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Traffic volume forecasting based on radial basis function neural network with the consideration of traffic flows at the adjacent intersections

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ABSTRACT

The forecasting of short-term traffic flow is one of the key issues in the field of dynamic traffic control and management. Because of the uncertainty and nonlinearity, short-term traffic flow forecasting could be a challenging task. Artificial Neural Network (ANN) could be a good solution to this issue as it is possible to obtain a higher forecasting accuracy within relatively short time through this tool. Traditional methods for traffic flow forecasting generally based on a separated single point. However, it is found that traffic flows from adjacent intersections show a similar trend. It indicates that the vehicle accumulation and dissipation influence the traffic volumes of the adjacent intersections. This paper presents a novel method, which considers the travel flows of the adjacent intersections when forecasting the one of the middle. Computational experiments show that the proposed model is both effective and practical.

1. Introduction

The traffic flow forecasting, especially the short-term traffic flow forecasting, has been recognized as a critical need for the intelligent transportation systems. It provides the theoretical and data supports for the traffic management systems, traveler information systems, emergency processing systems, and other related systems. On the one hand, Traffic Management Center (TMC) collects the traffic flow information to evaluate the real-time traffic condition of the road network, and to predict the traffic condition in the next moment by applying the short-term traffic flow forecasting techniques. The related information can be provided to the decision makers to adjust the route guidance strategy and other traffic management plans. On the other hand, the traffic information can be released to road users to efficiently assist them in choosing the travel route, the departure time, and the travel mode so as to avoid the traffic congestion (Stathopoulos and Karlaftis, 2003).

The short-term traffic flow forecasting means that the observation period is quite short, which is generally less than 15 min. The Highway Capacity Manual 2010 suggests using a 15-min traffic flow rate for operational analyses. In the past decades, a variety of models and methodologies have been applied to the traffic flow forecasting by researchers. There are two main trends in the area of traffic flow forecasting. One is to develop more efficient methodologies and models to fit different situations.

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Current model of the traffic flow forecasting involves two main approaches: parametric and non-parametric techniques (Vlahogianni et al., 2004). The famous model base on parametric technique, namely the Box–Jenkins model (ARIMA model) provides a perfect solution to most of the time-series problems. It is obviously that traffic volume values are time series data. And the ARIMA model was first introduced to the forecasting of traffic flow by Ahmed and Cook in 1979. Then the ARIMA model was proved to be a regular practice in time-series transportation data analysis, especially in traffic forecasting (Levin and Tsao, 1980; Davis et al., 1991; Hamed et al., 1995; Williams and Hoel, 2003; Stathopoulos and Karlaftis, 2003). Afterwards, researchers found that ARIMA model cannot tackle the problem of the extreme volume values forecasting (Davis et al., 1991; Hamed et al., 1995; Vlahogianni et al., 2004).

As for non-parametric models, the most widely used one is Artificial Neural Network (ANN), the one of Computational Intelligence (CI) models (Karlaftis and Vlahogianni, 2011). ANN has been widely used for forecasting of transportation data, especially the short-term traffic flow forecasting. The ANN is a nonlinear dynamic system, which is characterized in the parallel co-processing and distributed information storage. Although each individual neuron has very simple and limited function, the network consisting of a large number of neurons can achieve the functions are extremely abundant.

Multi-Layer Perception (MLP), Back-Propagation Neural Networks (BPNN) and Radial Basis Function Neural Networks (RBFNN) are the most widely used ANN models in short-term traffic flow forecasting (Karlaftis and Vlahogianni, 2011). Compared with BPNN, RBFNN required less network training time and showed better performance (Park et al., 1998). Amin et al. (1998) used the RBFNN to predict the traffic flow. Jayawardena and Fernando (1998) present an application of the RBFNN for hydrologic modeling and runoff simulation in a small catchment and report that it is more efficient computationally than the BP algorithm. Chen's research (2001) has also been shown that the RBF performed slightly better than the MLP. And the structure of RBFNN is simpler than MLP because it has only one hidden layer. Nevertheless there are some discussions about the structure of ANN. The 'black-box' structure of ANN was considered to hide from the user (Ripley, 1993, 1994). But for the traffic flow forecasting, we can take advantages of the structure to use the traffic volume of different locations to make prediction. On the contrary, the time series approach takes no account of the structural relationship that exists between one point and another.

Another trend is to develop more efficiency hybrid methods, specially the combination of the ANN and other methods. Hybrid ANN models were proved to forecast the traffic flow more efficiently. Van der Voort et al. (1996) proposed a hybrid model that combined Kohonen self-organizing maps with ARIMA models. The fuzzy-neural model was also applied to traffic flow forecasting (Yin et al., 2002). Bayesian combined neural network was proved to have better performance (Zheng et al., 2006). Genetic algorithms were also adopted to improve the performance of ANN (Abdulhai et al., 1999; Vlahogianni et al., 2005).

Although many different methodologies have been applied for the forecasting, the ultimate goal remains the same: to obtain the forecasting result more precisely and faster. Researchers also focused on improving and optimizing the existing methodologies and models. An object-oriented neural network was proposed for traffic forecasting through a time-lag recurrent network (Dia, 2001). Vlahogianni et al. (2008) proposed a multilayer strategy considering the temporal patterns by using the neural network approaches.

In recent years, data analysis based multi-section of road networks has become a hot issue in the area of traffic flow forecasting. Whittaker et al. (1997) used a number of different points' average speed and traffic volume to analyze the influence of each point in the road network in Netherlands. Williams (2001) forecast traffic flow through four traffic collection points near the city of Bonn, Germany. Stathopoulos and Karlaftis (2001) used the spectrum analysis and the cross-spectral analysis on the traffic flow in different locations. The result shows that the traffic volume of the section in different location has the character of autocorrelation and correlation. This correlation varied with different period and distance of different location. Kamarianakis and Prastacos (2003) demonstrated the application of univariate and multivariate techniques in an urban network using the data sets originating from a set of loop detectors.

Research about the multi-section traffic flow forecasting reveals that the traffic volumes of each collection points are significantly correlated. The intersections, as the node of road network, are easily to form the flock of vehicles. The accumulation and dissipation of one intersection obviously affect the state of traffic flow of adjacent intersections. We can exploit the spatio-temporal features of the volume of adjacent intersection to optimize the performance of the forecasting model. In this paper, a RBFNN-based method by using the traffic flow data of adjacent intersections is proposed to obtain more accurate forecasting result and to solve the problem of missing data.

2. RBF neural networks and the flocking phenomena

2.1. RBFNN for traffic flow forecasting

The Radial Basis Function Neural Network (RBFNN) is a three-layered feed-forward neural network with one radial basis layer. It can uniformly approximate any continuous function with a prospected accuracy. The RBFNN has local generalization abilities and fast convergence speed. The entire network includes three layers: an input layer, a nonlinear hidden layer (radial basis layer) and a linear output layer, as can be seen in Fig. 1.

Fig. 1 shows the typical structure of an n–h–m RBFNN, which has n inputs, h nodes of hidden layer, and m outputs. The vector $\mathbf{x} = (x_1, x_2, \cdots, x_n)^{\mathrm{T}} \in \mathbb{R}^n$ is the input vector of the network, and $\mathbf{W} \in \mathbb{R}^{h \times m}$ is the output weight matrix. The vector