A method of short term traffic flow prediction that based on the time series theory

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Abstract

Road flow is an important base data for traffic control and management, especially, short term future traffic flow is a critical parameter for dynamic travel induction and its control. Many methods have been developed for the problem. But previously models have some deficiency, such as bad adaptability, large amount of calculation needing and many history data requirement. The purpose of this study is to develop a model that can estimate traffic flow on road using the theory of time series treatment and prediction. Karhunen-Loeve transform and spectral analysis have good performance in time series evaluation, describes the method that applied the function of Karhunen-Loeve transform to decompose the history detection traffic flow data series, at the same time get the eigenvector coefficients, use the coefficients and current detection flow reconstructed the future some step traffic flow series, so get the goal of short term traffic prediction. The case study suggest that, the proposed method has a good performance on the prediction, furthermore, a fewer history data needing and several step can be predicted.

Keywords: short-term traffic prediction, Karhunen-Loeve transform, stochastic time series

1 Introduction

Road network Traffic state data is playing a key role for traffic management and control. In current days, more and more traffic data detector has been installed on road, and extensive data has been collected. Those data provide important support for traffic operation. But unfortunately, traffic system is a dynamic system. All detected data are current or previous. Using the data to make control solution directly may lead the solution did not very fit for its traffic state. Because when the solution running, the traffic state may have a large change from detection time, so the better traffic control or induce solution should based on the near future traffic state. For this goal, road traffic short-term prediction is the first major step in that direction. Many scholars say that short-term traffic state forecasting is of critical importance for traffic guidance and control system. In this regard, short-term traffic forecasting method have been developed and applied to assist the continuous flow of traffic-related information in near-term future, the same as to estimate 5, 10, 15 or 30 minutes interval road network traffic state. Prominent short-term traffic forecasting method use different theoretical techniques, all of those employ statistical methodology and heuristic methods. The former include non-parametric or parametric regression model [1,2], auto regressive model, auto regressive integrated moving average time-series model, Kalman filter model, wavelet theory model and chaos theory and so on [3]. The latter is known as fuzzy logic system methods [4,5], genetic algorithm [4,7], and neural network model [8,9]. Those heuristic methods can express the variation of traffic flow by self-learn, instead of relying on traffic flow model.

The basic indexes of traffic state include the flow, speed, density, travel time, delay etc. In all above index, the flow is detected most easily then others and some other index can be calculate from flow, in addition, the flow data can be used in traffic signal control design and route guidance solution. So the near future traffic flow is extremely important for traffic management and individual travelers. Therefore this paper takes the traffic flow as an objective to study short-term forecasting method.

Short-term traffic flow forecasting, there has been a lot of research results [10]. applied day to day flow distribution statistical data to forecasting short-term traffic. The essence of the method is using historical data s mean or a percentile value to estimation future traffic flow. But the method ignores the influence of traffic incident on the traffic flow, so only when traffic fluctuation is small the model can obtain better accuracy prediction. van Hinsbergen and van Lint (2008) [11] combined linear regression model and locally weighted linear regression model in a Bayesian framework to improve prediction accuracy and reliability. Although their proposed combined methodology exhibits accurate results, their model may produce larger prediction errors when each sub-model in the model layer is biased. Bajwa et al. (2005) [12] used a pattern recognition method to search in a database for traffic patterns similar to current conditions. However, abnormal traffic patterns caused by non-recurrent congestion or incidents deteriorate the performance of their model. Jiyoun Yeon et al. [13] applied discrete time Markov chains to short-term traffic prediction, in which, defined discrete traffic state series as congestion or no congestion and established a state transition matrix, use the matrix and current traffic state to forecasting next interval traffic state.

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This method also is average series estimation, did not satisfied all traffic conditions.

Although so many methods have been used for short term traffic forecasting, it is often difficult for traffic analysts to choose a good method for a specific road at a given time, because traffic conditions complication. One method that usually performs better than other methods under a specific traffic condition may degrade or even completely fail under other traffic conditions. Moreover, previous methods have their own drawbacks in dealing with predictions, albeit they have their strengths. For example, the historical average method has the key weakness in responding to unexpected events. The KF method is prone to produce high over predictions or under predicttions that deteriorate prediction accuracy when the state (traffic flow) undergoes drastic changes. The drawbacks of the exponential smoothing method (ESM) are reflected in leading to large variations of states and the difficulty of determining an appropriate smooth constant. The performance of the ANN largely depends on the network training, and is particularly influenced by the amount and quality of training data and many design parameters, such as the number of hidden layers, the number of epoch, and the number of elements in each hidden layers.

In order to achieve more accurate and robust traffic flow forecasting, we propose a Karhunen-Loeve analysis methodology. For random process, Karhunen-Loeve (K-L) provides possibility from a collection of independent random variables of stochastic process decomposition , its basic idea is that the random process described as uncorrelated random coefficient (principal component) of the function to determine the model location (linear combination of orthogonal mode) [14]. Moreover, K-L transform is a minimum mean square error transform method, which can describe the characteristic information of historical data optimally. Road historical flow series variety information contains a wealth of future traffic state trend information. So it is possible to use K-L transform to forecasting near future traffic state.

2 K-L transform decomposition and reconstruction

The discrete of a random process on the interval k = 1, 2, ..., N can be defined by the following series:

$$x_m(k) = \sum_{i=1}^{K} c_{mi}\phi_i(k) + e_m(k)\text{, } m = 1, ..., M, \tag{1}$$

where $x_m(k)$ denotes the discrete m-th member of a group of M stochastic functions at the k-th interval, and $e_m(k)$ represents the expansion error. For this problem, $x_m(k)$ represents the discredited traffic flow on day m at time interval k within the given day. The total number of days is M, and each day is divided into N times intervals. $\phi_i(k)$ Represents a set of orthogonal vector functions with the following properties:

$$\sum_{k=1}^{N} \phi_j(k)\phi_i(k) = \delta_{ij}\text{ ,} \tag{2}$$

where δ_{ij} is the Kronecker delta, c_{mi} are coefficients. In matrix form, the discrete time series of Equation (1) truncated to K terms is given by

$$X = C\phi^T + E\text{ ,} \tag{3}$$

where:

$$X = \left[x_m(k)\right], M \times N\text{ , } C = \left(c_{mi}\right), M \times K\text{ ,}$$

$$\phi^T = \left[\phi_i(k)\right], K \times N\text{ , } E = \left[e_m(k)\right], M \times N\text{ .}$$

Minimization of the error matrix:

$$J = (X - C\phi^T)(X - C\phi^T)^T\text{ .} \tag{4}$$

With respect to coefficient matrix C, with the assumed orthogonally condition $\phi^T\phi = I$, then gives:

$$C = X\phi(\phi^T\phi)^{-1} = X\phi\text{ .} \tag{5}$$

Each coefficient may be independently determined and forms a basis for prediction, Davenport and Root [15], It is found that the decomposition of the covariance matrix can be represented by the discreet form of the K-L integral equation, i.e.,

$$\lambda_i\phi_i(k') = \sum_{k=1}^{N} R_{k'k}\phi_i(k), \tag{6}$$

$$k' = 1,\ldots,N; i = 1,\ldots,K\text{ ,}$$

where:

$$R = X^T X\text{ ,} \tag{7}$$

Using Equation (6) eigenvector matrix ϕ and its eigenvalue λ are received, which been used in analysis of time series can possesses a smaller integrated mean-square error. [16] and [17] applied this character to traffic flow forecasting, and its performance show very good.

3 Application of K-L transform

As the second section describes, when solved the coefficient of C, combined with the eigenvector matrix ϕ, use Equation (3) can get another sequence $\tilde{X}$. In theory, the k in Equation (3) approaches infinity, $\tilde{X}$ is equal X . This property indicated that by the coefficient C and eigenvector matrix ϕ can re-composition a series that is similar to origin series. The goal of traffic flow prediction is to estimate near future one or several interval flow sequence. Take advantage of K-L transform good performance at describes stochastic sequence features and its re-composition function, use the principle of consecutive several days traffic state similarity in same road , as well as current observed sequence can estimate the road next one or number of interval traffic flow sequence.

On the same road, during the same weekday or weekend the traffic similarity is strongest, therefore, count a weekday history flow series of a road in 15 minutes interval, total of 96 sets in all day 24 hours, continuous S weeks, get a S×96 historical sequence matrix. Then, use the Equation (5)-(7) can solve the coefficient matrix C_h, which is $S \times K$ dimensions. The same time get the eigen-vector ϕ.

Previously flow series of current is impact on subsequent interval traffic flow series, therefore, using those T previously series which from $T_c \sim T_t$ to solve $1 \times K$ coefficient vector C_c using Equation (5). Attaching C_c to C_h obtain a $(s+1) \times K$ dimension matrix C, give a weighted vector W, which have $1 \times (S+1)$ dimensional, the cell of W be present as the weight of i each row. So the comprehensive coefficient C_a can be defined:

$$C_a = WC \quad (1 \times K). \tag{8}$$

Therefore using Equation (3) can calculate all current day 96 flow series.

With the going of the time, new detected data updating continually, C_c will changed too. For the forecasting series, the time point that further from current, the impact by those change is lower. The trial show that those far time points forecasting value more close to corresponding mean series of history. In practice, short-term traffic prediction is to predict 5~30 minutes interval traffic, so there is no need to consider the time series that far future from current. Based on these reasons, always use a interval before current time to estimation b interval after current time. This can be achieved through the rolling processing on the eigenvector matrix ϕ. That is, when calculate C_c, select $\bar{\phi}$ from ϕ as flow:

$$\bar{\phi} = \begin{vmatrix} \phi^1_{t-a+1} & \phi^2_{t-a+1} & \cdots & \phi^K_{t-a+1} \\ \phi^1_{t-a+2} & \phi^2_{t-a+2} & \cdots & \phi^K_{t-a+2} \\ \cdots & \cdots & \cdots & \cdots \\ \phi^1_t & \phi^2_t & \cdots & \phi^K_t \\ \phi^1_{t+1} & \phi^2_{t+1} & \cdots & \phi^K_{t+1} \\ \cdots & \cdots & \cdots & \cdots \\ \phi^1_{t+b} & \phi^1_{t+b} & \cdots & \phi^1_{t+b} \end{vmatrix}, \tag{9}$$

$$X = (T_{t-a-b+1}, T_{t-a-b+2}, .. T_t). \tag{10}$$

When forecasting, the estimation series $\bar{X} = C_a \bar{\phi}^T$, $\bar{X}$ series subscript is as the same as $\bar{\phi}$ row's. The series before time t is past, and the later is forecasting, for example $\bar{X}_{t+1} \sim \bar{X}_{t+b}$ is b interval forecasting data that after time t. So give a proper scope of a and b, by the time go, every time observer data updating, by calculating can get flowing b interval forecasting data, in *rotation can* realize the goal of short term traffic flow forecasting through *whole day*'s.

4 Calculation of weight for the coefficients

The combined weight of eigenvector coefficients should be optimal so can get good prediction accuracy, note that, each row element in c_h are calculated by a historical sequence. As introduced above, traffic state similarity on same road in different day, current observed sequence is more or less similar to its history , and in those history data, some days more similar then the others days. For more accurate forecasting, the history day that more similar to currents should have more weight than the others in prediction sequence, therefore, we can us Euclidean distance that between current detection sequence to corresponding period historic sequence to present the weight of each row in c_h.

Assume current observed series to i-th days Euclidean distance is $d(i)$, so can defined the weight of each row in c_h as

$$w(j) = \frac{1/d(j)}{\sum_{i=1}^{S} 1/d(i)}, \; j=1,2,..., K. \tag{12}$$

Equation (12) indicates that the weight have inverse relationship with Euclidean distance. $d(i)$ Be defined as flow:

$$d(i) = \sqrt{\sum_{T=t-a+1}^{t} (X_c(T) - X_{hi}(T))^2}, \tag{13}$$

where X_c is current observed sequence, X_{hi} is i-th history sequence, time section is a interval before current until t. So the temporary integration coefficient vector c_{tmp} can be present as: $c_{tmp} = wc_h$. Final coefficient is present as: $c_a = \alpha c_c + (1-\alpha) c_{tmp}$, $0 \le \alpha \le 1$, the α can be determined by trails.

5 A test case of the method

Apply the described method to Nanchang City Hongdu Bridge short term traffic flow forecasting. Take six consecutive weeks Tuesdays detection traffic flow as trail data, the former five days as history sequence and sixth as current or test data. The detection time interval is 15 minute. The bridge has 8 km length, and is an expressway bridge, which show a little congestion in peak hours but other time operated will. In trail, use current before 5 interval sequence to forecasting later 1~3 step interval sequence. All the algorithms are realized by Matlab, the result is showed as follows.

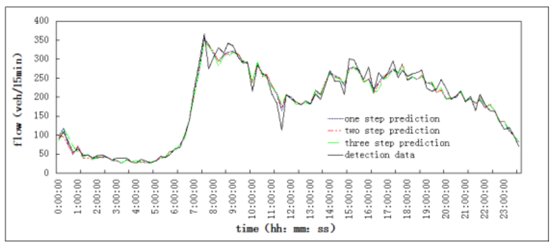

FIGURE 1 1~3 step forecasting and the real data

Use the ARE to present the absolute relative error which defined as:

$$ARE(i) = \frac{|x(i) - \hat{x}(i)|}{x(i)}, \quad (14)$$

$x(i)$ is a detection flow value, $\hat{x}(i)$ is a prediction flow value. Draw the ARE figure as follow:

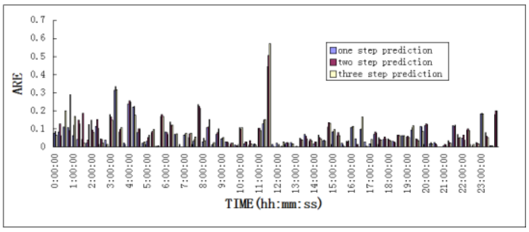

FIGURE 2 1~3 step forecasting ARE

Figures 1 and 2 show that the describes method have a good performance on one to three step prediction, but at the fluctuation time section where one step prediction performance is a little good then two or three step prediction. Figure 2 shows one ~three step forecasting absolute relative error is below 0.1 except those big fluctuation times.

In order to compare the performance of this describes to some others study in current, the test have been done. In the test, applied reference [1] method to forecast the sixth days traffic flow, and use the error of percentage absolute mean relative (*EPMR*) as a compare index. The (*EPMR*) be defined as:

$$EPMR = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}(i) - x(i)}{x(i)}\right|, \quad (15)$$

where n is whole day time intervals, $x(i)$ is a detection flow value, $\hat{x}(i)$ is a prediction flow value.

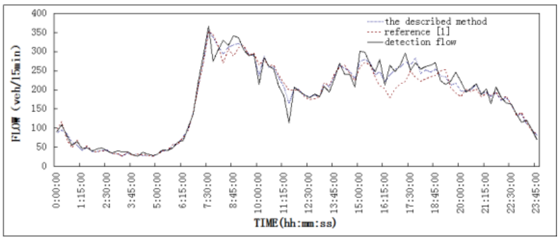

FIGURE 3 1~3 prediction of two method and real detection flow

Figure 3 show that the method which described in this paper has a good performance than reference [1] method.

TABLE 1 The EPMA of two method

	EPMA (%)		
	One step Fore.	Two step Fore.	Three step Fore.
[1]	14.523	14.831	14.945
The desc.	8.6214	9.8867	11.1408

Table 1 show the describes method prediction accuracy good then reference [1] not only one step prediction but also two and three step prediction. Consider the calculation number, this describes only calculate the Euclidean distance from current series to five history corresponding times series, but reference [1] must search all 96×5 series and find a best similar pattern to forecast future flow. Obviously, this describes need little calculate resource than reference [1].

6 Conclusions

The case study result show that K-L transform and re-composition can be used to forecast the short term ttraffic flow, compared with the existing short-term traffic flow prediction method, the method also can predicted multi-step perfectly. As reference [1] method, the average relative error of prediction for one step, two steps and three steps is 14.52%, 14.83%, 14.95% respectively. Although this method shows the pattern that the error rate increased with prediction step extension, but its only growth 0.43 percentage points, the result indicated the reference [1] method have a good performance in short traffic state prediction. By the means of this describes, the prediction precision can be significantly improved, contrast with reference [1] ,the one step prediction mean relative error is reduced from 14.52% to 8.62%, and reduced by 5.9 percentage points. the two step prediction mean relative error is 9.89%, three step is 11.14%, for traffic inducement, the error less than 10% can satisfy the traffic control system requirements, therefore, this descriptions two step forecastting accuracy can meet its requirements, that is to say the method be able to fulfil 15~30 minute interval traffic flow forecasting.

Of course, the method may have further optimization means, for example, how to use K-L transform memory and reproduction performance on time series fully, how to optimize historical sequence eigenvector coefficient, so the coefficient can more reflect the current traffic condition and its trend, in order to obtain higher forecasting accuracy.

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