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Short-term Traffic State Forecasting for Dynamic Traffic Routing System

Huasuo Ru[1, a] , Depin Peng[1, 2, b], Lianxiong Gao[3, c] , and Yuan Zhou[1]

[1]Yunnan Land and Resources Vocational College, Kunming, Yunnan, 650217,China

[2]Beijing University of Posts and Telecommunications, Beijing,100876, China

[3]Yunnan University of Nationalities, Kunming, Yunnan, 650031, China

[a]715543134@qq.com, [b]depinpeng@gmail.com, [c]gaolianxiong@gmail.com

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Abstract: The paper researches the problem of how to forecast traffic information in one minute interval. A kalman filter algorithm for short-term traffic forecasting based on the construction of dynamic traffic routing system of Nanning city of China was proposed in this paper, and selected National Road as field calibration, which compared with the real traffic conditions, and the error of predicted results is less than 10%. The results demonstrate the effectiveness of the proposed forecasting model in paper, and the research has a significant contribution for data process of Dynamic Traffic Routing System.

Introduction

Reliable and accurate traffic information enables traffic participants to make better choices of route which may result in a more efficient use of road networks. The provision of reliable and accurate traffic information is increasingly becoming a key service in modern traffic monitoring and dynamic traffic routing system.

The problem of short-term traffic information forecasting is to determine the traffic states in the next time widow, usually in the range of five minutes to half an hour, which cannot meet the requirement of real-time traffic systems, such as dynamic routing system. In practice, traffic information is usually gathered by a single detector. Overall traffic information is then estimated from the individual traffic information observed within a short-time interval. Such a traffic information forecasting problem is characterized by the determination of overall traffic information from a single detector of collection within a time window. If the measurement errors are random and uncorrelated, the overall traffic information can be simply the average of all individual traffic information. However, real traffic information data usually contains outliers which differ substantially from the main body of the data. Such outliers can arise from measurement processes and/or unrepresentative traffic pattern, and can significantly bias overall traffic information forecasting.

Generally speaking, the use of real time information is quite natural since it is always assumed that the change in traffic at a given location is normally gradual rather than abrupt if the time window we consider is of moderate size (e.g. 5 to 30 minutes). Under most situations, one would not expect a drastic drop or surge in traffic flow between two neighboring time intervals under recurrent traffic conditions unless there is a severe incident. It is unlikely that one would be able to predict the occurrence of such an incident. Therefore, most of time, the traffic state at a given time interval should be correlated with the traffic state at the previous time interval. On the other hand, the use of historical information is also reasonable since, at a macroscopic level, traffic patterns at a particular time do seem to repeat themselves from day to day. The key issue to the traffic forecasting problem is how to make use of these two sources of information.

This paper introduces approach for the forecasting of overall traffic information from individual traffic information measurements in one minute interval using kalman filter algorithm for dynamic traffic routing system. The algorithm is general and can be used to forecast traffic information from individual traffic information observations. It is shown that the algorithm is robust and can be readily used in real-time traffic monitoring and dynamic traffic routing system.

The remainder of the paper is organized as follows. In section 2, we will review the past research on the short-term forecasting of traffic information. The forecasting model building will be given in section 3. In section 4, we will evaluate a case study results and calibrate the model. Finally, the conclusions are presented in section 5.

Review of short-term forecasting research

The short-term forecasting of traffic information is the basis of traffic control and guidance. In the past, various approaches have been developed to forecast traffic flow, including ones that are based on the time series model, Kalman filter theory, non-parametric methods simulation models, local regression models, and neural network approaches. From the standpoint of how information is used in different model, we can summary the main short-term prediction method of traffic states as: statistical regression, state estimation, time series, neural network, dynamic traffic assignment and traffic simulation [1-4]. In recent years, scholars continue to propose new algorithms, such as state-space models, Kalman filtering, improved neural network, the cusp catastrophe theory, nonparametric regression, wavelet, fractal, chaos and other nonlinear systems theory [5 - 9].

At present, there are a lot of researches in terms of short-term traffic flow. Anderson and Van Arem used time series model to predict the travel time of sections [3, 10]. Florio and Mussone, Park and Rilett applied artificial neural network to establish the prediction model [11, 12]. Park and Rilett constructed neural network prediction model combined with the Kohonen algorithm to improve prediction results of the neural network model, while it is not suitable for real-time prediction due to high complexity [13, 14]. Dongjoo Park etc.. used expansion of the input layer BP network to build forecasting model for traffic flow, which prediction accuracy is higher than the BP neural network and Kalman filter method [15]. Hussein Dia applied time-delay recurrent neural network to predict travel times of highway, but the prediction accuracy is not high under congested condition, which not suitable for urban traffic prediction [16]. Haino Chen, and Susan Grant-Muller studied that using dynamic neural network model with the number of hidden layer unit adjustable to predict short-term traffic flow [17]. Hongbin Yin used fuzzy neural network based on classification to predict the traffic flow of the upper and lower sections for intersection, and the prediction accuracy was relatively high [18].

In general, the existing short-term traffic flow prediction methods can be roughly divided into two categories: The first category is the traditional mathematical model based on mathematical statistics and calculus; the second type is non-mathematical model prediction methods. The accuracy of the first class prediction algorithm is high, but it is very poor subjected to the restriction of randomness and non-linear of traffic flow changes under incident condition. The second category-based intelligent algorithms get rid of the restrictions to establish a precise mathematical model, but the complexity is high, and the convergence speed ware impacted by the data dimension.

Most of the predictive models and algorithms ware mainly studied for highway or city road traffic flow and travel time prediction, the prediction results of sections' speed is still relatively rare, and the interactive calibration and practicality of forecasting results remain to be verified. Therefore, this paper builds the traffic state forecasting model–based Kalman filter for speed and travel time of sections based on the construction of Nanning dynamic route guidance system, it is verified through actual traffic data of Nanning, and the forecasting results are released using VMS display after data fusion and data processing.

Forecasting model

Kalman filter algorithm. Kalman published his famous thesis using recursive method to solve the problem of discrete data linear filtering. Since then, Kalman Filter has become the subject of promotion and application of research. Kalman Filter is widely applied to estimate system status variable and compress measurement noise and is widely applied in aviation, navigation, radar tracking, control system, manufacturing and many other fields. The basic idea is applying status space model of signal and noise, using the previous estimated value and current measurement value to update estimation value of status variable and then obtain present estimation value. It is usually used to estimate status variable $x \in R^n$ of discrete time process. The equation of this process is presented as follows:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{1}$$

Where u_k is control input, $A \in n \times n$ is status matrix.

Measurement variable as $z \in R^m$ is defined, obtain measurement equation:

$$z_k = Hx_k + v_k \tag{2}$$

Random signal w_k and v_k is separately represented process noise and measurement noise. It is assumed that $w(k)$ and $v(k)$ are zero mean Gaussian white noise process and independent:

$$p(w) \sim N(0,Q) \tag{3}$$

$$p(v) \sim N(0,R) \tag{4}$$

In real system, the covariance Q and R probably change with each iteration calculation.

So, the algorithm procedure of Kalman Filtering is divided as two stages as follows:

Stage 1：time update equation

$$\hat{x}_k^- = A \cdot \hat{x}_{k-1} + Bu_{k-1} \tag{5}$$

$$P_k^- = A \cdot P_{k-1} \cdot A^T + Q, \tag{6}$$

Stage 2：measurement update equation

$$K = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{7}$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-) \tag{8}$$

$$P_k = (I - K_k \cdot H) \cdot P_k^- \tag{9}$$

Where “–”represents a priori, “^”represents estimation.

When filter is realized, the covariance R obtained by measurement is the known conditions. Generally, Q is hard to determine because we can’t measure process signal x_k directly. In both cases, whether we have a reasonable criterion to select coefficient, we also can adjust filter coefficient to get better property (Statistically), and adjusting always is off-line and compare with another determinate linear filter on line.

Experimental results and analysis—A case study of Nanning city

The study field is shown in Fig. 1.

The study area includes five intersections and 18 road sections, that is Southern Ring Road and National Avenue intersection, Xinmin Road and National Avenue intersection, Old Town Road and National Avenue intersection, Park Lake Road and National Avenue intersection and Camellia Park Road and National Avenue intersection. Collect the GPS velocity data and the corresponding time traffic data of these junctions and sections and forecast the traffic information using the Kalman filter algorithm.

Fig. 1 The study area

Case 1. Select the Camellia Park Road and National Avenue intersection as case 1, which is shown in Fig. 2. The data collected from 7:00 to 9:00 2009, January 25 in one minute interval. Through the correlation analysis, the speed of export sections of National Avenue (ID248) is greatest impacted by that of the West entrance of National Avenue (ID247), and the speed of left turning entrance of Camellia Park Road has a direct relationship. Adjust the Kalman filter parameters through trial and error method, and define the error standard as Eq. 10:

$$RME = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{10}$$

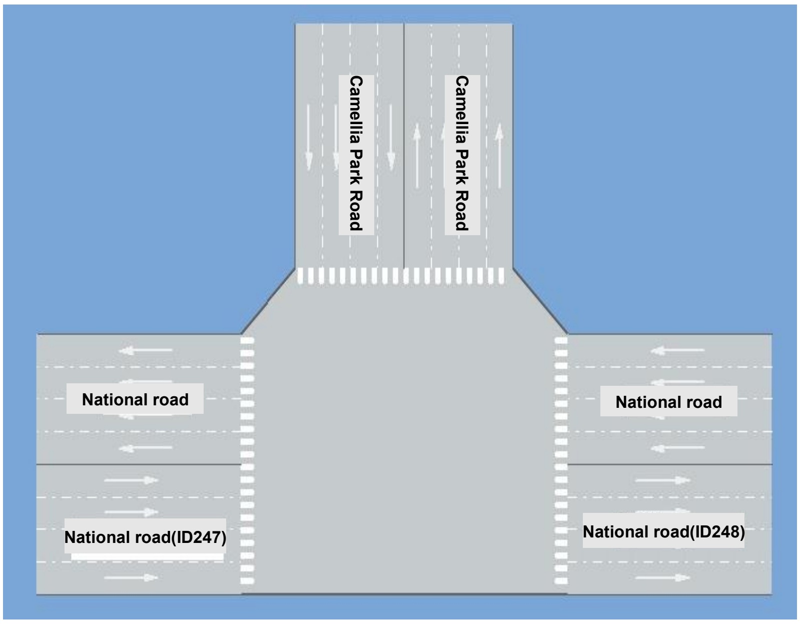
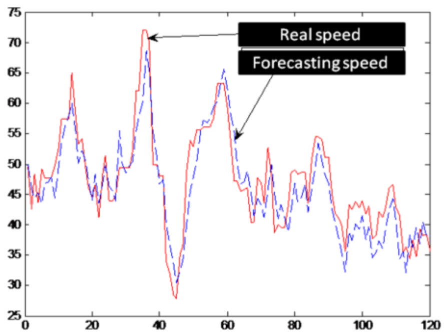


Fig. 2 Camellia Park Road and National Avenue intersection



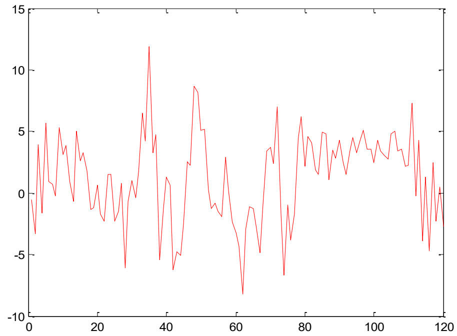


Fig. 3 Left chart is the comparison between real speed and forecasting speed, right chart is error curve

The experimental speed of export section of the National Avenue (ID248) and the comparison between experimental predictions and the actual speed are shown in Fig. 3.

Through the comparison of experimental results and error analysis, the forecast results are approaching to the actual speed, although the predictive value of some points are slightly larger or slightly less than the actual speed, but the relative error is 3.125% less than 10%, therefore, it theoretically meets the actual demand for dynamic traffic routing system.

Case 2. Select the intersection of Park Lake Road and National Avenue as study object, the model is shown in Fig. 4. Data collection is still 7:00 to 9:00 January 25, 2009. a total of 120 sets of data. Forecast the speed of entrance section of Park Rd (ID225), the experimental results are shown in Fig. 5.

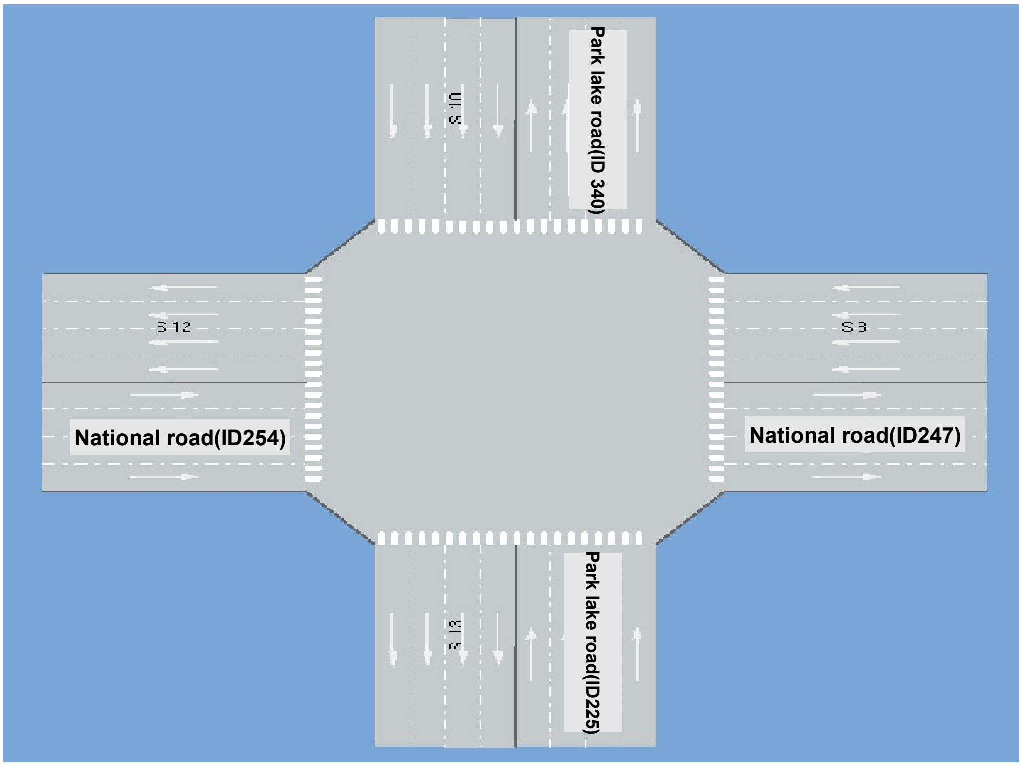


Fig. 4 Park Lake Road and National Avenue intersection

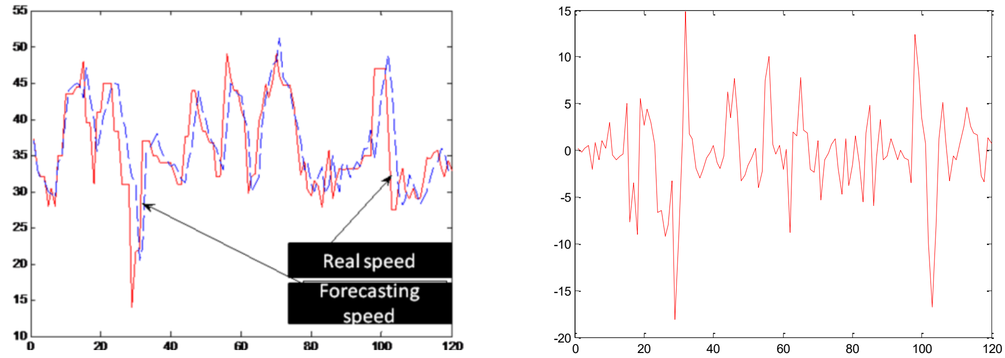


Fig. 5 Left chart is the comparison between real speed and forecasting speed, right chart is error curve

Through the comparison of experimental results and error analysis, the forecast results are approaching to the actual speed, although the predictive value of some points are slightly larger or slightly less than the actual speed, but the relative error is 3.189% less than 10%, therefore, it theoretically meets the actual demand for dynamic traffic routing system.

Conclusions

The effectiveness of kalman filter-based short-term forecasting model is verified by the actual data of Nanning and the experimental results. Although the prediction results error is relative small within 10%, but the prediction results deviation points still exist. And the results are more accurate to meet the real-time requirements predicted by kalman filter algorithm for a single junction, but the parameter adjustment is more complex for area forecasting, and it is not conducive to the practical application, while, it has theoretical value. In addition, the accuracy of the original data has a considerable impact on the traffic forecasting through the comparison between prediction results and real data. In a short, the prediction model proposed in paper is valid and effective verified by the experimental results.

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