Traffic Flow Forecasting Technology

Subjects: Sociology
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The sustainable development of mankind is a matter of concern to the whole world. Environmental pollution and haze diffusion have greatly affected the sustainable development of mankind. According to previous research, vehicle exhaust emissions are an important source of environmental pollution and haze diffusion. The sharp increase in the number of cars has also made the supply of energy increasingly tight. In this entry, we have explored the use of intelligent navigation technology based on data analysis to reduce the overall carbon emissions of vehicles on road networks. We have implemented a traffic flow prediction method using a genetic algorithm and particle-swarm-optimization-enhanced support vector regression, constructed a model for predicting vehicle exhaust emissions based on predicted road conditions and vehicle fuel consumption, and built our low-carbon-emission-oriented navigation algorithm based on a spatially optimized dynamic path planning algorithm. The results show that our method could help to significantly reduce the overall carbon emissions of vehicles on the road network, which means that our method could contribute to the construction of low-carbon-emission intelligent transportation systems and smart cities.

Keywords: sustainability ; intelligent transportation system ; IoT ; vehicle emissions ; environmental protection

1. Introduction

The study of vehicle navigation technology has a long history. In the early days, navigation technology was mainly physics-based. A milestone was the Honda Electro Gyrocator, which was the first commercially available automotive navigation technology in the world. Without the support of GPS (Global Positioning System) satellites, it used gyroscope sensing to determine the vehicle's travel direction, and different sophisticated map cards were used to show roads [1][2].

In recent years, with the popularization of GPS technology and the development of mobile computing devices, navigation technologies have become more and more data-driven. In 2012, James Bicego [3] proposed a navigation system based on notifying about traffic incidents. The system consists of a large number of sensors, base stations, and communication systems. It is claimed to be able to effectively provide drivers with navigation routes that avoid going through traffic accidents. Bicego's idea is interesting, but to identify a route as negative or positive by simply considering whether there are any traffic incidents could not be comprehensive enough. Traffic incidents would affect roads' status and, thus, affect the road priorities for navigation, but in order to fully evaluate the influence on road networks, the networks need to be reflected in the terms of real-time traffic flow.

The shortest path algorithm, which selects the optimal route simply based on the evaluation of the physical lengths of different routes in the static road network, had been widely used in many car navigation systems, such as Google Maps or Baidu Maps. In recent years, short-term traffic flow forecasting has become a hot topic in the field of intelligent traffic navigation. Plenty of applications based on short-term traffic flow forecasting have come up online. They are either implemented based on traditional mathematical methods or artificial intelligence methods.

2. Short-Term Traffic Flow Forecasting Methods

Short-term traffic flow forecasting methods based on traditional mathematical methods are usually built based on a conjecture that there is a law of traffic flow trends [4][5]. Once the trend of traffic flow is depicted by statistical calculations based on a mathematical model (for example, the kinematic theory model), the short-term future traffic flow changes can be inferred. Those methods, such as the linear regression model, autoregressive moving average model, and Kalman filter algorithm, are commonly used. However, these methods can only predict the temporary changes in traffic flow under normal conditions, but cannot reflect the change of traffic flow parameters in real time, let alone predict large-scale data with high accuracy.

Therefore, plenty of researchers turned to more complex machine learning methods or neural network methods with the purpose of depicting the real-time traffic flow more precisely in order to implement better prediction methods [6][7]. E.S. Yu implemented a feedforward back-propagation neural network algorithm to analyze the linear and non-linear changes in traffic flow [8]. Yu's experiments confirmed that the short-term traffic flow prediction method based on neural networks is more robust against noise data than traditional mathematical methods. N. Messai's research [9] presented a feedforward neural network approach for short-term traffic flow prediction on freeways. The accuracy of the approach was verified by the results of their experiments [9]. Lopez-Garcia et al. presented a method of optimizing the elements of a hierarchy of fuzzy-rule-based systems (FRBSs), which was a hybridization of a genetic algorithm and the cross-entropy (CE) method. It was used to predict congestion in a 9-km-long stretch of the I5 freeway in California, with time horizons of 5, 15, and 30 min [10]. Feng et al. proposed a short-term traffic flow prediction algorithm based on an adaptive multi-kernel support vector machine (AMSVM) with spatial–temporal correlation [11]. Linchao Li et al. proposed a deep feature learning approach to predict short-term traffic flow [12]. They implemented a deep belief network with several Restricted Boltzmann Machines to extract complex features of traffic flow.

One possible solution that serves navigation systems is the optimal path algorithm. In addition to navigation, optimal path planning technology could be used in many other applications, such as planet exploration, landmine detection, etc. [13]. The goal of an optimal path planning algorithm is to find the optimal path from the source point to the destination point in a given road network, with the restriction that the cost function gets a minimum value. Dijkstra's algorithm and the A* search algorithm are the most common and classical ones in optimal path planning. Plenty of navigation systems are developed based on them. Many other methods, such as genetic algorithms, ant colony algorithms, and other intelligent algorithms have also been involved to solve optimal path planning problems. Lorraine McGinty et al. were the first to put forward the notion of "route quality". They presented the idea that the route quality should be considered when choosing the optimal path [14]. In addition, Nie Y. suggested that the chosen path should consist of "reliable routes", which are routes that ensure that the vehicle can arrive on time [15].

An important point in the smart city paradigm is the possible use of traffic detectors. Matt Grote et al. [16] developed their road traffic emission model based on readily available data generated by inductive loop detectors installed as parts of urban traffic control systems. Silvio Nocera et al. [17] provided their method for handling imperfect information in order to obtain a more accurate quantification of CO2 emissions. Zhiwen Yang et al. [18] demonstrated their work of evaluating the benefits of using a speed-guided ITS based on real-world measurements.

According to our investigation of the literature, currently, there is little reporting about designing an optimal path planning algorithm that directly targets minimum vehicle exhaust emissions. Environmental protection and sustainable development are the keys to future construction of smart cities, which demand the restriction of overall vehicle exhaust emissions [19][20]. So, the designing of a sustainable intelligent navigation algorithm targeting the reduction of the overall carbon emissions of vehicles on road networks is necessary and important.

3. Conclusions

The sustainable development of mankind is a matter of concern to the whole world. Environmental pollution and haze diffusion have greatly affected the sustainable development of mankind. Environmental protection has become one of the most relevant topics in the world. More and more effort has been delivered for the construction of smart cities in order to improve people's lives and to make the world an ever better place [21][19][22][20].

One of the most important research topics in the construction of a smart city is dealing with the traffic problems in modern cities [23]. For decades, the development of cities has led to a rapid increase in vehicles. When the rapid increase of vehicles meets the relatively imbalanced development of urban road traffic facilities, traffic congestion becomes a common thing. The huge traffic volume and frequent traffic congestions lead to more vehicle exhaust emissions, which means more environmental pollution [24][25][26].

The development of the Internet of Cars and Intelligent Traffic System (ITS) makes it possible to handle traffic issues in modern cities through big data technologies. Based on traffic forecasting technology and intelligent navigation technology, we could implement a sustainable ITS focused on preventing environmental pollution.

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