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Research on short-term traffic flow prediction method based on real-time traffic status

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Abstract: In order to improve the accuracy of short-term traffic flow prediction, this paper focuses on the influence of road traffic status division on the accuracy of short-term traffic flow prediction. When dividing the road traffic status, the improved road load coefficient is adopted, and the kalman filter method and ARMA algorithm are selected to predict the short-term road traffic flow.

1. The introduction

In recent years, with the rapid increase in motor vehicles, the urban traffic congestion is becoming more and more severe, which has become the bottleneck to the development of the economy and social stability. However, limited land and economic constraints make it impossible for road construction to achieve satisfactory mileage. So intelligent transportation theory arises at this time, followed by intelligent transportation technology. And short-term traffic flow prediction is an important part of intelligent transportation theory and practice which predict traffic flow before it arrives. But there are various traffic flow prediction models nowadays, and to get the most effective and feasible prediction results requires to analyze and predict short-term traffic flow based on different traffic status.

1.1 Research status

The road congestion detection algorithm that was first developed and used in foreign countries is the California algorithm whose main function is to distinguish traffic emergencies. With the subsequent development, the double exponential smoothing algorithm identifying traffic emergencies have emerged, followed by and the bayesian algorithm identifying occasional and frequent traffic congestion.

The development of the domestic urban road traffic condition discrimination starts late, with the emergence of the classification method based on BP neural network, fuzzy clustering state classification method, support vector machine state classification method and state classification method of comprehensive application of various methods. Among them, applying an index to determine the state of the road is widely used.

The traditional load degree (V/C) refers to the ratio between the actual traffic flow and the traffic capacity of a section, which is often applied for dynamic analysis of urban expressway traffic operation status. However, according to the traffic flow theory, the same V/C value may correspond to two different traffic states, so it can be concluded that the load degree evaluation cannot truly reflect the road operation condition.

The prediction models for short-term traffic flow mainly include econometric model, neural network model, nonlinear system theory model, dynamic traffic allocation model, kalman filter method, etc,



among which autoregressive sliding average model, autoregressive model, *kalman filter method and other early prediction* models have been widely used due to their less considerations and simpler operation. However, these three models do not take into account the different characteristics of traffic data under crowded and uncrowded traffic conditions when making short-term traffic flow prediction, so unified prediction may affect the prediction accuracy.

1.2 Target contribution

This paper aims to use the improved time occupancy rate and flow rate as the evaluation criteria for road operation status. The traffic data is divided according to different traffic states, and then the real-time traffic data on the divided road are used to make the prediction by the short-time traffic flow prediction method in different states. The purpose is to study the influence of the data after the divided state on the prediction accuracy of the actual short-time traffic flow.

2. Research idea

This paper plans to divide different traffic states by processing multiple sets of measured traffic data, and then select a variety of short-term traffic flow prediction models to optimize the existing models in specific traffic flow states. The accuracy and the applicability of various traffic prediction methods are compared to improve the pertinence and accuracy of short-term traffic prediction.

3. State division

The effective measured traffic data are selected, and the missing and wrong data are preprocessed. Then the original unit method is used to process the data, and the division method of traffic state is selected and improved based on the feasibility. Traffic state is divided and its effectiveness is evaluated.

Since the traditional load degree (V/C) evaluation cannot truly reflect the road operation condition, the improved time occupancy rate combined with speed and flow rate is used as the evaluation criteria for road operation condition.

The specific principle analysis is as follows:

$$g_{i,t} = \frac{d_{i,t}}{d_{crt}} \quad (1)$$

$g_{i,t}$: load degree of section f at time t

$d_{i,t}$: actual density of section i at time t

d_{crt} : critical density of section i

$$occ = L \times d \quad (2)$$

L : vehicle length (m)

d : vehicle density(veh / km)

It can be concluded from the above formula that there is a linear relationship between density and time occupancy under a certain vehicle length. Therefore, the road section load degree under specified conditions can be calculated by the ratio of the actual time occupancy and the time occupancy at the maximum traffic capacity.

$$g_{i,t} = \frac{d_{i,t}}{d_{crt}} = \frac{L \times d_{i,t}}{L \times d_{crt}} = \frac{occ_{i,t}}{occ_{crt}} \quad (3)$$

$occ_{i,t}$: actual time occupancy of section i at time t

occ_{crt} : time occupancy of section i under the maximum traffic capacity

It can be concluded from formula (3) that we can directly use the ratio of time occupancy to judge the road traffic performance.

4. Prediction method

4.1 Kalman filter prediction model

Kalman filtering was proposed by Kalman in 1960. It regards the signal process as the output of a linear system under the action of white noise. The filtering algorithm is composed of the equation of state of the system, the observation equation, the observation noise and the statistical characteristics of the system noise.

Table 1. Summary of formula variables and parameters derived by Kalman filtering.

Variable	Definition
x_n	The state at time n
y_n	Observed value at time n
$F(n+1, n)$	Transfer matrix from time n to time n+1
$C(n)$	Measurement matrix at time n
$Q_1(n)$	Correlation matrix of process noise
$Q_2(n)$	Correlation matrix of the observed noise
$G(n)$	Kalman filter gain at time n
$R(n)$	The correlation matrix for the new information vector
$k(n, n-1)$	The error correlation matrix in $x(n)$

The core algorithm of Kalman prediction model:

$$x(n) = F(n, n-1)x(n-1) + G(n)\bar{y}(n) \quad (4)$$

$$G(n) = F(n+1, n)k(n, n-1)C^H(n)R^{-1}(n) \quad (5)$$

$$k(n, n-1) = F(n, n-1)K(n-1)F^H(n, n-1) + Q_1(n) \quad (6)$$

$$k(n) = k(n, n-1) - F(n, n+1)G(n)C(n)k(n, n-1) \quad (7)$$

$\bar{x}(n)$: The optimal estimation of the state under the criterion of minimum mean square error x_n

\bar{y}_n : The optimal estimate of y_n

$$y_n = C(n)x(n)$$

$\bar{y}(n)$: ignores errors caused by observation noise and process noise

$$\bar{y}(n) = y_n - y_n$$

4.2 Autoregressive sliding average prediction model

Autoregressive Moving Average Model is an important method for time series research, which is composed of autoregressive model (AR model) and moving average model (MA model). ARMA can describe both the statistical characteristics of data and the dynamic characteristics of the system. The

stochastic nature of the process is time-invariant, all sample points fluctuate randomly above and below a certain horizontal line. The basic principle is as follows:

The data sequence formed by the predictors over time is regarded as a random sequence, and the dependence of this group of random variables reflects the continuity of the original data in time. On the one hand, it is affected by the factors; on the other hand, it has its own variation rule. It is assumed that the influencing factors are x_1, x_2, \dots, x_k , and the regression equation obtained by regression analysis is as follows:

$$Y_t = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + Z$$

Where Y is the observed value of the predicted object and Z is the error. As a predicted object, Y_t is affected by its own changes, and its rule can be reflected in the following equation:

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + Z_t$$

The error term has a dependency relationship in different periods, which can be expressed as follows:

$$Z_t = \epsilon_t + \alpha_1 \epsilon_{t-1} + \alpha_2 \epsilon_{t-2} + \dots + \alpha_q \epsilon_{t-q}$$

5. Example

5.1 Data acquisition and processing

This paper is based on the data collected by six RTMS of second ring road in Beijing from December 1, 2003 to December 5, 2003.

The RTMS detector selected in the experiment is located in the Second Ring Road of Beijing with four lanes in total. The selected time period is a working day.

Invalid data refers to the loss and error of data caused by machine failure, weather or other factors.

$$0 \leq q_d \leq \frac{cf_c}{60} \quad (8)$$

q_d : Traffic volume

C : road traffic capacity (veh/h)

T : time interval of data collection (minute)

f_c : Correction coefficient (generally 1.3-1.5)

Formula (8) defines the reasonable range of flow data. In this test, according to the working principle of RTMS and road characteristics, $C=2000$ vehicles /h, $t=30$ ms, $f_c=1.4$.

$$0 \leq v_d \leq f_v v_t \quad (9)$$

v_t : The speed limit of the road is different for different road classes;

f_v : Correction coefficient (generally in 1.3 1.5)

Formula (9) defines the reasonable range of road speed. According to the working principle of RTMS and road characteristics, it is determined that $v_t=40$ km/h, $f_v=1.4$.

5.2 Road operation state division

We calculate $g_{i,t}$ after choosing traffic conformance $g_{i,t}$ as the main basis for the state division. Combined with traffic compliance $g_{i,t}$, and the time-varying law in the z-graph of time-traffic load degree, the classification criteria are determined in this paper as follows:

Table 2. Road traffic status classification standards.

Road traffic condition	Conform to the degree of $g_{i,t}$
crowded	≥ 0.9
open	≤ 0.9

5.3 Traffic flow prediction model design based on Kalman filtering

Supposing the traffic flow at time T of a certain section is Y(T), and the traffic flow at the following moments after T is Y(T+). Considering that the traffic flow at time T is closely related to the traffic flow at the first three moments, the predicted value of Y(T) Y*(T) can be obtained from equation (10).

$$Y^*(T)=H_0*Y(T-\tau)+H_1*Y(T-2\tau)+H_2*Y(T-3\tau)+w(t) \quad (10)$$

Where Y(T-), Y(T-2), Y(T-3), respectively for this segment T-, T-2, T-3 measured traffic flow, H0, H1, H2 as parameter matrix, w(T) as observed noise (defined as gaussian white noise), in practice we take 2 minutes.

The Kalman filtering theory is applied to predict the traffic flow. The prediction steps are as follows:

Transfer matrix parameter calibration, in Matlab using armax function based on the prediction error parameter estimation for calibration;

Set initial parameters:

The initial value of the state transition matrix F in the Kalman filter equation is set to the parameter matrix trained after parameter identification.

Initial value of process noise correlation matrix: in Matlab simulation software, random function and covariance function are used to solve.

Initial value of measurement noise correlation matrix: in Matlab simulation software, the random function is used to solve. In this paper, the observed data are one-dimensional time series.

The initial value of the state vector predictive estimation is designed as a random function, and the initial value of the state vector filtered estimation is F times the initial value of the state vector predictive estimation.

Recursive prediction using Kalman filter theory:

- (1) Set recursive loop variable I, and the number of recursions is the predicted length;
- (2) Observation matrix update:

$$C(I) = [Y_{real}(I), Y_{real}(i-1), Y_{real}(i-2)] \text{ is the initial value;}$$

The Kalman filter gain calculation: $G(I) = F(I+1, I), K(I, I-1) C^T H(I) R^{-1}(I)$;

- (3) Calculate the information error matrix:

$$y'(i) = y(i) - C(i)F(i, i-1)X(i|i-1) [y(i) \text{ is the observed value}]$$

$$X(i, i) = F(i, i-1)X(i-1, i-1) + G(i)y'(i)$$

$$K(i+1, i) = F(i+1, i)K(i)F^T H(i+1, i) + Q1(i)$$

- (4) Calculate the estimated value of state vector at time i+1: $X(i+1, i) = F(i+1, i)X(i, i)$;
- (5) According to the estimated state value, the estimated predicted value of the observed value is:

$$y(i+1, i) = C(i)X(i+1, i) + R$$

(6) The loop variable increments by 1, repeating the above steps until the loop variable equals the predicted length.

5.4 ARMA prediction model design

ARMA sets the order of autoregressive as 3 and the order of noise characteristics as 2.

5.5 Error index and significance of traffic flow prediction

In the research system of traffic flow prediction, there are relatively perfect performance evaluation indexes, which are as follows:

- (1) Mean absolute error:

$$MAE = \frac{1}{N} \sum |Y_{real} - Y_{predict}|$$

MAE mainly reflects the mean absolute value of the error between the real value and the predicted

value.

- (2) Mean relative error:

$$\text{MRE} = \frac{1}{N} \left\{ \sum \frac{|Y_{\text{real}} - Y_{\text{predict}}|}{Y_{\text{real}}} \right\} * 100\%$$

Mean relative error (MRE) can be used to characterize the degree of deviation between the predicted value and the true value. The smaller the value is, the smaller the deviation between the predicted value and the actual value is, and the better the prediction effect is.

- (3) Mean square error:

$$\text{MSE} = \frac{1}{N} \sum (Y_{\text{real}} - Y_{\text{predict}})^2$$

Mean square error (MSE) is used to reflect the error distribution. The smaller its value is, the more concentrated the error distribution will be and the better the prediction effect will be.

- (4) Mean square percentage error:

$$\text{MSPE} = \frac{1}{N} \left\{ \sum \left(\frac{Y_{\text{real}} - Y_{\text{predict}}}{Y_{\text{real}}} \right)^2 \right\} * 100\%$$

The mean square percentage error (MSPE) also reflects the error distribution and the deviation between the predicted value and the actual value to a certain extent.

- (5) Equality coefficient:

$$\text{EC} = 1 - \frac{\sqrt{\sum (Y_{\text{real}} - Y_{\text{predict}})^2}}{\sqrt{\sum Y_{\text{real}}^2 + \sum Y_{\text{predict}}^2}}$$

The value of the equality coefficient (EC) is used to indicate the fitting degree between the predicted value and the real value. The larger the value is, the higher the curve fitting degree is, and the better the prediction effect is. Generally speaking, when $\text{EC} > 0.9$, the system has a good prediction effect.

5.6 Analysis of traffic flow prediction results

5.6.1 Analysis of status prediction results

The RTMS data collected in Beijing east second ring road from December 1, 2003 to December 5, 2003 is into two states: C (congestion state) and NC (non-congestion state). The longest continuous data is used for parameter calibration and prediction, and 2min counting is used for flow prediction, the C state basic at 17:00 PM to 18:00 PM, the other for NC State.

After Matlab programming calculation, the experimental results of the two models are as follows:

- (1) Prediction comparison between the two models in the crowded state is shown in figure 1 and 2.

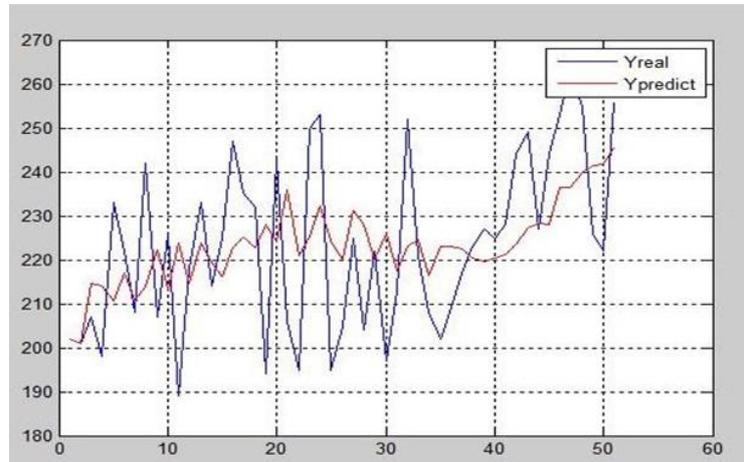


Figure 1. Comparison between the predicted value and the actual value of the ARMA model predicting the C state of congestion.

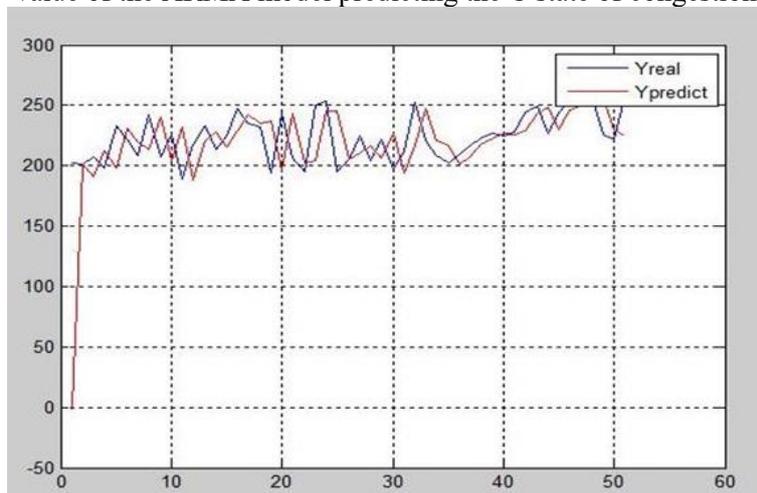


Figure 2. Comparison between the predicted value and the actual value of the model predicted crowded C state based on Kalman filtering.

(2) Prediction comparison between the two models in the uncrowded state is shown in figure 3 and 4.

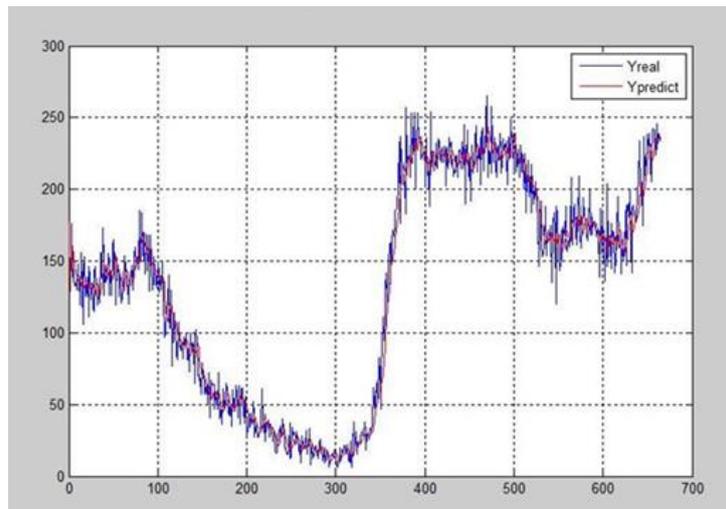


Figure 3. Comparison between the predicted and actual values of uncrowded NC state predicted by ARMA model.

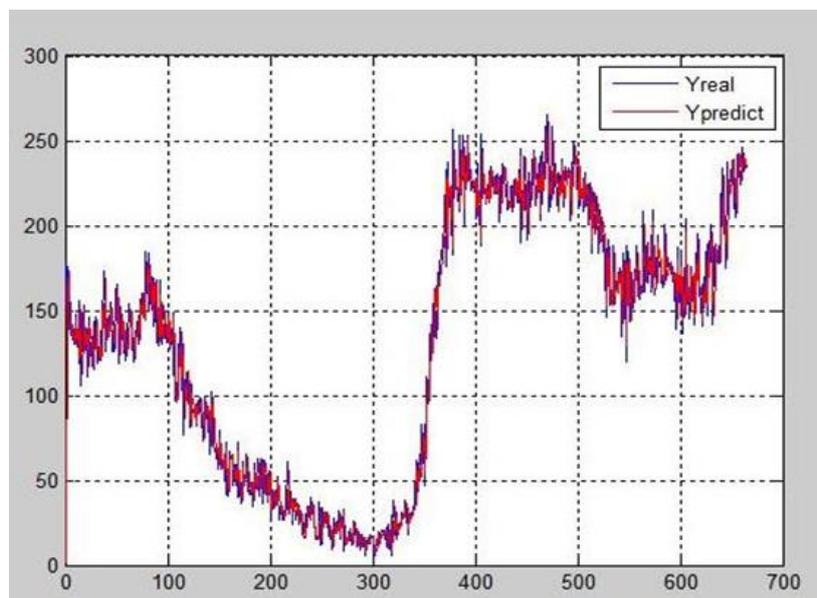


Figure 4. Comparison between the predicted value and the actual value of the predicted uncrowded NC state by the model based on Kalman filtering.

Refer to the definition of error index in the previous chapter, and then calculate the performance index of the prediction model. The results are shown in the following table:

Table 3. Performance indexes of traffic flow prediction under divided conditions.

	MAE	MSE	MRE(%)	MSPE(%)	EC
ARMA-C	14.6236	308.7221	6.60	0.65	0.9607
ARMA-NC	11.2517	216.7367	13.96	5.88	0.9518
Kalman-C	18.6177	514.9939	8.42	1.08	0.9496
Kalman-NC	12.99	294.1591	15.57	7.53	0.9438

Cross analysis can get from this table four cases has obvious characteristics, C status of MAE, MSE is higher than NC state, and the state of the C MRE, MSPE than NC state is much lower, MAE and

MRE abnormal suggested that in the greater the peak traffic congestion state, the difference of the denominator of the MRE is obvious. The relationship between MSE and MSPE is similar for this reason.

In comparison, in the condition of C, ARMA model in the first four indicators are smaller than the Kalman model, EC indicators, the indicators dominant, more should use ARMA model, the NC state, the ARMA model also show the result more accurate, investigate its reason, we can think of in the case of volatility, ARMA model can obviously maintain their volatility, on the contrary kalman is more suitable for prediction when state changes, after our separation form two data sets, but their own movements, ARMA model is better obviously.

5.6.2 Analysis of undivided state prediction results

The RTMS data collected in Beijing east second ring road from December 1, 2003 to December 5, 2003 is selected and preprocessed according to the classification state.

After Matlab programming calculation, the experimental results of the two models are as follows:

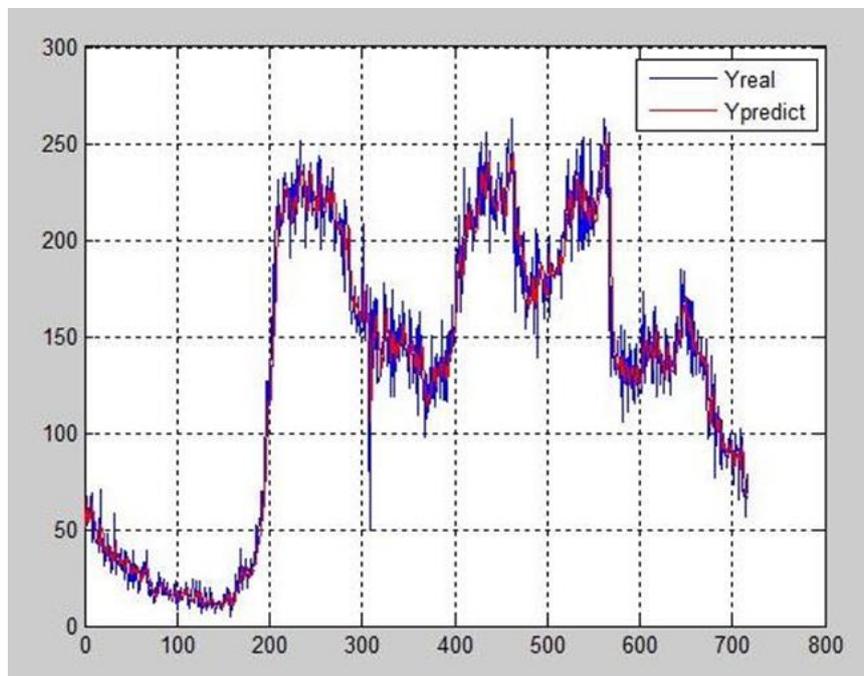


Figure 5. Comparison between the predicted value and the actual value of ARMA model prediction

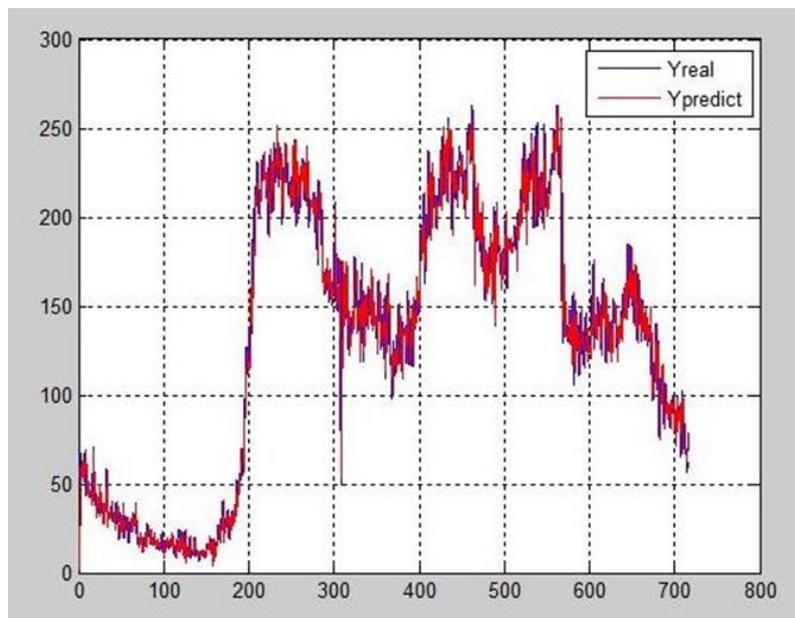


Figure 6. Comparison between the predicted value and the actual value of the model based on kalman filtering.

Refer to the definition of error index in the previous chapter, calculate the performance index of the prediction model, and the calculation results are shown in the following table:

Table 4. Performance indexes of traffic flow prediction in the undivided state.

Method	MAE	MSE	MRE	MSPE	EC
ARMA	12.0473	269.9683	13.53%	5.01%	0.9458
Kalman	14.2065	373.4959	16.01%	7.17%	0.9364

Comparing with the results and indicators of the previous section, we can predict that whether or Kalman model ARMA model, MAE and MSE indicators should be in the model points between the two results of condition forecasting, but EC contrast, undifferentiated state after state points than before the model to predict both EC value lower, EC value is the bigger the better, as you can see points in predicting more targeted, prediction effect is also more accurate.

6. The research conclusion

6.1 Research results

This paper predicts the measured data using Kalman filtering theory and the theory of autoregressive moving average. It first divides the measured traffic data in different road traffic state into two groups, and then respectively evaluates the indexes of the predicted results. Finally, some suggestions on road traffic state forecasting and traffic flow forecasting are formed. It can be seen in table 3 that one state is not absolutely superior to the other in the same model, that is to say, different states have their own advantages and disadvantages, but it can be concluded that the state-separated ARMA model is more accurate than the Kalman model in any state. And it can be seen from table 3 and 4 that the EC value in the undivided state is lower than that in the undivided state, which also proves that the prediction in the undivided state is more accurate than that in the undivided state.

6.2 Applicability of the method

This study has some extensibility but also some limitations. The results of this study prove that for short-term traffic flow prediction, state partitioning has a great impact on the prediction accuracy of the ARMA model of the Kalman filter model. At the same time, ARMA model prediction can be extended to improve the accuracy when the tidal characteristics of road traffic are obvious and the conditions of each lane are similar. However, different state partitioning methods and different model predictions may lead to different predicted results.

6.3 Application prospect

In recent years, with the traffic congestion problem becoming increasingly severe, to solve the urban traffic congestion problem and to maximize the efficiency of the whole transportation system are important issues to us nowadays. Short-term traffic flow prediction can predict the traffic flow before it arrives, so as to allocate the traffic flow in advance. However, nowadays there are numerous prediction models for traffic flow, so how to get the most effective and feasible prediction results still needs further study.

The analysis and prediction of short-term traffic flow based on different traffic conditions in this paper can improve the accuracy of the prediction results, which are applicable to all large and medium-sized cities. It is of great significance to alleviate traffic congestion and give full play to the operation ability of the traffic system.

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