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Construction of traffic state vector using mutual information for short-term traffic flow prediction

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ABSTRACT

Short-term traffic flow prediction is an integral part in most of Intelligent Transportation Systems (ITS) research and applications. Many researchers have already developed various methods that predict the future traffic condition from the historical database. Nevertheless, there has not been sufficient effort made to study how to identify and utilize the different factors that affect the traffic flow. In order to improve the performance of short-term traffic flow prediction, it is necessary to consider sufficient information related to the road section to be predicted. In this paper, we propose a method of constructing traffic state vectors by using mutual information (MI). First, the variables with different time delays are generated from the historical traffic time series, and the spatio-temporal correlations between the road sections in urban road network are evaluated by the MI. Then, the variables with the highest correlation related to the target traffic flow are selected by using a greedy search algorithm to construct the traffic state vector. The K-Nearest Neighbor (KNN) model is adapted for the application of the proposed state vector. Experimental results on real-world traffic data show that the proposed method of constructing traffic state vector provides good prediction accuracy in short-term traffic prediction.

1. Introduction

1.1. Traffic flow prediction

With the economic development and ever-growing traffic demand, traffic congestion is becoming a severe problem in urban areas around the world. The excessive congestion on urban roads causes many social problems including economic, health, and environmental problem such as stress, fuel consumption, waste of time, traffic accident, etc (Vlahogianni et al., 2014; Younes and Boukerche, 2015). Due to the fact that ITS can significantly alleviate the traffic congestion by using various technologies including modern information communication, computing, and control technologies, higher requirements for ITS with accurate intelligent traffic service are presented (Zhang et al., 2016; Li, 2016).

Traffic flow prediction aims at estimating traffic parameters such as traffic volumes, travel speeds and occupancies given a specific region and a time interval. Traffic flow prediction which can provide accurate information of the real-time traffic conditions to drivers and passengers is one of the most important functions for maintaining successful ITS. Moreover, the traffic guidance system

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which is core technology of ITS is mainly based on the traffic flow prediction technology (Rice and Van Zwet, 2004; Zhu et al., 2014). By predicting future traffic state information, ITS can improve the service level and efficiency of urban transportation system, which make it more efficient and reliable. For this reason, a lot of efforts have been devoted to develop and improve the effective traffic flow prediction models aiming to increase the accuracy and reliability of the prediction system over the past three decades (Vlahogianni et al., 2014).

1.2. Related works

Extensive and elegant approaches have been published in the studies for the traffic flow prediction. Although the existing prediction methods can be categorized in many ways, the most significant classification scheme is to classify them into three kinds: traffic model-based methods, statistical methods and data-driven methods (Fangce et al., 2013; Meng et al., 2015).

Traffic model-based methods use rigorous mathematical derivation to describe the basic rules of traffic phenomena from mathematical models. These methods recover the traffic variables including traffic speed, volume and density, and capture various dynamics within the traffic flow (Lint et al., 2005; Stathopoulos and Karlaftis, 2003). Traffic models are constructed under the assumption that the traffic flow has a similarity to the flow of liquid or gas dynamics (Jia et al., 2014; Tang et al., 2012). However, because of the complexity and uncertainty of the traffic flow, it is difficult to establish the models that fully express the complex relationship among traffic instances (Yu et al., 2016). Therefore, many researchers have generally adopted the statistical methods.

Statistical methods tend to predict the future traffic condition by training the given dataset to estimate the optimal parameters with theoretical background on the relations between independent and dependent variables or classical state space theory. Typical statistical methods include local linear regression model (Sun et al., 2003), auto-regressive and moving average (ARMA) (Williams, 2001; Ishak and Al-Deek, 2002), seasonal auto-regressive integrated moving average (SARIMA) (Williams and Hoel, 2003), and Kalman filtering method (Xie et al., 2007; Guo and Williams, 2010; Guo et al., 2014). These methods have high computational efficiency and good accuracy, but are best suited for the stationary or linear time series (Meng et al., 2015).

Currently, due to the rapid development of information technology, urban freeway networks are usually equipped with various sensors (e.g. loop detectors, probe vehicles, cell-phones, and video cameras) which can enrich the data sources for use in the transportation systems. Therefore, nonparametric data-driven methods that extrapolate short-term future traffic flow directly from the given big data without the explicit modeling of traffic phenomena are widely used in recent years. Support vector regression (SVR) models (Castro-Netoet al., 2009; Asif et al., 2014; Yao et al., 2014), K-Nearest Neighbors models (Yu et al., 2016; Akbari et al., 2011; Hong et al., 2015), and neural network based models (Castillo et al., 2008; Li, 2016) are included in this category. Some researchers compared data-driven methods with Kalman filtering and ARIMA, and concluded that they are clearly superior to the statistical methods in terms of prediction accuracy and have other opportunities for improving the prediction performance (Smith et al., 2002; Yoon and Chang, 2014; Lam et al., 2010). In recent years, a considerable number of studies based on deep learning, which is a promising area of machine learning, for traffic prediction and interpolation have been published. Huang et al. (2014) proposed a deep architecture for the traffic flow prediction which consists of a deep belief network (DBN) at the bottom and a multi-task regression layer at the top. Yang et al. (2016) designed a type of deep architecture of neural network approach using the Taguchi method to develop an optimized structure and to learn traffic flow features through layer-by-layer feature granulation with the greedy layerwise unsupervised learning algorithm. Polson and Sokolov (2017) developed a deep learning architecture by combining a linear model that is fitted using l_1-regularization and a sequence of tanh layers to predict traffic flows. They demonstrated that deep learning is capable of providing superior performance over other prediction models for the traffic prediction.

Among data-driven methods, the KNN model is known to be a widespread method of nonparametric regression in the traffic flow prediction. Many studies have successfully applied the KNN model to making future traffic predictions (Yu et al., 2016). Two core issues in the application of this method are the case database foundation and searching speed (Meng et al., 2015). The size and completeness of the case database has a great impact on the prediction performance of KNN model. Generally speaking, the traditional traffic database without pre-processing is obviously containing a lot of noisy data and redundancy that can degrade prediction performance. On the other hand, the KNN model based on traffic pattern matching requires relatively large historical databases, so it is costly to operate and search large case databases, which may not be suitable for real-time predictions. In order to overcome these difficulties, researchers proposed various modified versions of KNN model such as clustering based search method (Akbari et al., 2011), condition-monitoring method (Turochy, 2006), multivariate matching regression (Clark, 2003), balanced binary tree based search (Meng et al., 2015), hybrid multi-metric regression (Hong et al., 2015), and time constraint window based method (Zheng and Su, 2014).

1.3. Motivation

An important issue in the application of KNN model is the setting method of pattern (Akbari et al., 2011). The KNN model is essentially an instance based learning (IBL) method based on pattern recognition, since it matches historical patterns with a pattern associated with the current state by measuring the degree of closeness between them in a given data space. This method uses the similarity between the current traffic pattern and K similar sets of the historical patterns to obtain the best estimation of the variables we want to predict. Therefore, if unsuitable patterns are selected, it results in false estimation of the similarity. Consequently, the prediction may be risky. Because the road sections are interconnected in urban road network and the traffic flows on these sections are highly correlated with each other, it is desirable to consider the spatial correlation between the road sections in the traffic prediction. From this perspective, some researchers have come up with the prediction methods that consider both spatial and