

Available online at www.sciencedirect.com

ScienceDirect

Procedia - Social and Behavioral Sciences 138 (2014) 811 – 818

Procedia
Social and Behavioral Sciences

The 9th International Conference on Traffic & Transportation Studies (ICTTS'2014)

Travel Time Prediction Model for Urban Road Network Based on Multi-source Data

Zhou Jiang*, Cunbao Zhang, Yinxia Xia

Intelligent Transport System Research Center, Wuhan University of Technology, No.1040 Heping Road., Wuchang District, Wuhan 430063, P.R. China

Abstract

In view of the deficiencies of single data source for travel time prediction, multi-source data are used to improve the precision of travel time. Floating car and fixed detector are commonly used in traffic data collection, and they have certain complementarities in data types and accuracy. Therefore, the real-time traffic data of these two detectors are used as input parameters of prediction model, and Kalman filtering theory is used to establish travel time prediction model of urban road network. Finally, the model is simulated by Vissim 4.3 and the simulation results show that the average absolute relative error of travel time based on multi-source data is 5.18%, and it is increased by 13.4% comparing with fixed detector data and increased by 7.2% comparing with floating car data.

© 2014 Elsevier Ltd. This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/3.0/>).

Peer-review under responsibility of Beijing Jiaotong University(BJU), Systems Engineering Society of China (SESC).

Keywords: multi-source data; travel time prediction; urban road network; Kalman filtering; Vissim simulation

1. Introduction

The amount of cars is growing rapidly these years and urban road networks become more and more crowded. Due to the limitation of urban space, it is difficult to improve the capacity of network only by building new roads. In order to make travelers use the existing road system effectively, it's necessary to release dynamic traffic information for travelers. Travel time prediction (TTP) is an important part of traffic information release, which has been a hot

*Corresponding author. Tel.: +86-158-2722-7641.

E-mail address: 15827227641@163.com

spot for about two decades. Many previous studies have been focused on travel time prediction using various methods, such as the time-series models (Al-Deek et al., 2002), the artificial neural network models (Rilett and Park, 2004), the non-parametric regression method (Rilett and Park, 2004), the weighted moving average and cross correlation methods (Sisiopiku et al., 2006), etc. Among them, the kalman filter model is widely used because of its high efficiency and accuracy. For example, Zhu and Yang (1999) and Wen et al. (2006) used kalman filter model to predict travel time base on the fixed detector data; Tang (2011) and Zhu (2007) used the floating data to predict travel time by the kalman filter model. Mostly a single data source was used to predict travel time, and the result was not accurate enough because single data source can not reflect traffic state of road network exactly.

As floating car and fixed detector have strong complementarities in traffic data types and accuracy, this paper uses the kalman filter model based on multi-source data to improve the accuracy of travel time prediction for urban road network.

2. Selection of Model Parameters for Travel Time Prediction

Currently, floating car and fixed detector are widely used in traffic data collection. The cost of floating car detection is low, and the accuracy of data is high, but it only gets the speed and real-time position information. In addition, because of the arbitrariness of floating car running routes, it affects the coverage and accuracy of detection data. The accuracy of fixed detector measurement is relatively high, but the equipment is easily affected by external environment. Fixed detectors cannot acquire some important parameters such as travel time, average speed of road section, etc.

The advantages and disadvantages of these two detection methods have certain complementary in order to improve the accuracy and reliability of released information, two kinds of detection data can be used as model input parameter to improve the accuracy of travel time prediction. Data fusion is necessary especially in the dynamic traffic information acquisition system, which is jointly determined by the advantages of data fusion and the characteristics of traffic information.

The selection of model parameters is need to consider after deciding to use floating car and fixed detector testing data for travel time prediction. Because urban road travel time is associated with the time a few hours before the forecast period; and path is a part of network that the travel time is affected by the traffic conditions of surrounding roads and connecting roads. So different periods of route travel time and traffic flow, traffic density are chosen as input parameters of forecasting model, and it can reflect the change of traffic status through the change of parameters. Considering actual application, the speed data from loop detector is related with its location, so it is difficult to fully reflect traffic state of road area. Therefore, this paper chooses traffic flow and traffic density detected by fixed detector, and travel time data collected by floating car as input parameters of the proposed travel time prediction model.

3. Travel Time Prediction Model for Urban Road Network Based on Multi-source Data

Travel time is an important parameter for describing the state of urban road network, and it can directly reflect the condition of road congestion. Owing to the changing of traffic data consistently, the predicted travel time must meet real-time requirements. Therefore, this paper fully considers the requirements of real-time, and establishes travel time prediction model based on Kalman filtering, which utilize real-time floating car data and loop data.

3.1. Basic Idea

Kalman filtering model for travel time prediction considers that the actual travel time is the sum of basic travel time and random error. Basic travel time is obtained by calculation with the detector data in forecast section, and random error is gained by the recursive calculation with the measuring equation (Hang et al., 2002). Because of the dynamic randomness of traffic flow and the error in observation, a random error term w_k is added to revise the deviation. On the whole, the mathematical expectation of random error term w_k is zero and the variance is σ^2 , and $(C_k X_k + w_k)$ is the unbiased estimate of actual travel time.

For example, there is a road with 4 intersections (shown in figure 1), The section point A to point B in figure

1(the region arrows represent) is the section to be investigated. The section contains three intersections and it is equipped with four groups of detectors (No. 1, 2, 3, 4). Detectors detect four sizes of traffic density, and it can be deemed to that the forecast section is divided into different traffic states. Traffic flow and density data detected by each group detector stands for the traffic state in every section. The section here is defined as the road between the upstream intersection stop lines to the downstream intersection stop lines. According to the section distinguished, travel time in AB section is the cumulative value of travel time t_1 , t_2 , t_3 and t_4 . Then the random error is added to correct the deviation. Considering the shortage of the data detected by fixed detectors, travel time in AB section detected by floating car is used to make predictions to improve the accuracy.

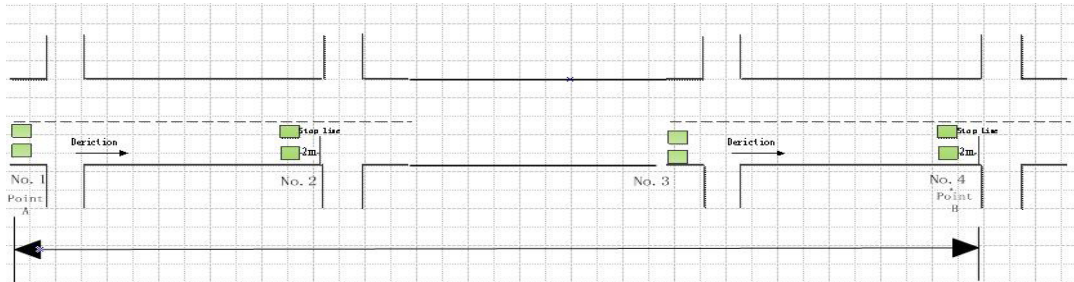


Fig. 1. The road sections for travel time prediction

Three parameters including traffic flow, density and travel time are used as input parameters of the kalman filtering model. The weight coefficient is regarded as the system state variable to establish the prediction model, and the form of forecast model established by different input parameters is the same. Therefore, the travel time data, traffic density data and traffic flow data are combined to make a parameter matrix and the weight coefficients make up a state matrix to create a travel time prediction model combined with Kalman filter equations. The model not only can avoid the shortage of single data source, but also can reflect the change of traffic state in the whole section in time and space.

3.2. Travel Time Prediction Model Based on Multi-source Data

Based on the basic ideas above, the travel time prediction model based on multi-source data is established using kalman filtering theory. Let $T(\tau + 1)$ is the travel time of next period after τ period, which is the time to be predicted. It is related with traffic density and traffic flow in the τ period, and it is also related to the travel time in τ period and the time before τ period. Let $T(\tau)$ is the travel time of τ period; $T(\tau - 1)$ is the travel time one period before τ period; $T(\tau - 2)$ is the travel time two periods before τ period. $K_n(\tau)$ and $Q_n(\tau)$ are the average traffic density and velocity detected by loop detector n in τ time. Therefore, travel time prediction model for urban road network can be established as follows:

$$T(\tau + 1) = [Ht_0T(\tau) + Ht_1T(\tau - 1) + Ht_2T(\tau - 2) + Hk_1(\tau)K_1(\tau) + Hk_2(\tau)K_2(\tau) + \dots + Hk_n(\tau)K_n(\tau) + Hq_1(\tau)Q_1(\tau) + Hq_2(\tau)Q_2(\tau) + \dots + Hq_n(\tau)Q_n(\tau)] / 3 + w(\tau) \tag{1}$$

Where Ht_0 , Ht_1 , Ht_2 are the weight ratio of $T(\tau)$, $T(\tau - 1)$, $T(\tau - 2)$; Hk_1 , $Hk_2 \dots Hk_n$ are the weight ratio of $K_1(\tau)$, $K_2(\tau)$, $\dots K_n(\tau)$; Hq_1 , $Hq_2, \dots Hq_n$ are the weight ratio of $Q_1(\tau)$, $Q_2(\tau)$, $\dots Q_n(\tau)$. They are closely related to the change of the state in road network, and they are the state variables.

Let $A = [T(\tau), T(\tau - 1), T(\tau - 2), K_1(\tau), K_2(\tau), \dots, K_n(\tau), Q_1(\tau), Q_2(\tau), \dots, Q_n(\tau)] \tag{2}$

$$X(\tau) = (Ht_0, Ht_1, Ht_2, Hk_1, Hk_2, \dots, Hk_n, Hq_1, Hq_2, \dots, Hq_n)^T \tag{3}$$

$$Y(\tau) = T(\tau+1) \tag{4}$$

Then,
$$X(\tau) = B(\tau)X(\tau-1) + u(\tau-1) \tag{5}$$

$$Y(\tau) = A(\tau)X(\tau) + w(\tau) \tag{6}$$

Where $y(\tau)$ is the observation vector which is the travel time to be predicted next period, $X(\tau)$ is the state vector which is the weight ratio in τ time. $A(\tau)$ is the observation vector which is the detected data such as Q_n , K_n and $T(\tau)$ in τ time. $B(\tau)$ is the state transition matrix, and it expresses the relationship of state between $\tau - 1$ period and τ period. $w(\tau)$ is the measurement noise which is assumed to be a Gaussian sequence with zero mean and covariance $R(\tau)$. $u(\tau-1)$ is the noise of model which is assumed to be a Gaussian sequence with zero mean and covariance $Q(\tau-1)$.

As is known to all, Kalman filter equations can be represented as follows:

$$\bar{X}(\tau) = \bar{X}(\tau / \tau - 1) + K(\tau)[y(\tau) - A(\tau)\bar{X}(\tau / \tau - 1)] \tag{7}$$

$$\bar{X}(\tau / \tau - 1) = B(\tau)\bar{X}(\tau - 1) \tag{8}$$

$$K(\tau) = P(\tau / \tau - 1)A^T(\tau)[A(\tau)P(\tau / \tau - 1)A^T(\tau) + R(\tau)] \tag{9}$$

$$P(\tau / \tau - 1) = B(\tau - 1)P(\tau - 1)B^T(\tau - 1) + Q(\tau - 1) \tag{10}$$

$$P(\tau) = [I - K(\tau)A(\tau)]P(\tau / \tau - 1) \tag{11}$$

Kalman filter algorithm above constitutes a loop which is shown in figure 2:

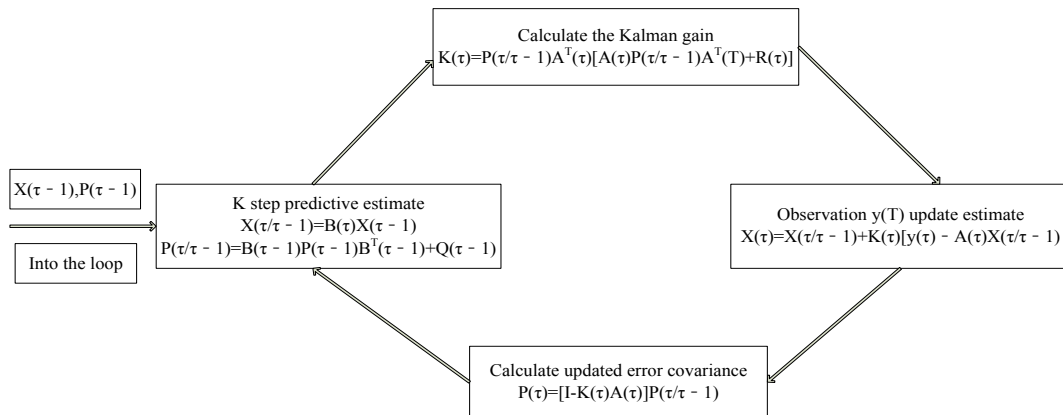


Fig. 2. Kalman Filter loop

Thus, travel time prediction value $T(\tau+1)$ of urban road network can be obtained by the Eq. (1) to Eq. (11).

3.3. Improved input parameters of prediction model

Because every day’s traffic state is similar, the original value of traffic flow and the density is replaced by the ratio of traffic flow and lane occupancy of two days which are corresponded in two weeks. The original data of travel time is replaced by the ratio of travel time in two days. Travel time is predicted by predicting the size of travel time ratio.

$$\text{Let } T(\tau) = T(d, \tau) / T(d-1, \tau) \tag{12}$$

$$Q(\tau) = Q(d, \tau) / Q(d-1, \tau) \tag{13}$$

$$K(\tau) = K(d, \tau) / K(d-1, \tau) \tag{14}$$

Where $T(d-1, \tau)$, $Q(d-1, \tau)$, $K(d-1, \tau)$ represent the travel time, traffic flow and traffic density respectively of τ period at corresponding day last week. While $T(d, \tau)$, $Q(d, \tau)$, $K(d, \tau)$ represent the travel time, traffic flow and traffic density respectively of τ period this week.

The actual predictive value of travel time can be calculated like this:

$$T(d, \tau+1) = T(d-1, \tau+1) * T(\tau+1) \tag{15}$$

Where $T(\tau+1)$ is calculated by Kalman filter equation.

4. Simulation Experiment and Analysis

In order to verify the effectiveness of travel time prediction model based on Kalman filtering theory, we use the Vissim simulation software to simulate the traffic status of urban road. We can get traffic data such as travel time, lane occupancy and vehicle velocity data, and input them to the model to predict travel time of each time period. Then, apply the simulation data respectively to the kalman prediction model based on single source data and multi-source data.

4.1. Simulation Experiment Scheme

A simple road network for simulation experiment is shown in figure 3. In the network, the number of vehicles is set according to the traffic flow of every day, and each intersection is controlled by the timing. The predicted path is shown in figure 3 which is yellow (point A to point B), it contains six intersections, and the length of total is 3.1 km. The data of path travel time, average traffic density and vehicle velocity is obtained by detectors, and the data is satisfied every 5 minutes.

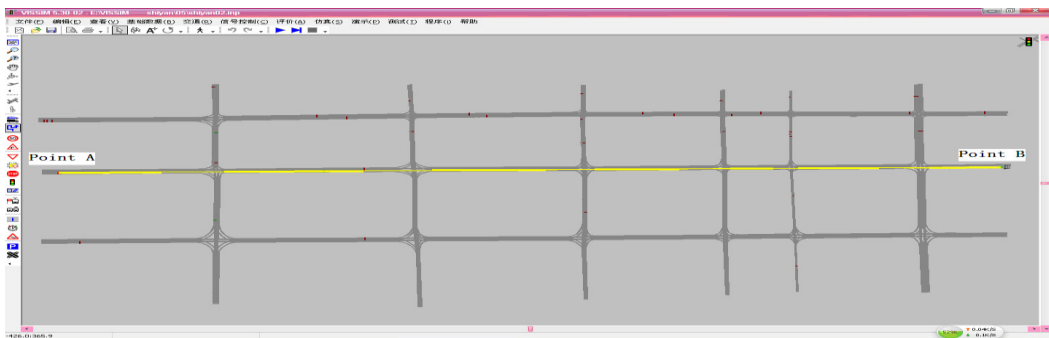


Fig.3 Transportation network diagram of Vissim simulation experiment

4.2. Evaluation of travel Time Prediction Accuracy

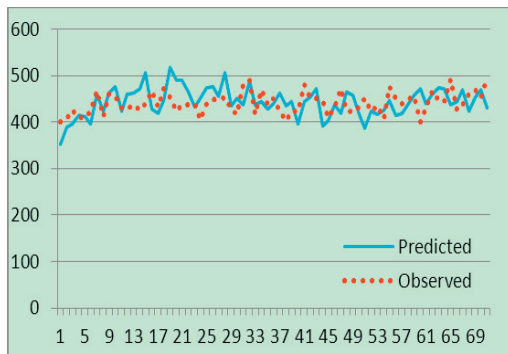
In order to evaluate the forecasting results, the error indicators are introduced as follows:

Relative error:
$$Rerr = \frac{T_{pred}(t) - T_{real}(t)}{T_{real}(t)} \tag{16}$$

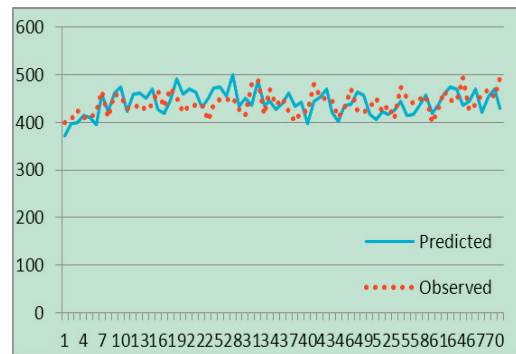
Mean relative error:
$$Mrerr = \frac{1}{N} \sum \frac{T_{pred}(t) - T_{real}(t)}{T_{real}(t)} \tag{17}$$

Mean absolute relative error:
$$Marerr = \frac{1}{N} \sum \left| \frac{T_{pred}(t) - T_{real}(t)}{T_{real}(t)} \right| \tag{18}$$

Applying the simulation data to prediction model based on multi-source and its improved model, the prediction result got by the Matlab programming is shown as follows:

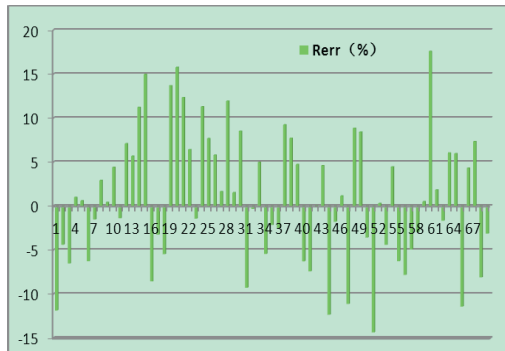


(a) Prediction result based on multi-source data

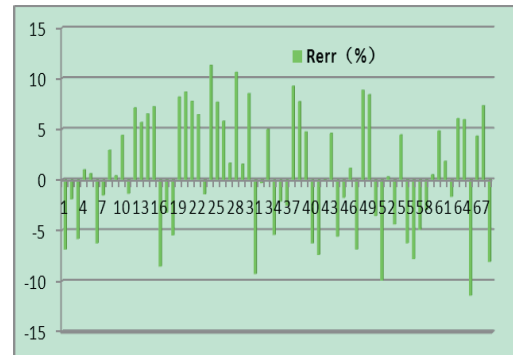


(b) Prediction result based on improved multi-source data

Fig4. Travel time prediction result of urban road network based on multi-source data



(a) Relative error based on multi-source data



(b) Relative error based on improved multi-source data

Fig5. Travel time prediction error of urban road network based on multi-source data

Figure 4(a) and Figure 4(b) show that the predicted values fluctuate up and down near the observation values, and the variation tendency is consistent. For figure 5(a) and figure 5(b), the maximum error of travel time prediction in urban road network based on multi-source data is less than 18% and 12% respectively.

In order to compare the accuracy with other prediction models, the simulation data were applied to kalman prediction model based on single source data (fixed detector data or floating car data). Error indicators of three kinds of prediction models are as shown in Table 1 by calculation:

Table 1. The prediction error of three kinds of models

category	Fixed detector data,	Floating car data	Fixed detector and floating car data
M_{ka}	28%	22% ,	12%
M_{er}	-1.63%	1.26% ,	-0.66%
M_{ar}	18.52%	12.37%,	5.18%

Table 1 shows that the error value of kalman prediction model based on multi-source data is relatively small and the prediction accuracy compared with other two kinds of prediction models increases by 13.4% and 7.2% respectively. Obviously, prediction model based on multi-source data is more accurate than single source data.

5. Conclusion

In this paper, we described the advantages of kalman filtering for travel time prediction and discussed the necessity of data fusion with floating car data and fixed detector data. Then travel time prediction model based on kalman filtering theory is established using the real-time floating car data and inductive loop data, and the model parameters are improved accordingly. Finally, experiment results show that the effect of travel time prediction model based on multi-source data is better than single source data, which can provide theoretical support for practical application.

The prediction effect of the proposed model is quite good, but there still have some problems should be studied further. For example, the related factors influencing the prediction accuracy of kalman filtering model is not studied in this paper, and the application of travel time prediction model in the case of traffic incident needs further verification.

Acknowledgement

This study is supported by the National Natural Science Foundation of China (51108361) and the Science and Technology Projects of Zhejiang Provincial Communication Department (2012T21), China.

References

- Al-Deek, M., D'Angelo, M. & Wang, M. (2002). Travel time prediction with nonlinear time series. *Proceedings of the 5th ASCE International Conference on Applications of Advanced technologies in Transportation*, 317-324.
- Hang, M., Yang, X. & Peng, G. (2002). Study of predicted travel time in urban expressway based on Kalman filter. *Journal of Tongji University*, 30, 1068-1072.
- Rilett, K. & Park, D. (2004). Direct forecasting of freeway corridor travel times using spectral basis neural network. *Transportation Research Record*, 1617, 16 -170.
- Sisiopiku, V. P., Roupail, N. M. & Santiago, A. (2006). Analysis of correlation between arterial travel time and detector data from simulation and field studies. *Transportation Research Record*, 1457, 166-173.
- Tang, J. (2011). *Freeway link travel time prediction research and system implementation based on float car data*. China Academic Journal Electronic Publishing House.

Wen, H., Xu, J. & Fu, H. (2006). Estimation algorithm with Kalman filtering for road travel time based on Grey relation analysis. *Journal of South China University of Technology (Natural Science Edition)*, 34, 66-75.

Zhu, A. (2007). *Research on link travel time prediction method based on data collected by floating car*. China Academic Journal Electronic Publishing House.

Zhu, Z. & Yang, Z. (1999). A real-time travel time estimation model based on the kalman filtering theory for traffic flow guidance system. *Systems Engineering-theory & Practice*, 9, 74-78.