Urban Traffic Congestion Prediction Using Floating Car Trajectory Data

Qiuyuan Yang[1], Jinzhong Wang[1], Ximeng Song[1], Xiangjie Kong[1,2,3](✉), Zhenzhen Xu[1], and Benshi Zhang[1]

[1] School of Software, Dalian University of Technology, Dalian 116620, China
xjkong@ieee.org

[2] Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai 200240, China

[3] Key Laboratory of Control Engineering of Henan Province, Henan Polytechnic University, Jiaozuo 454000, China

Abstract. Traffic congestion prediction is an important precondition to promote urban sustainable development. Nevertheless, there is a lack of a unified prediction method to address the performance metrics, such as accuracy, instantaneity and stability, systematically. In the paper, we propose a novel approach to predict the urban traffic congestion efficiently with floating car trajectory data. Specially, an innovative traffic flow prediction method utilizing particle swarm optimization algorithm is responsible for calculating the traffic flow parameters. Then, a congestion state fuzzy division module is applied to convert the predicted flow parameters to citizens' cognitive congestion states. We conduct extensive experiments with real floating car data and the experimental results show that our proposed method has advantage in terms of accuracy, instantaneity and stability.

Keywords: Floating car · Particle swarm optimization · Traffic congestion prediction · Traffic flow prediction · Fuzzy comprehensive evaluation

1 Introduction

Urban traffic congestion has become a critical problem that not only reduces residents' life quality, but also restricts the sustainable development of society and economy [1, 2]. Nevertheless, urban traffic flow is complex and constantly changing, which is difficult to acquire the current and future traffic conditions. Especially, there are two major challenges that should be answered to perform urban traffic congestion prediction. Firstly, how to predict traffic congestion in large-scale urban areas? Secondly, how to improve the accuracy, instantaneity and stability of traffic congestion prediction simultaneously?

Fortunately, floating car, namely Global Position System (GPS)-equipped taxi, is an effective way to collect the real-time traffic data in a large-scale road network [3]. In addition, these ubiquitous mobile sensors have lower cost than the fixed sensors which collect data at fixed trunks or major intersections. From this point, we propose a novel method using floating car trajectory data to improve the overall performance of traffic congestion prediction.

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The proposed method includes Traffic Flow Prediction (TFP) and Congestion State Fuzzy Division (CSFD) modules. The former predict traffic flow parameters by using Particle Swarm Optimization (PSO) algorithm. The latter converts the predicted traffic flow parameters to citizens' cognitive congestion state using a Fuzzy Comprehensive Evaluation (FCE) method. Furthermore, TFP module is composed by three sub modules: Traffic Volume Prediction (TVP), Traffic Speed Prediction (TSP) and PSO. TVP sub module predicts the traffic volume, while TSP sub module is for predicting average speed. PSO sub module optimizes the punish coefficients and the multi-kernel functions' parameters of Support Vector Machine (SVM) in TVP and TSP sub modules. The reason for choosing PSO algorithm is that it can get the optimum solution in a short time with a low computing complexity which meets the performance requirements of congestion prediction in terms of accuracy, instantaneity and stability.

The rest of this paper is organized as follows. In Sect. 2, we present related works about urban traffic congestion prediction. Then, our proposed congestion prediction method is introduced in Sect. 3. In Sect. 4, experiment results are described. Finally, the paper is concluded in Sect. 5.

2 Related Work

Kong et al. [4] presented a systematic solution to efficiently predict traffic state by extracting the spatio-temporal average velocity from a large number of GPS probe vehicles. The method was based on a curve-fitting and vehicle-tracking mechanism. In order to improve the estimation accuracy, they calculated mean speed at road section from multi-source traffic data to estimate the traffic states [5]. Zhang et al. [6] proposed a weighted approach to estimate traffic state using GPS data by increasing the weights of recent velocity information. Li et al. [7] presented a hybrid learning framework to appropriately combine estimation results of freeway traffic density state from multiple macroscopic traffic flow models. Feng et al. [8] proposed a cooperative approach to estimate arterial travel time states including Bayesian and Expectation Maximization algorithms using GPS probe data. Shankar et al. [9] explored advantages of fuzzy inference systems to evaluate the level of road traffic congestion using traffic density and speed information.

Related to traffic flow and congestion prediction, Xu et al. [10] presented a spati-temporal variable selection method based on Support Vector Regression (SVR) model to predict traffic volume. In this method, the spatial and temporal information of all available road segments was taken into account. Hong et al. [11] presented a SVR traffic flow forecasting model using Gaussian Radial Basis Function (RBF) kernel. In this method, a hybrid Genetic Algorithm (GA) with Simulated Annealing is used to forecast the RBF suitable parameters accurately. Li et al. [12] applied SVR model with Gauss loss function (Gauss-SVR) to forecast urban traffic flow and they proposed a Chaotic Cloud Particle Swarm Optimization algorithm to optimize the parameters of Gauss-SVR model. Wang and Shi [13] proposed a traffic speed forecasting model using chaos–wavelet analysis and SVM to choose the appropriate kernel function. Wang et al. [14] proved that selecting the appropriate SVR parameters improve the prediction of traffic flow in terms of the instantaneity and accuracy performance metrics.

The discussed methods above only considered one kernel function of SVM to improve the accuracy of urban traffic state prediction, while the road traffic congestion cannot be predicted by these methods accurately. The reason is that various SVM kernel functions have different prediction accuracy and adaptability. In addition, the predicted traffic flow cannot intuitively forecast the future traffic congestion for travelers and traffic administrators. To tackle these shortcomings, Chen et al. [15] proposed an accurate particle filter method to predict multi-step traffic state using speed measurements. Similarly, Dunne and Ghosh [16] proposed a regime-based multivariate traffic condition prediction method using an Artificial Neural Network (ANN) structure with adaptive learning strategies. Min and Wynter [17] presented a scalable multivariate spatial-temporal autoregressive model to predict the traffic volume and speed jointly. Zhang et al. [18] proposed a robust traffic congestion prediction method based on hierarchical fuzzy rule-based systems and GA, which combines the variable selection, ranking and lateral tuning of the membership functions with optimization of the rule base.

Closely related to traffic congestion estimation and prediction, Herring et al. [19] proposed two statistical learning algorithms which uses data from GPS-equipped smart phones. In this method, logistic regression and spatio-temporal auto regressive moving average models are employed to estimate and forecast the arterial traffic conditions. Castro et al. [20] proposed a method to construct a model of traffic density based on large scale taxi traces, and used the model to predict future traffic conditions according to the probabilistic transition matrix. To conduct a comprehensive and accurate traffic flow analysis, Zhou et al. [21] proposed a traffic condition estimation and prediction method based on Least Squares Support Vector Machine (LS-SVM) classification and regression using the floating car data.

The above-mentioned methods have not considered the traffic capacity as well as the spatial information of the roads. In addition, most of them only have considered one single performance metric and there is a lack of a systematic method to address accuracy, instantaneity and stability at the same time. In order to tackle this issue, we propose a new method to predict traffic congestion to improve the three performance metrics simultaneously. In the next section, we will describe our proposed method in detail.

3 Traffic Congestion Prediction

In this section, we describe the proposed congestion prediction method, which includes TFP and CSFD modules. TFP module is used to predict the traffic flow parameters and consists of TVP, TSP, and PSO sub modules. TVP sub module is used for predicting traffic volume, while TSP sub module is used for predicting average traffic speed. And PSO sub module is applied to optimize the punish coefficients and the parameters of the multi-kernel functions of SVM in TVP and TSP. Furthermore, CSFD modules converts the predicted traffic flow parameters to citizens' cognitive state with the help of FCE method.

In our method, SVM and PSO algorithms are chosen as optimization methods. This is because SVM has effective nonlinear mapping and generalization abilities, and SVM can solve small sample, over learning and local minimum problems, while PSO is a heuristic algorithm that has an advantage in search speed and stability. Our method can benefit from these excellent features.

3.1 The TFP Module

TFP module includes TVP, TSP, and PSO sub modules. In TVP and TSP sub modules, we use LIBSVM library [22] to calculate ε-Support Vector Regression (ε-SVR). The regression function for prediction is calculated using Eq. (1) as follows:

$$y = f(x) = \sum_{i=1}^{N} \left(a_i - a_i^*\right) K(x_i, x) + b \tag{1}$$

where a_i, a_i^* are the Lagrange multipliers related to punish coefficient c. $K(x_i, x)$ is the kernel function, and b is the bias.

In addition, we use linear in Eq. (2), and radial basis function (RBF) in Eq. (3) as the kernel function $K(x_i, x)$ of Eq. (1) respectively.

$$K(x_i, x) = (x_i \times x) \tag{2}$$

$$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right) \tag{3}$$

Most of the existing congestion prediction methods such as [10–14] only consider one kernel function: linear, polynomial, or RBF. Different from these methods, our proposed TFP module considers multiple kernel functions since different kernel functions have different prediction accuracies and fitting abilities.

The TVP Sub Module. Assuming that the current time is denoted by t, we aim to predict the traffic volume of time $t + 1$ at some road sections. The input variables include six parameters AS_{t-2}, AS_{t-1}, AS_t, Vol_{t-2}, Vol_{t-1}, Vol_t and the output variable is Vol_{t+1}. Among these, AS_i indicates the average speed of time i, and Vol_i indicates the traffic volume of time i. Then, the TVP model is trained considering the punish coefficient c and multiple kernel functions. At last, the TVP model is tested using the real floating car data.

The TSP Sub Module. Training and testing methods in TSP sub module are similar to those in TVP sub module, except that the input variables in TSP include Vol_{t-2}, Vol_{t-1}, Vol_t, AS_{t-2}, AS_{t-1}, AS_t and the output variable is AS_{t+1}.

The PSO Sub Module. In this module, we aim to optimize the punish coefficient c and multiple kernel functions based on kernel parameters of the SVM model in TVP and TSP sub module.

- Firstly, we determine the parameters of PSO algorithm such as maximum evolution number, maximum population number, cross validation number, the range of punish coefficient *c*, the corresponding kernel parameter *kp* of the selected kernel function, the position and speed of the particle swarm, etc. In this module, the parameters *c* and *kp* are selected as the position of the particle swarm.
- Secondly, the parameters *c* and *kp* of the current particle are selected as *pbest*, and the optimal value of all particles as *gbest*. Then, the fitness function value is identified in order to construct and update the position and speed using Eqs. (4) and (5) [23] as follows.

$$v_i(t+1) = \omega \times v_i(t) + c_1 \times r_1 \times (p_{best} - x_i(t)) \\ + c_2 \times r_2 \times (g_{best} - x_i(t)) \tag{4}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

- Thirdly, if *pvalue* is better than *pbest*, set *pbest* = *pvalue*.
- Fourthly, if *gvalue* is better than *gbest*, set *gbest* = *gvalue*.
- Finally, if the evolution number reaches the maximum value, the optimization stops. Otherwise, the procedure returns to the second step.

After PSO optimizes the parameters of SVM in TVP and TSP sub modules, it transmits the parameters back to TVP and TSP. Then, the traffic volume and average traffic speed are predicted in case different kernel functions are selected in the SVM model. We compare the predicted traffic volume in the case of different kernel functions in the SVM model of TVP and select the best result with minimum error. The TSP sub module follows the same process to obtain the best result. In addition, the corresponding kernel parameters in the SVM improve the prediction accuracy and ensure the real-time performance.

3.2 The CSFD Module

We calculate traffic volume and average traffic speed values using TFP which we have introduced in the preceding section. However, the congestion state fuzzy division cannot be performed directly since the predicted parameters do not characterize the traffic congestion state accurately. Considering the length, the lane number of the road section and traffic volume, we calculate the traffic density. Then, the road saturation is calculated using traffic capacity and traffic volume. Finally, congestion state division is applied with the following FCE method using road saturation, traffic density, and average traffic speed.

Traffic Congestion Factor and Evaluation Sets. The traffic congestion factor sets are expressed as $U = \{u_1, u_2, u_3\}$ corresponding to the road saturation, traffic density, and traffic speed. The evaluation sets are also expressed as $V = \{v_1, v_2, v_3, v_4, v_5\}$ corresponding to 'very smooth', 'smooth', 'mild congestion', 'moderate congestion' and 'serious congestion'. Moreover, we denote that $u_1 (or\ u_2) \rightarrow \{v_1, v_2, v_3, v_4, v_5\}$ and $u_3 \rightarrow \{v_5, v_4, v_3, v_2, v_1\}$, which mean that the smaller road saturation (or traffic density) indicates the lighter traffic congestion, while the smaller road section average speed indicates more serious traffic congestion.

Determining Weights of the Evaluation Factors. The weights of each evaluation factor is expressed as $W_a = \{w_1, w_2, w_3\}$ and $W_b = \{w_4, w_5\ w_6\}$.

Performing the Single Factor Fuzzy Evaluation. For the i_{th} factor in factor set U, we get the membership r_{ij} of the j_{th} evaluation in evaluation set V through the trapezoidal membership function. The single factor fuzzy evaluation set is expressed as $R_i = \{r_{i1}, r_{i2}, r_{i3}, r_{i4}, r_{i5}\}$ in Eq. (6).

$$R = \begin{pmatrix} R_1 \\ R_2 \\ R_3 \end{pmatrix} = \begin{pmatrix} r_{11} & r_{12} & r_{13} & r_{14} & r_{15} \\ r_{21} & r_{22} & r_{23} & r_{24} & r_{25} \\ r_{31} & r_{32} & r_{33} & r_{34} & r_{35} \end{pmatrix} \tag{6}$$

Performing the Fuzzy Comprehensive Evaluation. After identifying the weights and performing the single factor fuzzy evaluation, the fuzzy comprehensive evaluation matrix B is calculated using a fuzzy transformation based on Eqs. (7) and (8) as follows:

$$\begin{aligned} B = W \circ R = W \circ & \begin{pmatrix} r_{11} & r_{12} & r_{13} & r_{14} & r_{15} \\ r_{21} & r_{22} & r_{23} & r_{24} & r_{25} \\ r_{31} & r_{32} & r_{33} & r_{34} & r_{35} \end{pmatrix} \\ = (b_1, b_2, b_3, b_4, b_5) & \end{aligned} \tag{7}$$

$$b_j = \sum_{i=1}^{n} w_i \times r_{ij}, \quad i = 1, 2, \ldots, 6, \ \ j = 1, 2, \ldots, 5 \tag{8}$$

where $\circ$ is the fuzzy compositional operation and b_j is the fuzzy comprehensive evaluation index which means the membership of the jth factor of the evaluation object.

Determining the Traffic Congestion State. Based on the maximum membership principle, the biggest membership b_j is calculated as the final evaluation index b, namely traffic congestion state, as follows.

$$b = \max(b_1, b_2, b_3, \ldots, b_5) \tag{9}$$

4 Experiment and Discussion

4.1 The Floating Car Data

The floating car data are the real traffic GPS data collected by 12,000 taxis in Beijing China over a period of one month (November 2012) [24]. The traffic data are recorded once per minute approximately. The format of a GPS data is showed in Fig. 1.

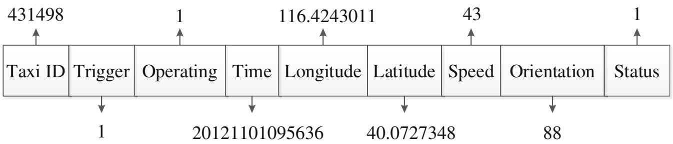

Fig. 1. Data format of a GPS data entry.

In experiments, we select a road section from Lian Hua Qiao to Liu Li Qiao at third ring near Beijing west railway station as the research area, of which exists seriously recurrent traffic congestion. We first preprocess the data in order to eliminate noisy sample points, of which perceived positions are chaotic. In the second step, the sample points with the same vehicle ID are linked to each other according to their time correlate on. Then, we capture the floating car trajectories on the urban road network space. In the next step, map matching is carried out according to the floating car trajectories, the latitude and longitude of the vehicles, and the urban geographic information. Finally, the traffic flow parameters are extracted in five minutes.

The traffic flow parameters include the traffic volume and traffic speed. The traffic volume is equal to the floating car number divided by a floating car detection ratio. The floating car detection ratio equals the total number of floating cars divided by the total number of vehicles on the road. Based on the annual report of Beijing traffic development in 2012 [25], the floating car detection ratio is 19 %. The traffic speed is equal to the average speed of floating car in five minutes. The average speed of each floating car trajectory can be acquired by GPS sample points.

4.2 Performance Indexes

We consider the performance indexes from the TFP and CSFD modules, which include the traffic flow prediction and congestion state division indexes. These concepts are identified in the rest of this subsection.

Traffic Flow Prediction Indexes. The prediction accuracy indexes include mean absolute error (*maerr*) and mean absolute relative error (*mareer*) as shown in Eqs. (10) and (11):

$$maerr = \frac{1}{N}\sum_{t=1}^{N} |p_{redict}(t) - R_{eal}(t)| \tag{10}$$

$$marerr = \frac{1}{N}\sum_{t=1}^{N} \frac{|p_{redict}(t) - R_{eal}(t)|}{R_{eal}(t)} \tag{11}$$

where P_{redict} denotes the predicted value and R_{eal} denotes the real value.

The real-time performance indexes include the time for training model and traffic flow prediction (*tptime*). The stability performance indexes are related to the process of the punish coefficient selection and the prediction accuracy.

Congestion State Division Indexes. The congestion state prediction accuracy is given by the formula that the prediction congestion states divide by the real congestion state. The real-time performance indexes include the time to perform congestion state division.

4.3 Traffic Flow Prediction

Through estimating the traffic congestion, we aim to induce travel cost and prevent congestion from further spreading. To this target, a congestion prediction method is applied, which includes the traffic flow prediction and the congestion state fuzzy division. Thus, we do experiments from these two aspects.

The traffic volume and traffic speed prediction results are explored in our experiments. We compare the results of prediction with different optimization techniques. Specifically, PSO optimization method is used in the RBF kernel function (PSO-R), as well as the linear kernel function (PSO-L) of SVM. In addition, GA optimization method is used in the RBF kernel function (GA-R), as well as the linear kernel function (GA-L) of SVM.

In order to evaluate the performance of PSO and GA optimization methods, their common parameters are set as follows: the maximum evolution number is 100, the maximum population number is 20, the cross validation number of SVM is 3, punish coefficient c is [0.1, 100], RBF kernel parameter is [0.01, 1000]. Moreover, the crossover probability and mutation probability of GA are set to 0.4 and 0.01, respectively.

We compare PSO-R, PSO-L, GA-R, and GA-L methods in terms of four evaluation metrics called *maserr*, *marerr*, *tptime* and stability, respectively. The evaluation results

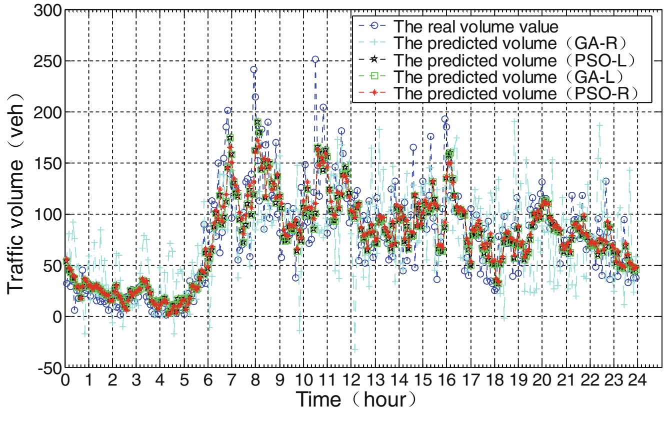

Fig. 2. Comparison among the real traffic volume and prediction results of proposed method with different optimization techniques.

Table 1. Performance comparison among different optimization techniques of proposed method about traffic volume prediction

Metrics	GA_R	PSO_L	GA_L	PSO_R
maerr	37.9212	22.2051	22.2027	21.5979
marerr	1.0464	0.5472	0.5476	0.5370
tptime	1.108 s	1.794 s	1.529 s	0.265 s
c, σ	0.18, 8.2	100, 0.1	91.84	100
Stability	No	Yes	No	Yes

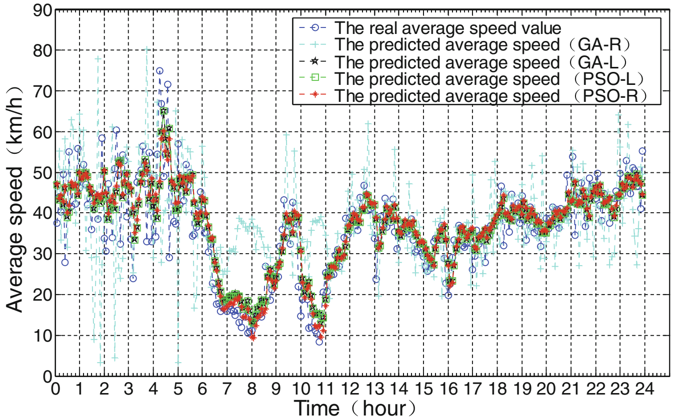

Fig. 3. Comparison among the real average speed and prediction results of proposed method with different optimization techniques.

Table 2. Performance comparison among different optimization techniques of proposed method about average speed prediction

Metrics	GA_R	PSO_L	GA_L	PSO_R
maerr	9.92	4.87	4.86	4.74
marerr	0.36	0.15	0.15	0.14
tptime	2.136 s	1.056 s	2.036 s	0.171 s
c, σ	91.4, 35.2	40.99	100	100, 0.1
Stability	No	No	Yes	Yes

for the traffic volume prediction are shown in Fig. 2 and Table 1. Similarly, the traffic speed prediction results are shown in Fig. 3 and Table 2. The evaluation results demonstrate that PSO-R has better performance in terms of the prediction accuracy and stability metrics. However, different kernel functions in SVM have different prediction accuracies and fitting abilities. We take advantages of the SVM multi-kernel functions to carry out experiments with the congestion state fuzzy division in the next subsection.

4.4 Congestion State Prediction

From the previous subsection, we can acquire the predicted traffic volume and average speed. Then, considering the length and lane number of road section as well as the traffic volume, the traffic density can be acquired with the help of Google Earth. The experiment area is 1.127 km^2 with 8 lanes. The road saturation can also be calculated using the traffic capacity and traffic volume. We acquire the traffic capacity from China highway capacity manual, which defines that the maximum traffic capacity of multi-lane highway designed with 80 km/h is 1800 pcu/h/lane. In other words, the maximum traffic capacity of the explored road in this paper is 150 pcu/5 min/lane. At last, the congestion state division in our proposed FCE method is performed using the road saturation, the traffic density, and the traffic average speed. Accordingly, the weight sets are assigned as $W_a = [0.43, 0.27, 0.3]$ and $W_b = [0.23, 0.17, 0.6]$.

In this step, we present our experiment results of traffic congestion state prediction using the PSO optimization method in SVM by selecting the RBF kernel function (PSO-SVM-R), the linear kernel function (PSO-SVM-RL), genetic algorithm optimizing SVM selecting RBF and linear kernel function (GA-SVM-RL).

We compare PSO-SVM-R, PSO-SVM-RL, and GA-SVM-RL methods in terms of accuracy, instantaneity, and stability metrics. In order to analyze the results of traffic congestion prediction before and after morning and evening peak accurately, one day is divided into five periods which are before morning peak (befmor), morning peak (mor), between morning and evening peak (betmoev), evening peak (eve), and after evening peak (afteve). The evaluation results for the congestion state prediction are shown in Figs. 4, 5 and 6, as well as Table 3.

In summary, the following results are concluded from our experiments:

- The PSO-SVM-RL method has better prediction accuracy than the PSO-SVM-R method, especially in the morning and evening peek.
- The PSO-SVM-RL method outperforms the GA-SVM-RL in terms of prediction accuracy, real-time and stability.

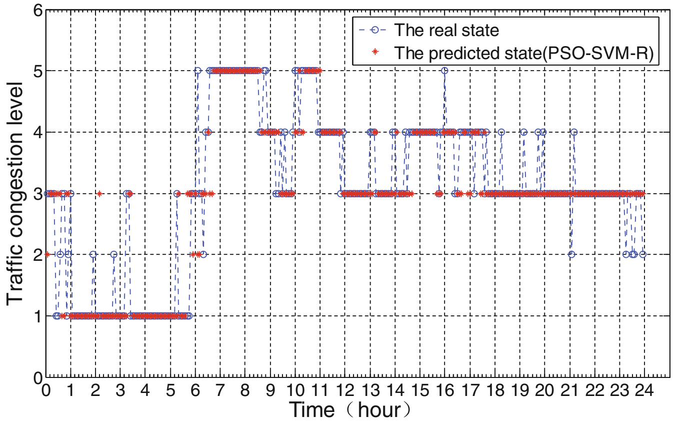

Fig. 4. Comparison between the real congestion state and prediction result of proposed method with PSO-SVM-R.

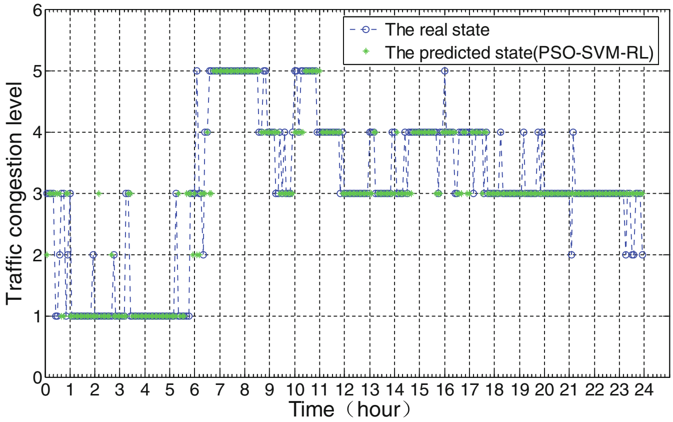

Fig. 5. Comparison between the real congestion state and prediction result of proposed method with PSO-SVM-RL.

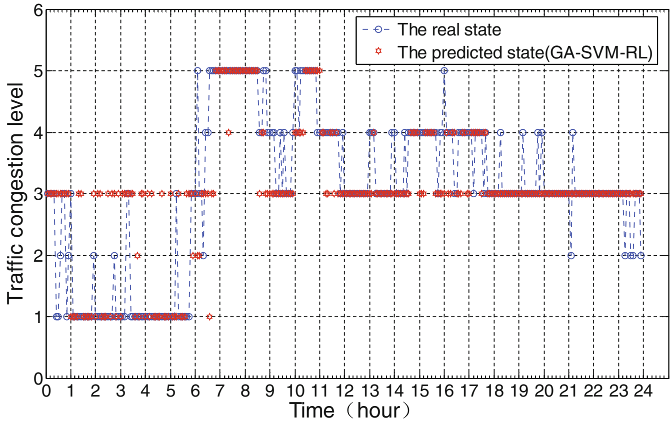

Fig. 6. Comparison between the real congestion state and prediction result of proposed method with GA-SVM-RL.

Table 3. Performance comparison among different optimization techniques of proposed method about traffic congestion prediction

Metrics	GA-SVM-RL	PSO-SVM-R	PSO-SVM-RL
Accuracy	67.25 %	74.22 %	74.91 %
befmor	53.57 %	70.24 %	69.05 %
mor	75.0 %	87.5 %	87.5 %
betmoev	62.5 %	67.71 %	68.75 %
eve	83.33 %	75 %	83.33 %
afteve	84.75 %	84.75 %	84.75 %
Real-time	6.094 s	0.701 s	4.695 s
Stability	No	Yes	Yes

- Both the PSO-SVM-RL and PSO-SVM-R methods outperform the GA-RL method in all the performance metrics.
- The PSO optimization method has better performance on the multi-kernel function of SVM rather than the single kernel function.

The PSO optimization method has better performance on the multi-kernel and single kernel function of SVM in comparison to the GA optimization method.

5 Conclusion

In this paper, we propose a novel traffic congestion prediction method in large scale urban areas which has an advantage in accuracy, instantaneity and stability simultaneously. In order to predict traffic congestion more efficiently, the PSO optimization method is used to optimize the punish coefficients and multiple kernel functions' parameters of SVM in the process of predicting traffic flow parameters. In addition, the FCE method is responsible for helping citizens to make sense of the traffic congestion state based on the predicted flow parameters. In the future, we plan to further improve the comprehensive performance and take more factors into account.

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