, and has become the bottleneck. The cost of congestion in the United States is estimated to be 115 billion dollars, and in addition, it is estimated that more than 1.2 million deaths happen every year due to road accidents. According to a survey by the Texas Transportation Institute, commuters in the United States spend over 42 h per year trapped in traffic, and vehicles waste more than 3 billion gallons of fuel every year, costing $160 billion, which is equal to $960 per traveler [1]. Such issues will be exacerbated in the future because of the increasing population and migration to metropolitan regions in many countries throughout the world. The implementation of ITS to increase the efficiency and safety of transportation is one possible solution to this challenge. This would be accomplished through the use of sensing technologies, modern communications, information processing, and control technologies.

Data collection, data analysis, and data transmission are essential components needed for the advanced technologies and applications of ITSs. In data collection, information regarding the different parameters like traffic flow, road network, average travel time, number of pedestrians passing a transit line, etc. is collected by using sensing devices. Generally, in order to gather traffic information including vehicle speed and traffic volume, inductive loop detectors and pneumatic tubes are used to detect the presence of vehicles on the road using the induced current and pressure changes of the tube, respectively [2]. With the development of advanced sensing and imaging technologies, cameras and radio-frequency identification (RFID) scanners are widely being used for data collection in ITS. Typically, cameras are installed at different places within the network collecting motion videos of traffic scenes. By analyzing the images of the video, image-processing software is used to gather traffic information, such as traffic flow, vehicle types, and speed [3]. In addition, automatic license recognition plates and matching technologies are employed to obtain secondary traffic information such as traveling periods and routes [4]. With advanced communication technologies, more stable and secure communication in ITS can be established. Having cellular network equipment (GSM, GPRS, 3G, LTE) in the vehicle, it is possible to communicate with the cloud server to gather information [5]. Sensors in vehicles can form a wireless sensor network (WSN) and thus diverse applications [6,7] of the WSN can be applied to the ITS. Moreover, in order to have communication between the device of the vehicle and the bus stop used as a gateway, long-range technology is used [8]. The aim of data analysis focuses on providing different traffic information and control/management strategies from the collected data. For the evaluation of traffic conditions and the supplement of necessary solutions, predefined and pre-calibrated models, traffic flow models, and other models for intersection are usually used. With the

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improvements in computational performance and efficiency, agent-based models and micro-simulation schemes have been developed to perform accurate and detailed evaluations [9]. As the operation of smartphones significantly increases, mobile phone data, media access control addresses from wireless fidelity and bluetooth, and global positioning system (GPS) data are provided to analyze the traveling behavior and traffic circumstances. With more personalized and specified information from devices, a more detailed analysis of behavioral information can be performed.

Vehicle detection, one of the essential tasks in ITSs, is typically used to collect and provide information including identification of traffic accidents, vehicle counting, speed measurement, and traffic flow prediction. Edge computing, which is a distributed computing service that splits complicated computing tasks into multiple small components and allocates the separate tasks to local devices, is utilized for vehicular applications in ITS. Edge computing, an extension of cloud computing, has several characteristics including dynamics, mobility, low latency, and location awareness. The nodes in edge computing can implement allocation and cooperation for energy-efficient operation. Recently, various machine learning models and technologies have been applied to the transportation domain because a large amount of traffic information collected from GPS, road devices, and front board cameras is available. Deep learning, which is one of the machine learning techniques, has a significant role in computer vision-based applications. A study relevant to deep learning technique was implemented to improve the performance and efficiency of transportation safety, control, and management [10]. With computer vision-based applications, the vehicle obtains a decision-making capability depending on its surrounding objects. Convolutional neural network (CNN), which is especially effective at image classification and detection, can be applied to advanced driver assistance systems including object detection, lane departure, collision detection, traffic sign detection, and pedestrian detection.

This special issue of "Future Intelligent Transportation System for Tomorrow and Beyond" consists of recent research achievements from the experts in the field of ITS, bringing together contributions to the enhanced transportation systems. The goal of this special issue is to encourage research and development in future ITS while addressing their validation by using experimental data as possible.

2. Contributions

Decreasing fuel utilization, carbon dioxide (CO_2), and other air contamination emanations has long been a pressing issue for the transportation area, particularly the automobile business, which is currently mired in a deadlock over oil constraint and environmental concerns. Along these lines, authorities and automakers have been testing a variety of tactics and technologies to limit fuel utilization and emissions. The introduction of the model predictive control (MPC) algorithm into the adaptive cruise control (ACC) system has lately brought limelight to academic interest as a new research issue. The feasibility of adopting a hybrid MPC framework to vehicle tracking control investigated in [11] is based on the architecture of the intelligent ACC system. The ACC framework was proposed in view of eco-driving in ref. [12], and the results showed the adequacy and modern feasibility of the created algorithm. The MPC approach is used to develop a multi-objective coordinated optimization strategy for the ACC system which includes tracking capabilities, driving comfortability, and decreasing fuel usage. However, the distinctness of the cut-in driving circumstances and related specifics of developing an MPC-based ACC system was not fully defined. In addition to this, the suggested MPC-based ACC system's specific fuel efficiency performance gain over the classic controller-based ACC system was unclear. The MPC method is used to develop the ACC system in order to achieve the goals of eco-driving, driving safety, comfortability, and tracking capabilities. The proposed MPC-based ACC framework was assessed and contrasted with the standard proportional-integral-derivative controller-based ACC framework. Based on the simulation results, the MPC-based ACC system improved the fuel economy by 12–13%.

With the growth of urbanization, traffic congestion remains a major challenge for large cities. Drivers' route-based choices are primarily based on their limited perspectives in the absence of complete real-time traffic information. As a result of these options on improvident and non-cooperative routes, the efficiency of road network resource use is degraded. Some nations are focused on enthusiastically fostering ITS to accomplish a proficient traffic flow. Traffic prediction is an essential part of ITS, particularly on highways with high traffic volumes and high-speed driving. To deal with the intricacy of gigantic traffic information [13], robust traffic models are required, considering traffic information for the space-time connection to predict the traffic circumstances. These techniques are rehearsed to anticipate the traffic flow and volumes. All known machine learning approaches fail to grasp the spatial-temporal aspects of a traffic network when dealing with large amounts of data. Researchers used deep learning approaches to utilize historical traffic circumstances for predicting future traffic situations due to their excellent feature learning capabilities. A novel multi-branching technique to regulate the spatial-temporal aspects by modeling traffic flow using spatial correlations and various 3D volume layers is presented in ref. [14]. This methodology is helpful for investigating temporal dependencies through the 3D CNN.

Mobile gadgets have exploded in popularity in recent years. The proliferation of smartphones and GPS-enabled portable devices have resulted in an unanticipated increase in traffic trajectory data. Modeling the trajectory and forecasting the destination are important not only for monitoring urban traffic but also for a variety of other exciting applications, such as targeted advertising based on destination, location-based social networks (LBSNs), intelligent traveling schedules, and reducing travel costs, as well as energy consumption-optimized scheduling strategies [15]. The study of forecasting the future destination is a well-studied human mobility application for minimizing traffic congestion and improving the performance of the electronic dispatching system. A neural network approach to forecast the next destination according to taxi driver behavior is studied in ref. [16]. In this method, encoder and decoder are the essential units of the transformer. With the assistance of LBSN, the topographical data in view of visited semantic areas is encoded. The model is specifically trained to anticipate the future destination, using exact longitude and latitude data. The trials were run through two real-world datasets, Porto and Manhattan, and it was found that functioning is far better than earlier models. This study has the potential to minimize client wait times for rides and driver wait times to pick up customers.

People have become more connected as cellphones have turned out to be more widespread, and this has made everyday order delivery service much more convenient. Customers can be dropped/picked up by a cab at any time using apps like Kakao, Ola, and Uber, and in the same way food can be transported to the address of consumers in a relatively short time by utilizing food-ordering apps like Zomato, Meituan, and Freshhema. The delivery service routing system, which directs automobiles and couriers to convey orders, has played a critical role in serving large number of requests. A study on the delivery service sharing (DSS) and flexible time windows (DSS-Fle) variation with adjustable time frames, which allows orders to be shared and served at the same time, is carried out in ref. [17]. The practical DSS-Fle problem was investigated in this study, where client orders have variable drop-off time periods and can be served in a shared fashion. The suggested results showed with thousands of regions and client orders that the DSS-Fle algorithm is efficient in both enhancing order rate and adapting to city-scale scenarios.

Economy, mobility, environment, population, lifestyle, and organization are all cornerstones of a city. The goal of a smart city is to save costs and improve organization and the well-being of its residents. Unmanned aerial vehicles (UAVs) are now used in a wide range of everyday applications and are acquainted further to develop street traffic effectiveness [18]. The UAVs have a certain level of intelligence in most of applications, allowing them to be utilized as high-performance sensors, data collectors, or even communication relays, especially when ground cover is insufficient. The advancements in cooperative ITS technology, as well as the intriguing qualities of UAVs, present an ideal background for introducing a UAV into a use case involving a car and a pedestrian. In [19], the UAV is supposed to control the situation, gather data, and provide directions to the automobile driver in order to avoid a collision between the car and the pedestrian. The authors underline that the UAV might aid in improving both road safety and energy consumption.

Skyline localization is a crucial branch of optical geolocation, particularly in fields with few feature points. The location of the observation can be established by extracting features from photos or videos and comparing them to feature databases. The difficulties of detecting the skyline in hilly terrain, including lush vegetation and proximity to the skyline, is investigated in ref. [20]. This study proposes a new skyline localization approach that includes the enhanced angle chain code and skyline lapel point, as well as other matching technique that include the skyline pyramid and the skyline distance heatmap. The test results showed that this technique has high localization precision in hilly regions. However, the exactness of the technique is low when adjacent trees severely hide the skyline, or when the mountain in front of the camera is too close.

Electric vehicles (EVs) have become a fundamental part in the transportation system to diminish reliance on fossil fuel sources and grabbed the attention of researchers investigating different sorts of eco-friendly power assets in the microgrid (MG). Considering time-varying load demand similar to the work in ref. [21], the power management strategy of interdependent MG and EV fleets is presented in ref. [22]. This strategy is integrated with a novel EV charging/discharging scheduling algorithm to reduce the expenses of PV-based charging station. With the advancement of EVs on roads and parking stations, the EV aggregator can be used to provide energy-efficient and cost-effective charging and discharging solutions. Batteries installed in the EVs can act as an energy storage system, shifting load demand from peak to off-peak hours and lowering the electricity bills.

Predictive mobility is a major component that can help traffic operators assess traffic performance in smart cities. Using historical data from GPS, the authors incorporated the self-attention long short-term memory (SA-LSTM) model with a Butterworth low-pass filter to estimate the journey time on the road segments [23]. Initially, the LSTM is defined as a standard in this study. Due to the relatively high mean absolute error (MAE) of 27.12 min per 100 km, the SA-LSTM model together with the Butterworth low pass filter was implemented to reduce the MAE to 12.15 min per 100 km.

Visual odometry (VO)-based localization algorithms have been created as a result of the information in images. The ability of a mobile robot or vehicle to locate itself is a critical component in the advancement of autonomous robotics and vehicles. The use of a gated recurrent unit (GRU) network trained on pose data acquired by an accurate sensor is proposed in ref. [24] as a new pose estimation method. Reconstructing the rotation matrix with a yaw angle that is the fusion of the yaw angles calculated from the proposed GRU network and previous VO approaches improves performance in terms of translation error and rotation error. The network was trained by using the KITTI dataset [25], and the performance of the KITTI sequences increased by 1.426% in terms of translation error and 0.805 deg/100 m in terms of rotation error.

The future ITS will remain as an important aspect of urban planning and future cities, as it will help to enhance road and traffic safety, transportation and transit efficiency, energy efficiency, and pollution reduction. We believe that the articles in this Special Issue offer significant understanding of different infrastructures within the transportation system under different situations to ensure the efficiency and safety of the transportation system.

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